

Making a Difference?

The Role of Social Impact in College Major Choice*

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Abstract

Work is not only a means of earning a living, it can also be a source of meaning through the contribution people feel they make to society. Because the choice of academic major largely shapes future career paths, we ask: do students hold accurate perceptions of how fulfilling different fields are in terms of social impact, and how do these perceptions shape major choices? We address these questions through a survey experiment at a large U.S. public university. We find that students substantially underestimate how satisfied previous graduates report being with their contribution, with significant heterogeneity in the extent of underestimation by field. These beliefs are consistent with stereotyping: students believe that graduates in fields such as Health and Social Sciences are much more likely to be satisfied with their contribution than graduates in Physics & Mathematics or Computer Science, while nationally representative data on college graduates shows the gap is much smaller. We show that randomly providing information on previous graduates' experiences of impact across all fields significantly shifts students' perceptions, with revisions proportional to their initial misperceptions. These revised beliefs lead students who value societal contribution to recommend a broader set of majors to like-minded peers. We see more limited effects on students' intentions and class enrollment, with significant changes in intentions only among women, who value social impact most and shift toward fields whose social impact they had underestimated.

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1 Introduction

In modern societies, work is one way individuals shape their community. Each occupation contributes to collective welfare in its own manner and measure, and workers from various academic backgrounds seem to agree: in the latest U.S. National Survey of College Graduates (NSCG), most respondents report being satisfied with the contribution to society of their current job, and this holds not only for graduates in Nursing & Health Sciences, but also for those in Physics & Math and Computer Science. This raises a fundamental question: how do individuals yet to start a career, namely students, perceive the contribution to society of different career paths?

When students think of impactful work, only a narrow set of occupations tends to come to mind. When we asked undergraduates to name jobs that make meaningful contributions to society, the majority mentioned jobs in healthcare, with doctors and nurses by far the most common answer, followed by teachers; very few mentioned a job in software or IT, and only one student, out of more than six hundred, mentioned mathematicians. These beliefs may drive students away from fields where they expect to feel little sense of contribution to societal well-being, even when such potential is in fact present.

The aim of this study is to measure these beliefs directly and to test whether correcting them changes students' intended choices. We combine three components. First, we incorporate social impact concerns into a theoretical model of college major choice. Second, through a survey experiment in a large state university in the U.S., we document whether and to what extent students value the contribution to society of their future job, and we elicit their beliefs about the sense of impact they expect from the careers associated with different majors. We find substantial heterogeneity across disciplines in these expectations, and that students substantially underestimate how satisfied graduates report being with their societal contribution, particularly in certain fields. Third, we test the model's predictions by providing a randomly selected subset of students with accurate information about previous graduates' experienced impact, and examining whether and how the resulting changes in beliefs influence their major choices.

Where do these biased beliefs come from? The stereotyping framework of [Bordalo et al. \(2016\)](#), applied to the same NSCG data, offers an answer. While the share of dissatisfied graduates is low in every field, in Computer Sciences it is about three times higher than in Nursing & Health Sciences. As a result, Nursing & Health Sciences and Education are the majors most representative of graduates reporting high satisfaction with their contribution to society, whereas Computer Sciences and Mathematics are relatively more represented among the small share who report being dissatisfied. Because stereotypes overweight the most representative types, students may exaggerate these differences, magnifying gaps between fields of study.

These biases are worth studying given the importance of social impact beliefs. A growing literature shows that a sense of contributing to society is an important job feature for most students and workers, and especially for women (Dur and Van Lent, 2019; Chandler and Kapelner, 2013; Carpenter and Gong, 2016; Burbano et al., 2024b). Yet, while much is known about such preferences, far less is known about the beliefs through which they translate into choices. It is this belief side that our study brings into the picture. College students are an ideal population in which to study these beliefs: choosing a major is one of the first pivotal decisions in building a career, with lasting consequences for graduates' later prospects (Kirkeboen et al., 2016; Arteaga, 2018; Hastings et al., 2013; Bleemer and Mehta, 2022). The setting is also relevant for gender gaps: the fields that come to mind first when thinking about social impact are female-dominated and the neglected ones male-dominated, suggesting that impact considerations may matter for understanding occupational segregation (Burbano et al., 2024a,b).

Our survey experiment takes place at The Ohio State University (OSU), with first- and second-year students. First, after asking for their prior major intentions, we elicit students' preferences over several future job attributes, including contribution to society. Second, to measure their perceptions of social impact, we ask both how satisfied they expect to be with their own contribution to society under each of several majors (self-beliefs) and how satisfied they believe previous graduates in each field currently are with theirs (population beliefs).

We find that most students report valuing contribution to society when thinking about a job, and they are willing to trade off about 20% of their future salary for a job that provides a sense of purpose through its social impact. Consistent with previous literature (Burbano et al., 2024a,b), we find that women rate contribution to society as important or very important significantly more often than men: almost 60% of women say it is very important, compared to 35% of men. Moving to their beliefs, students' expected satisfaction with societal contribution is highly field-dependent, and these expectations are correlated with their second-order beliefs about how previous graduates feel about their own contribution. Comparing population beliefs against actual graduates' satisfaction, students systematically underestimate the extent to which graduates report being satisfied with the societal contribution of their jobs across all majors, with the largest misperceptions concentrated in three fields: Business, Economics & Management, Physics & Mathematics and Computer Sciences. Students exaggerate how much fields differ in the sense of contribution reported by previous graduates, even though the ranking they hold is correct—a pattern consistent with stereotyping. While the gap in the actual data between the highest-satisfaction majors (Nursing & Health Sciences and Education) and the lowest (Business, Economics & Management and Computer Sciences) is 15 p.p., in students' beliefs it widens to 41 p.p.

To better understand how beliefs about social impact shape college major decisions, we formalize the role of social impact in a theoretical framework. Social impact enters students'

expected utility through both preferences and beliefs: specifically, through the weight a student places on societal contribution and through their perceived probability of being satisfied with the contribution of the potential career paths following each major. These beliefs vary across majors and depend on the expected level of contribution in that field and on the student's own threshold for feeling satisfied. We allow this threshold to differ from that of graduates already working in the field: a student who cares strongly about contribution may hold themselves to a higher standard than the typical graduate, so their self-beliefs about satisfaction may not map directly onto observed satisfaction rates among graduates. Whether information about other graduates can nonetheless shift these self-beliefs is an empirical question we can test in our experiment. When it does, we use the model to derive predictions for how a revision in beliefs should translate into major choices. In particular, students who place a positive weight on societal contribution should reallocate their intentions toward the majors for which their perceived impact increased the most.

Estimating this model on students' prior major intentions gives a revealed-preference measure of how much they value social impact and allows us to give a magnitude to the above predictions. Consistent with the stated-preference gap described above, the weight on social impact estimated independently from self-reported importance is substantially larger for women than for men ($\bar{\theta}_W = 3.53$ vs. $\bar{\theta}_M = 2.05$, difference significant at the 1% level). Notably, this estimated weight rises with students' reported importance of contribution, and does so within both genders, confirming that it captures the preference they state directly in our survey. The estimates imply that a one-standard-deviation increase in the perceived probability of a satisfying contribution (25 p.p.) raises the model-implied probability of choosing that major by about 9 p.p. for women and 5 p.p. for men, comparable to a one-standard-deviation change in expected GPA (about 8 p.p.) and considerably larger than a one-standard-deviation change in expected salary (about 45%; roughly 1 p.p.). Finally, using the model to simulate a change in beliefs to the values reported by previous graduates in the NSCG, we predict a reallocation of major intentions for women who value contribution toward the most underestimated fields—Business & Economics, Physics & Math, and Computer Science—and away from those they already perceive as impactful, such as Social Sciences & Psychology and Health.

Our survey tests these predictions via an information intervention, designed to exogenously shift the perceived social impact in different fields. Specifically, treated students are provided with information on previous graduates in each major: the proportion of previous students satisfied with the contribution of their job, as reported in the National Survey of College Graduates, together with social-impact narratives collected from alumni at the same university.

First, we find that giving information about how previous graduates experience their societal contribution leads to significant revisions in students' expected likelihood of being satisfied with their own contribution under different majors. The intervention also reduces

stereotyping across majors over this dimension: the revision in self-beliefs is proportional to the prior population-level misperception. As the model anticipates, because the information concerns other people rather than themselves, students do not update one-for-one with their misperception; still, they revise their self-beliefs upward by at least 6 p.p. in every major, with an additional 4 p.p. for every 10 p.p. ($p < 0.01$) by which they had initially underestimated that major's share of satisfied graduates. As a result, the intervention reduces the dispersion in self-beliefs across majors: the gap between the most and least underestimated majors shrinks from about 32 to 18 p.p., a result that holds for both men and women and regardless of how much students value contributing to society.

Second, we assess whether and how these belief shifts translate into the primary outcomes we pre-registered: students' own major choices and the advice they give to peers. For their own academic choices, the model predicts that, following a belief revision, students who value contribution shift their intentions toward the majors they most misperceived and away from those they misperceived least. Our design allows us to isolate this revision-driven reallocation. Beliefs about social impact cannot be measured without prompting students to think about impact, and this alone may shift intentions toward the fields they already perceive as impactful. The control group students answer the same belief questions but receive no information, so any change in their intentions reflects salience rather than new information. Treated students differ only in that they also learn that a sense of contribution is present in every field. The comparison between the two groups therefore identifies the effect of belief revision, net of salience.

Consistent with those predictions, in our pre-registered regression the treatment effect on the stated probability of pursuing a given major is increasing in how much that major's social impact was underestimated relative to the student's own average underestimation. These effects are significant ($p < 0.05$) for the full set of students who report preferences for socially impactful careers.¹ This average, however, masks substantial heterogeneity. As pre-registered, we examine treatment effects separately by gender. We observe larger effects for women: treated women declare post-information a higher probability to pursue the most underestimated major and a lower probability to choose the least underestimated one. Specifically, controlling for prior intentions, treated women assign a 1.3 p.p. ($p < 0.01$) higher probability to the most underestimated major than control women, and a 2 p.p. ($p < 0.10$) lower probability to the least underestimated. Interestingly, this gap also reflects the shift we anticipated among control women: making contribution salient led those who value this dimension to move toward the fields they already perceive as most fulfilling, while treated women, whose perceptions the information corrects, did not change. In line with the survey itself bringing attention to this dimension, both treated and control students reported contribution as highly

¹Since our model predicts no reaction to the information for individuals who place no weight on this aspect, we pre-registered our analysis of treatment effects on academic choices for students who report contribution to society as important or very important.

top-of-mind while taking the survey, with no significant difference by treatment status.

Access to administrative data from OSU Registrar's office lets us test whether these changes in stated intentions persist in real academic choices. First, across all students, the number of credits enrolled for the coming semester in a given field is strongly associated with the post-treatment probability of pursuing that field, indicating that stated intentions map into behavior. As with intentions, the differences between treated and control students in class enrollment are concentrated among women who consider contribution to society as important. Looking at the aggregate effects by field, enrollment follows the same pattern as in intentions: treated students take more credits in Computer Science and fewer in Social Sciences & Psychology. These differences are marginally significant in the Registrar's snapshot of planned schedules before the semester starts, and they maintain the same sign but not the significance after the semester started. Treated women, who drive these differences, take more credits in the three most underestimated fields taken together (Business & Economics, Computer Science and Physics & Maths): about 0.6 additional credits in those three fields (14% of the control mean). As for declared programs, treated women who care about contribution are more likely to have declared a minor in Business, Management & Economics, one of the most underestimated fields, and less likely to have declared a major in Social Sciences & Psychology, one of the least underestimated. Both differences, however, come from a handful of students changing their declared majors and minors, so we read them as suggestive.

Information about social impact matters beyond student's own choices: making students believe they could be satisfied with their job's contribution across all fields of study is reflected in the type of advice they would give to similar peers. To make the advice consequential, students were told it would be shared with real peers we recruit, namely undergraduates choosing a major who want an impactful career. Treated students who value contribution recommend a more diverse set of majors to a like-minded peer. Specifically, when asked to rate from 1 to 10 how strongly they would recommend each major to such a peer, treated students give significantly higher scores than the control group, and increasingly so the more a major's social impact is underestimated, consistent with the belief revision induced by the intervention. Notably, this effect does not differ by gender. Unlike students' own choices, where contribution is weighed against other considerations (a trade-off in which women appear to weight contribution more) the advice task fixes the peer's preferences on contribution alone, leaving no room for this trade-off. We use the recommendation task to isolate the effect of the intervention as it would operate absent any competing trade-offs that students may face for their own choices.

Our main contributions are three-fold. First, we provide novel evidence on the role of social impact in college major choice. A large literature studies the determinants of major choice (see the review by [Patnaik et al., 2021](#)), examining how students' preferences and expectations over job attributes shape their decisions, and documenting that students often hold inaccurate

beliefs about future career outcomes (Wiswall and Zafar, 2015; Bayer et al., 2019; Christian et al., 2024; Ersoy and Speer, 2025; Conlon, 2021; Conlon and Patel, 2026). Much less is known, however, about how students perceive the social impact of different fields; we document these beliefs and show that they, too, are inaccurate. As in Wiswall and Zafar (2015), we correct beliefs through an information intervention, but we target beliefs about social impact rather than more conventional job attributes as salary.

Second, our project speaks to the recent literature on meaning at work. Meaning at work refers to the sense of impact or purpose derived from and what is believed to be achieved as a result of a person's work (Brief and Nord, 1990; Cassar and Meier, 2018; Cassar, 2019). This literature defines meaningful work on four dimensions: three of them are derived from self-determination theory (autonomy, competence and relatedness) and the fourth one refers to beneficence, which is the one we focus on in this study. While current studies (Ariely et al., 2008; Burbano, 2016; Kahn and Ginther, 2017; Lee and Huang, 2018; Nikolova and Cnossen, 2020; Ashraf et al., 2020; Burbano et al., 2024b; Ashraf et al., 2024) highlight the importance of meaning at work for those already in the workforce, we explore the role of meaning—particularly its social dimension—in students' major choice.

Moreover, we find evidence of gender differences in social impact preferences, consistent with studies in the meaning literature (Grove et al., 2011; Burbano et al., 2024a,b) and with research in psychology showing that women are more interested than men in working with people rather than things (Su et al., 2009), a difference that helps explain why women's representation varies across STEM fields (Su and Rounds, 2015). These differences have important implications for gender segregation in the labor market (Cortes and Pan, 2018), given that the most misperceived fields in terms of impact are those with lower female representation and higher drop-out rates by women (Astorne-Figari and Speer, 2018, 2019; Kugler et al., 2021). Therefore, we also contribute to the literature on the underrepresentation of women in STEM and economics, and on the interventions tested to narrow this gap (Zafar, 2013; Kahn and Ginther, 2017; Li, 2018; Pugatch and Schroeder, 2021; Del Carpio and Guadalupe, 2022; Breda et al., 2023; Johnston et al., 2026). Our results show that young women already care about the social impact during college, and that this draws them away from fields seen as not impactful. Our experiment shows that providing information on the social impact of fields whose contribution students underestimate shifts women's intentions toward these fields, suggesting a low-cost way to narrow the gap.

When exploring students' beliefs on the perspective of having a socially impactful job, we also build on the literature on stereotyping (Gennaioli and Shleifer, 2010; Bordalo et al., 2016, 2019). Our work takes the theoretical foundations from this literature and brings them to the context of college major choice, where we test the presence of stereotypes regarding the societal contribution of different fields of study. Indeed, when comparing different fields, students may exaggerate their differences in post-graduation outcomes, thereby creating belief

distortions. [Conlon and Patel \(2026\)](#) find that students stereotype fields of study in terms of careers they map into, greatly exaggerating the likelihood that majors lead to their distinctive jobs. This bias may also apply to perceptions of social impact. Supporting this idea, research in psychology ([Diekmann et al., 2011](#); [Boucher et al., 2017](#)) suggests that students’ stereotypes shape their views of STEM fields as being less aligned with community well-being and more with individualistic goals. Our results are partly aligned with this evidence, since some of the fields students perceive as offering less sense of contribution are the most technical and abstract STEM fields. Providing information on how alumni perceive their own contribution may improve student understanding of the societal role of these fields.

Lastly, we speak to the vast behavioral literature that documents an association between social preferences and occupational choice, with more prosocial individuals working in the public sector or nonprofit organizations ([Buurman et al., 2012](#); [Gregg et al., 2011](#); [Fehr and Charness, 2025](#)) and less prosocial individuals moving toward sectors perceived as immoral ([Schneider et al., 2024](#)). We contribute to this literature by causally testing if the same association exists for the student population, by exogenously varying the perceived social impact of different majors.

This paper is organized as follows. Section 2 presents descriptive evidence from previous graduates on satisfaction with their current job’s contribution and discusses how these patterns create scope for stereotypical beliefs across majors. Section 3 introduces the theoretical framework and derives predictions on how social impact influences college major choice. Section 4 describes the experimental design implemented in the main survey, while Section 5 reports the results from the survey experiment. Section 6 concludes.

2 Social Impact Across Majors

This section documents how previous graduates feel about the contribution to society of their current job. We show how these feelings vary among different majors and how these differences may shape others’ beliefs about the societal contribution of different fields of study.

The National Survey of College Graduates (NSCG) is a nationally representative survey that examines the relationship between degree field and occupation, along with other characteristics of college-educated individuals in the U.S., including work activities, salary, and demographic information.² Graduates have to answer several questions about their current job and, in particular, they are asked the grade of satisfaction with several aspects: *“Thinking about the principal job you held during the week of February 1, 2023, how satisfied or dissatisfied were you with the following aspects of the job?”*. These aspects are: salary, benefits, job security, job location, opportunities for advancement, intellectual challenge, level of responsibility, degree of independence and contribution to society. For each of those, there are four possible answers

²The survey is conducted by the Census Bureau in partnership with the U.S. National Science Foundation every two years. In this paper, we use data from the most recent wave, conducted in 2023.

to this question: *very dissatisfied*, *somewhat dissatisfied*, *somewhat satisfied* and *very satisfied*. In the rest of the paper and in our main survey, we use as a measure of social impact being satisfied with contribution to society, which in the NSCG means being either somewhat or very satisfied. Figure A.1 shows the share of previous graduates aged 30 to 35 and currently employed full-time in 2023 who report being satisfied with their current job’s contribution, grouped by the most recent bachelor degree they earned.³ As one would expect, graduates in Nursing & Health Sciences and Education are the most satisfied with this job feature, followed by those in Biological & Life Sciences. However, it is worth noting that a large majority of graduates in other fields also report being satisfied. If we look at the full distribution of answers in Figure A.2, we see that it is quite similar across majors, with the main differences coming from the two extreme answers. Across all majors, few respondents report being *somewhat* dissatisfied with their job’s contribution, and even fewer report being *very* dissatisfied. For instance, according to the data, only 6% of Computer Sciences graduates report to be very dissatisfied with their job’s contribution to society, similarly to 5% of graduates in Business, Economics & Management and 4% in Physics & Math. However, these numbers are respectively four to six times the same statistics for respondents who graduated in Nursing & Health Sciences or Education. This pattern has the potential to create stereotypes: individuals overweight the frequency of a certain type when its relative frequency is much higher in that group than in the comparison group. In our specific case, we expect stereotypes to arise when students are comparing different fields of study. When comparing majors, in line with the framework of Bordalo et al. (2016), students may overweight the dissatisfied group for fields such as Computer Sciences, and underestimate the overall share of people in this field who are actually satisfied with their contribution.

Notably, when thinking about a job that contributes to society, the most representative types come to mind first (Gennaioli and Shleifer, 2010). In Figure 1, we formalize the stereotype logic with the 2023 NSCG data to measure how representative each major is of the group of graduates satisfied with contribution. We plot the distribution of fields of study of previous US college graduates for two distinct groups: those who feel satisfied with their job’s contribution to society (darker bars), group G , and those who feel not satisfied (lighter bars), the comparison group $-G$. For each major, we also plot the representativeness of that major for group G , which is defined as the likelihood ratio:

$$\frac{P(m|G)}{P(m|-G)}, \quad (1)$$

where $P(m|G)$ is the probability that a college graduate that is satisfied with their job’s contribution to society graduated in major m . As Figure 1 shows, there is a considerable number of

³Throughout the study we will group majors according to similarity to simplify the survey and the interpretation of results. Therefore, every time we refer to majors, we mean groups of majors. In Table A.1 we show the grouping of majors into categories.

graduates from different fields that are satisfied with their job’s contribution to society. However, the most representative types of the satisfied group are college graduates in Nursing & Health Sciences, followed by those in Education. Other groups such as Computer Sciences and Business & Economics are not representative of G.

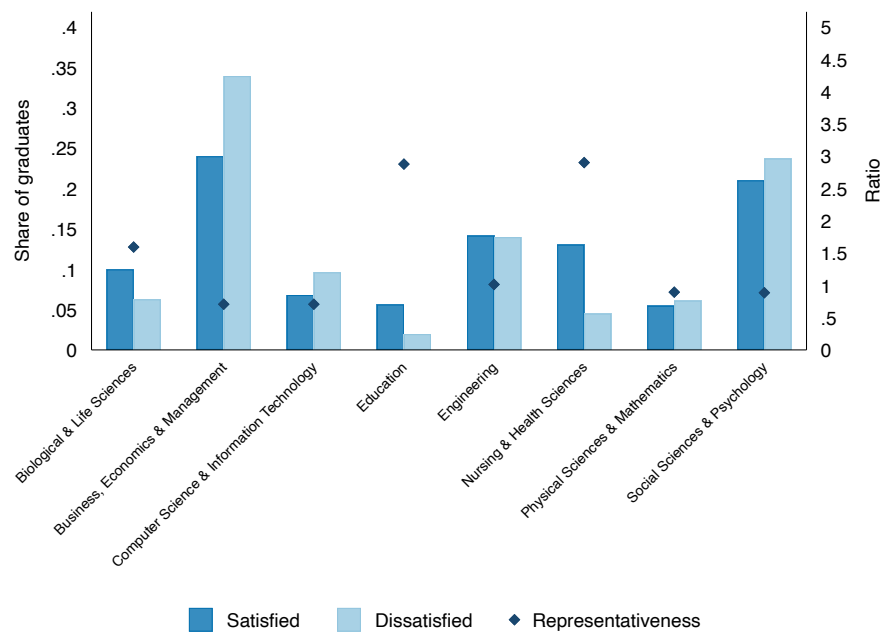


Figure 1: Representativeness of Majors for Satisfaction with the Job’s Contribution to Society

Notes: The graph shows the distribution of majors in which respondents from the 2023 NSCG graduated. The dark-blue bars represent the distribution for graduates who are satisfied with their current job’s contribution to society, while the light-blue bars show the same distribution for those who are not satisfied with this job attribute. The diamonds indicate the representativeness of each major for the group of satisfied graduates, defined as the share of the major among satisfied graduates divided by its share among dissatisfied graduates, with their values shown on the secondary y-axis on the right.

To see these stereotypes in action, we asked students to write down one or more examples of jobs they consider to contribute to society. The word cloud in Figure A.3 displays the most frequently cited terms in the answers to this open-ended question. Overall, almost 54% of students mentioned a health-related job (41% doctors or nurses), 35% mentioned teachers or educators, while only 4% mentioned computing jobs⁴, 0.3% (two students out of more than 600) an economist, and 0.2% (one student) a mathematician. These answers suggest that jobs typically following health and education studies, the most representative majors, come to mind first, as predicted.

Importantly, even looking at other job attributes, we do not see a pattern that could give rise to stereotypes as strongly as for contribution. Table A.3 reports the representativeness of each major for every job attribute in the NSCG. Only for contribution two majors reach

⁴Computing jobs include any mention of software, computers (e.g., computer scientists or computer engineers), programmers or coders, cybersecurity, IT, web development, artificial intelligence, and data science. Categories are not mutually exclusive, since students could list several jobs: a student naming both a doctor and a teacher is counted in both groups.

a representativeness close to three times that of the other fields. For the other attributes, at most one or two majors are somewhat representative of the group satisfied with that aspect, but never with such a large gap from the rest.⁵ This large gap arises because dissatisfaction with contribution is rare in every field (at most about one in five graduates, even in Computer Sciences and Business) but this small minority is very unevenly distributed across fields: it is almost absent among Health Sciences and Education graduates and over-represented among those in Computer Sciences and Business & Economics.

Two further features of the data are worth noting. First, there is no trade-off between how satisfied graduates are with their societal contribution and with their salary. This is not obvious a priori: fields where graduates are least satisfied with their contribution, such as Computer Sciences and Business & Economics, are also among those least likely to report being very dissatisfied with their salary (Figure A.4). Yet, as Table A.4 shows, at the individual level the relationship is, if anything, positive: it is positive and significant both when pooling graduates across fields and, for most majors, within field. Second, contribution is among the attributes most strongly associated with overall job satisfaction, second only to salary once field fixed effects are added (Table A.5). Though only correlational, this suggests that feeling one contributes to society is an important component of overall job satisfaction.

In this study, we use data from the last NSCG to elicit students' social impact beliefs about previous graduates in different majors and to construct a quantitative measure of the extent of these stereotypical views.

3 Theoretical Framework

As first step to understand the role of social impact in students' decision of major, we start by proposing a theoretical framework where we extend a standard model of college major choice⁶ to account for social impact. In this section we present such a model, that we estimate in Section 5.3 with the OSU students' answers in our survey.

Set-Up. A student i selects a major $m \in \{1, \dots, M\}$, where M is the number of possible majors. Given choice m , student i expects a probability $\tilde{\pi}_m^i$ to be satisfied with their contribution to society: in that case they will get a benefit from social impact of θ^i ; we distinguish this perceived probability from the true one in the next subsection. The expected utility of student i from choosing m is defined as follows:

$$EU^i[m] = \alpha_1 E^i[w_m] + \tilde{\pi}_m^i \theta^i + \alpha_2 E^i[GPA_m] + \mu_m^i + \epsilon_m^i. \quad (2)$$

⁵Although graduates are broadly satisfied across job attributes, not only with contribution, satisfaction does vary by dimension. Opportunities for advancement and salary show the lowest rates. For example, only 62% of Education graduates are satisfied with their salary (19% are very dissatisfied), and only 67% of Business & Economics graduates are satisfied with their opportunities for advancement (12% are very dissatisfied). This suggests that graduates do not rate every dimension highly. In Figure A.4, we report the full distribution of answers for salary.

⁶see for example Wiswall and Zafar (2018) and Conlon and Patel (2026)

According to Equation (2), student i 's expected utility from choosing m depends on some career-related features, namely wage w_m and social impact, and major-related features, which we simplify to be subjective ability in each major, captured by their expected GPA , and non-ability benefits from majoring in m , captured by μ_m^i . Social impact influences the expected utility through the weight student i puts on contribution, captured by θ^i —the higher θ^i the larger the influence of social impact on expected utility—and through the perceived probability of being satisfied with contribution, captured by $\tilde{\pi}_m^i$. We assume μ_m^i to be normally distributed and i.i.d. across students with mean μ_m and variance σ^2 , and ϵ_m^i to be a type 1 extreme value random variable i.i.d. across students and majors. Given these assumptions, we define individual i 's relative probability of pursuing major m rather than m' as:

$$\log \frac{q_m^i}{q_{m'}^i} = \alpha_1 \left(E^i[w_m] - E^i[w_{m'}] \right) + \theta^i \left(\tilde{\pi}_m^i - \tilde{\pi}_{m'}^i \right) + \alpha_2 \left(E^i[GPA_m] - E^i[GPA_{m'}] \right) + \mu_m^i - \mu_{m'}^i, \quad (3)$$

where the probability of choosing major m is denoted by q_m , and the probability of choosing major m' is $q_{m'}$.

Beliefs. To understand how social impact beliefs are shaped, we first start by defining the *actual* probability a student i has of being satisfied with their contribution after graduating in m , which we refer to as π_m^i and can differ from their *perceived* probability based on i 's available information, referred to as $\tilde{\pi}_m^i$. The first probability depends on the level of contribution they will actually have in that field. In particular, we assume π_m^i is a function of contribution c_m , where contribution c_m is a random variable that follows a normal distribution, i.i.d. across students, with major-specific mean and variance: $c_m \sim \mathcal{N}(\lambda_m, \sigma_m^2)$.

Individual i is satisfied with their job's contribution if the realized c_m is higher than a threshold, $\bar{c}^i$, which varies by individual. This threshold is positively related to individual's preferences for contribution θ^i :

$$\bar{c}^i = f(\theta^i).$$

Notably, the stronger the preferences for contribution, the more demanding is individual i about this job aspect: its social impact must be high to make them feel satisfied.⁷ Given this threshold, the actual probability that individual i is satisfied with their job's contribution after graduating in m is defined as:

$$\pi_m^i = \Pr(c_m > \bar{c}^i) = \Phi\left(\frac{\lambda_m - \bar{c}^i}{\sigma_m}\right). \quad (4)$$

⁷We assume that $\bar{c}^i$ cannot go above a certain value $\bar{c}_{max}$ and its first derivative with respect to θ^i is decreasing:

$$\frac{\partial \bar{c}^i}{\partial \theta^i} > 0 \quad \wedge \quad \frac{\partial^2 \bar{c}^i}{\partial (\theta^i)^2} < 0.$$

Equation (4) refers to the actual probability, meaning if individual i had the correct beliefs on the distribution of c_m . However, students may not have full information about the potential contribution in each field m . As a result, $\tilde{\pi}_m^i$, the *perceived* probability of being satisfied with job's social impact after graduating in major m , depends on i 's perceived average contribution $\tilde{\lambda}_m^i$ and their perceived variance of contribution $(\tilde{\sigma}_m^i)^2$. This is ultimately what is affecting student i 's expected utility in Equation (2). The perceived probability of being satisfied with contribution is therefore:

$$\tilde{\pi}_m^i = \Phi\left(\frac{\tilde{\lambda}_m^i - \bar{c}^i}{\tilde{\sigma}_m^i}\right). \quad (5)$$

As a consequence, the expected utility of choosing m ultimately depends on individual perceptions of how contribution is distributed across job's opportunities following a degree in m .

Selection. The goal of our intervention is to shift these perceptions by showing evidence from previous graduates in m . To this end, we need to take into account that students may internalize selection into different fields: individuals who care less about contribution may select into the fields students perceive as less impactful. Therefore, we first formalize the relationship between the probability that student i will be satisfied with societal contribution and the probability that people who already graduated in m are. We denote the latter as π_m^m :

$$\pi_m^m = \Pr(c_m > \bar{c}^m),$$

where $\bar{c}^m$ is the average threshold of contribution s.t. people who graduated in m are satisfied with it. As mentioned above, the threshold depends positively on contribution preferences θ . As a consequence, if, for example, student i thinks on average people in field m care less about contribution than they themselves do, it follows that student i thinks graduates in m hold a lower threshold than they do:

$$\mathbb{E}^i[\theta^j \mid q_m^j = 1] < \theta^i \quad \Rightarrow \quad \bar{c}^m < \bar{c}^i.$$

If this is the case, for a given distribution of $\tilde{c}_m$, i 's perceived probability that graduates in m are satisfied is larger compared to their own:

$$\tilde{\pi}_m^m = \Pr(\tilde{c}_m > \bar{c}^m) > \Pr(\tilde{c}_m > \bar{c}^i) = \tilde{\pi}_m^i. \quad (6)$$

In our survey students are asked both numbers: $\tilde{\pi}_m^m$ and $\tilde{\pi}_m^i$, so we will be able to see Equation (6) at play. The relationship between the two is important to understand the predicted effect of our intervention, where we give the true π_m^m . If individual i underestimated it, meaning $\tilde{\pi}_m^m < \pi_m^m$, our model can explain it in two ways: 1) $\bar{c}^m$ is misperceived, graduates in m care even less than what individual i thinks, meaning $\bar{c}^m < \bar{c}^i$ or 2) the distribution of c_m is misperceived, meaning that $\tilde{\lambda}_m$ and/or $\tilde{\sigma}_m$ differ from the true λ_m and σ_m . Only in the

second case, our intervention showing information on previous graduates shifts students' own probability of being satisfied with contribution $\tilde{\pi}_m^i$. Under case 1, learning the true graduate satisfaction tells i only that graduates care less (lower threshold), so i does not revise their own $\tilde{\pi}_m^i$; under case 2, it reveals the contribution distribution is better than i thought, so i revises $\tilde{\lambda}_m^i$ and/or $\tilde{\sigma}_m^i$ and hence their own choice.

3.1 Predictions

In this subsection, we briefly analyze the effects of a change in beliefs and preferences for social impact on individual choices, to formulate hypotheses to be tested with our experiment. Because the logit assigns every major positive probability, we state the predictions for interior choices.⁸ We start by considering a movement in beliefs. Suppose beliefs about contribution after a degree in m change, and specifically the chance of being satisfied with contribution increases, while beliefs about major m' and everything else stay the same. If $\theta^i > 0$, from Equation (3) we must have:

$$\tilde{\pi}_m^i \uparrow \Rightarrow \log \frac{q_m^i}{q_{m'}^i} \uparrow,$$

meaning the relative chance of pursuing m instead of m' increases. If m and m' are the only two majors available, then:

$$\Delta q_m^i > 0 \quad \wedge \quad \Delta q_m^i = -\Delta q_{m'}^i,$$

since the two probabilities need to sum up to one. Consider a more general case with M majors, where all beliefs shift upward:

$$\tilde{\pi}_1^i \uparrow \tilde{\pi}_2^i \uparrow \dots \tilde{\pi}_M^i \uparrow,$$

and the increase is such that:

$$\Delta \tilde{\pi}_1^i > \Delta \tilde{\pi}_2^i > \Delta \tilde{\pi}_3^i > \dots > \Delta \tilde{\pi}_M^i.$$

According to (3), it follows that the major with the largest shift in social impact beliefs gets a higher posterior probability:

$$\log \frac{q_1^i}{q_m^i} \uparrow \quad \forall m \neq 1 \quad \Rightarrow \quad \Delta q_1 > 0.$$

What happens to the other majors? Consider major 2, whose shift in beliefs was smaller than major 1 but still larger than other majors. If q_2 (the probability of choosing major 2) increases,

⁸In our estimation in Section 5.3 we consider all majors having at least a probability of 0.5%, so no major will have a probability of being pursued equal to zero. This is a mechanical result of the distributional assumption of the error term ϵ_m^i , which leads to the final functional form in Equation (3).

the relative change should be lower than that of major 1:

$$\frac{\Delta q_1}{q_1} > \frac{\Delta q_2}{q_2}.$$

If q_2 decreases, then other majors different than $m \neq 1, 2$ should diminish more than major 2 in relative terms:

$$\frac{|\Delta q_2|}{q_2} < \frac{|\Delta q_m|}{q_m} \quad \forall m = 3, \dots, M.$$

If q_2 stays constant, then all $m = 3, \dots, M$ must decrease. The same reasoning applies for major 3 and all the others whose shift in beliefs was lower. We can generalize this logic to understand how choices move as a consequence of any belief change. First, we need to order majors $m = 1, \dots, M$ according to the update in beliefs—about contribution in our case—from the highest to the lowest. Then, we identify the major with the lowest shift k^9 : for this major, the probability of pursuing it must decrease $\Delta q_k < 0$. All other majors whose belief shift is higher, will either move up or down but above the relative change in probability of pursuing k . More generally, in softmax form:

$$q_m^i = \exp(V_m^i) / \sum_{j=1}^M \exp(V_j^i) \Rightarrow \log q_m^i = V_m^i - C^i, \quad (7)$$

where $V_m^i = \alpha_1 E^i[w_m] + \theta^i \tilde{\pi}_m^i + \alpha_2 E^i[GPA_m] + \mu_m^i$ is the deterministic part of Equation (2) and $C^i \equiv \log \sum_j \exp(V_j^i)$ is common across majors. A belief shift changes only the $\theta^i \tilde{\pi}_m^i$ term in the utility function of pursuing m , hence:

$$\Delta \log q_m^i = \theta^i \Delta \tilde{\pi}_m^i - \Delta C^i. \quad (8)$$

For $\theta^i > 0$, $\Delta \log q_m^i$ is increasing in $\Delta \tilde{\pi}_m^i$: the order of (relative) choice revisions follows the order of belief revisions, and major m gains probability if and only if its shift exceeds the common threshold $\Delta C^i / \theta^i$, which in a first-order approximation equals the average shift across all majors (weighted by initial probabilities) $\sum_j q_j^i \Delta \tilde{\pi}_j^i$.¹⁰ Note that a major can lose probability even when its own social-impact belief rises: what matters is how its revision relates to those of other majors, not whether it is positive. This is a direct consequence of the probabilities summing to one: an overall upward shift in every belief brings choices toward the most revised majors. We can then formulate the first prediction of our model, which we will refer to as H1.

⁹Notice that the lowest shift can be positive, but smaller than all the other majors, or negative.

¹⁰Writing $\Delta C^i = \log \sum_j q_j^i \exp(\theta^i \Delta \tilde{\pi}_j^i)$ and expanding for small shifts we get:

$$\Delta C^i \approx \theta^i \sum_j q_j^i \Delta \tilde{\pi}_j^i \Rightarrow \frac{\Delta C^i}{\theta^i} \approx \sum_j q_j^i \Delta \tilde{\pi}_j^i.$$

H1. Shifts in beliefs about social impact move students with $\theta^i > 0$ towards the most revised majors: the order of revisions in choice follows the order of revisions in beliefs. Students increase the probability of pursuing majors whose belief revision exceeds the average shift; they decrease the probabilities of those below it.

In Appendix B, we also derive with a similar logic predictions under the scenario in which students become more interested in socially impactful careers, meaning they experience a rise in θ^i . Such a shift has a direct effect, for which students move toward majors they already perceive as impactful (according to the initial beliefs), and an indirect effect, since caring more raises the threshold for feeling satisfied and so lowers social-impact expectations. The indirect effect is larger for majors whose perceived contribution sits near the satisfaction threshold and barely touches those seen as clearly high-contribution, so under mild assumptions on how the threshold responds to preferences, the direct effect dominates. H2 states the final result.

H2. An upward shift in preferences for social impact moves students towards majors with a higher prior probability of contribution. The order of revisions in choice follows the order of priors in beliefs.

4 Experimental Design

The empirical setting of this project is Ohio State University (OSU), where we target freshmen and sophomore students. OSU provides the ideal setting for our experiment, as it reflects the broader structure of undergraduate degrees in the U.S. where students start college with the possibility of exploring different fields of study before having to declare the major in which they specialize. Moreover, as one of the largest state universities in the U.S., OSU enrolls a diverse student population and offers a great variety of majors across all the fields we include in our study, so our sample can cover a wide range of backgrounds and study options.¹¹ The survey took place between March and April 2026, before students start selecting classes for the next Fall semester. Students are contacted by email and receive an Amazon gift card of \$7.5 for completing the survey, and a randomized subsample of 30 students receive an additional gift card of \$30.

The survey includes five parts. The first one asks students about their current major intentions. The second one measures students' preferences for future job attributes, while the third captures their beliefs on the extent to which graduating from different majors leads to socially impactful careers. The fourth implements our key treatment by providing information to correct any distorted beliefs to a randomly selected group of students. Finally, after the information intervention, all students are asked again about their beliefs, their major intentions and to give an advice to other peers.

¹¹Ohio State University is the third biggest university in the U.S. by enrollment in the 2025-2026 academic year. In Spring 2026, when the survey was conducted, there were 49,757 undergraduate students enrolled. For our survey we contacted students who enrolled as first years at OSU in Fall 2024 or Fall 2025, corresponding to 21,175 students.

Prior Major Intentions and Top-of-Mind Beliefs. At the outset of our survey, students are asked to indicate their current (if already declared) or intended major and the likelihood of graduating in each major category¹². We refer to the probabilities to pursue each major in the list as prior major intentions.

We then ask students an open-ended question to understand the job characteristics they associate with each major, by asking them to think about the jobs they would get after that major and write down the aspects of those jobs that they would be satisfied with. Asked at the beginning of the survey, before students see any other content that could prime them, this question is designed to capture what is on top of mind for students when thinking about different fields of study, and together they provide an initial measure of how strong are stereotypes along the social impact dimension. We call these top-of-mind beliefs: they capture the extensive margin, that is, whether social impact comes to mind when students think about a given major.

Preferences. We directly ask students to individually rate the importance of several job attributes on a scale ranging from *not important at all* to *very important*. The attributes include items like their job's "contribution to society" and other well-studied attributes such as earnings and opportunities for career advancement¹³. To capture the relative importance of impact compared to earnings, we ask students for their reservation wages for a generic job and for an otherwise identical job that provides satisfaction from its contribution to society. We measure as willingness to pay (WTP) for social impact the reduction in wage students would be willing to accept for a job that makes them satisfied with its contribution. We randomize the order of the WTP question: in both the treatment and control groups, a random half of students answer it before the information stage and the other half after. This allows to test whether the treatment affects preferences for social impact.

Beliefs. After descriptively documenting preferences, we investigate more precisely perceptions about the contribution to society of potential career paths following different majors. While at the start of the survey we elicit an extensive-margin measure, the top-of-mind beliefs, capturing whether social impact comes to mind when thinking about each major, we then want to have an intensive-margin measure on how students see the potential sense of contribution they could have by pursuing different majors. As is common practice in the literature, we elicit both *self-beliefs* and *population beliefs*. Specifically, to measure self-beliefs, students are asked how likely they are to be satisfied with their future job's contribution to society if they successfully graduate in each major m of the list. To measure population beliefs, we also ask students to guess the share of previous graduates in each major m that are

¹²Throughout the study we group majors according to similarity to simplify the survey and the interpretation of results. In the survey, students are also shown the mapping between groups and corresponding majors before answering any question concerning majors. In Table A.1 we show the grouping of majors into categories.

¹³We use the same list of job attributes present in the NSCG described in Section 2: salary, benefits, job security, job location, opportunities for advancement, intellectual challenge, level of responsibility, degree of independence and contribution to society.

currently satisfied with their job’s contribution to society. As we also formalized in the model, the two beliefs can differ, but it is possible to measure accuracy, and provide information, only for population beliefs. To have a further measure of how students perceive the type of individuals selecting into different fields, we also ask students to imagine a world where people are randomly allocated to majors, regardless of their abilities and preferences, and to estimate the likelihood that an individual randomly allocated to a major m and graduated in that field would be satisfied with their job’s contribution to society. Respondents have to estimate this probability for each major in the list.

Treatment. Beliefs interact with preferences to determine major choice. If incorrect, beliefs can be influenced to some degree. With the use of our model of major choice described in Section 3, we can construct counterfactual scenarios in which we change beliefs and observe the consequences on students’ choices. However, one would want to test this in the real world, by providing actual information on the societal contribution experienced by graduates in different majors to students and see to which extent they shift their beliefs and, consequently, their choices. Given that these statistics concern other people, they may not have a 1:1 impact on students’ self-beliefs. As long as self and population beliefs are correlated, if the latter happen to be distorted, correcting them could ultimately change self-beliefs. This is the goal of the information intervention. Our student sample in OSU is randomly assigned to one of two groups: treatment and control.

Students in the treatment group see two types of information about the contribution to society reported by previous graduates in each major group. First, we provide the statistic that students had been asked to estimate earlier in the survey: the share of previous graduates in each major who report being satisfied with the contribution to society of their current job. Figure A.5 reproduces the first page shown to treated students, with the statistics drawn from the most recent NSCG. Students are also reminded of their answers. Second, following the statistics, we present short vignettes from previous graduates in each field, describing how they feel about their job’s contribution to society. As Graeber et al. (2024) show, stories are retained in memory longer than statistics; the vignettes therefore make the information more memorable and give students concrete examples of how graduates find a sense of impact in their work—something the statistics alone cannot convey. In Table A.2, we show the stories for all fields.

To build the vignettes, we run a survey with OSU alumni specifically, where we asked them their job title, the industry they work in, their role and how they feel they make a positive contribution, with the possibility of giving an example. We contacted 430 OSU alumni on LinkedIn,¹⁴ collecting 50 valid responses, distributed roughly equally across fields. To

¹⁴The alumni survey was not incentivized. So that the graduates whose stories we collected hold jobs representative of their field, we prioritized reaching alumni working in the ten most common industries for that field according to the last NSCG, but without restricting the sample to them only. As a result, these ten industries account for a substantial share of the alumni we contacted (at least 44% in every field).

standardize stories across fields, with the collected answers, we used Claude Opus 4.6 to summarize the testimonials of contribution in each field, mentioning three examples¹⁵ for each major group and keeping the same level of clarity, informativeness and engagement. Appendix C show the prompt we give to the LLM to generate the vignettes from our data. We also conducted a separate validation survey with 320 participants on Prolific, who rated each vignette on clarity, informativeness, and engagement. We find no statistically significant differences in ratings across major groups: results from our validation survey in Prolific are shown in Appendix Section D. Figure A.6 illustrates the page treated students see after the statistics: they need to click on each card and spend at least 10 seconds on it to be able to continue the survey. On the other hand, students in the control group receive information about college attainment in OECD countries. This follows the literature on information provision experiments (for a methodological revision see [Haaland et al., 2023](#)), where the idea is to have an active control group, which receives some kind of information unrelated to social impact. That way we can rule out the hypothesis that students might shift beliefs just by seeing *any* information.

Posteriors. After the intervention, all students, treatment and control, are asked again their self-beliefs, meaning how satisfied they expect to be with their future job’s contribution to society if they graduate in each major m . This allows us to measure self-beliefs updating and assess whether students updated their own expectations of impact, after they see what is the experience of previous graduates. If there is any updating, we expect the size of it to depend on the correlation between self- and population beliefs, and on how far off a student’s prior population beliefs were from the actual data. The more biased the initial belief, the greater the scope for learning.

Ultimately, we want to understand if this belief updating is also reflected in changes in students’ choices. We pre-registered two outcome measures. Our first outcome of interest is students’ major intentions, captured as the post-intervention probabilities they assign to graduating in each major listed in our survey. Another outcome of interest—measured in the survey—is the advice students give to a peer who is uncertain about their major and values social impact as a future job characteristic. Specifically, students are asked to assign each major a score from 0 to 10, reflecting how strongly they would recommend that major to such a peer.

Administrative Data. To assess the persistence of treatment effects on real choices, thanks to our collaboration with OSU, and with student consent, we also access administrative

¹⁵Although this procedure did not target occupational representativeness, in the fields whose social impact students most underestimate—Computer Science, Business & Economics, and Physical Sciences & Mathematics—the featured graduates hold jobs that are among the most common for their field in the NSCG (e.g., software developer, accountant, strategy/financial analyst, chemist, actuary, and data scientist), so the treatment cannot be dismissed as showcasing atypically impactful careers where it matters most. Examples in the other fields are likewise drawn from common occupations, with the exception of Education, where they fall outside the classroom, mostly given the types of graduates in this group who answered the survey; because Education is not a field whose impact students underestimate, this does not threaten the intervention’s validity.

records on students' declared majors, minors, and coursework, allowing us to analyze how updated beliefs influence students' ultimate academic decisions. In particular, we observe their academic plans, including majors and minors, and their class enrollments (with credits and descriptions of each class) in Fall 2025, Spring 2026 (the two semesters before and during the survey) and Fall 2026 (the semester after the survey)¹⁶.

5 Results

5.1 Sample

Our final sample comprises the 657 first- and second-year undergraduates at Ohio State University who passed all four attention checks embedded in the survey, as pre-registered.¹⁷ Table A.7 reports the main demographics of the final sample. Table A.8 summarizes their baseline characteristics by treatment status. The large majority attend the main Columbus campus (about 90%), with the remainder spread across five regional campuses. Roughly two-thirds are women (65%), the average age is about 19, and students are split fairly evenly between their first and second year, with only a small share further along. Prior major intentions are spread across fields, with Business & Economics and Engineering drawing the highest average probabilities, followed by Biology & Life Sciences, Nursing & Health Sciences, and Social Sciences & Psychology. Most students are still unsure about their intended major (about 70%), meaning they do not assign a 100% probability to pursue only major category listed in the survey.

Randomization produced a well-balanced sample: the treatment and control groups are not statistically different on campus, gender, year of study, stated importance of contribution, and prior major intentions in nearly every field (Table A.8). Only two differences are significant. First, treated students are about 0.2 years younger on average ($p < 0.05$), a gap that is statistically significant but negligible in magnitude. Second, they assign a higher prior probability to Engineering. Because this difference is in pre-treatment intentions, and we control for prior intentions throughout our analysis of post-intervention choices, it does not threaten identification; no other field shows a significant imbalance.

Of the initial 977 randomized respondents, about one third failed at least one of the four attention checks and are excluded.¹⁸ The included and dropped groups look similar on observables (Table A.6), with one exception that matters for identification: control students are somewhat more likely to be dropped than treated students. This gap comes entirely from the

¹⁶We use again a LLM model (Claude Opus 4.6) to classify classes into the major categories, using their title and their description. Notice, a class such as *Calculus for Business* is classified as Business & Econ, not as Mathematics.

¹⁷Our sample size is comparable to that of other information experiments on college major choice (Wiswall and Zafar, 2015; Conlon and Patel, 2026; Conlon, 2021), two of which were also conducted at OSU.

¹⁸The four checks confirm: the respondent understood that the self- and population-belief questions were about contribution, understood the source of information (a separate comprehension question in each arm), and passed an attention check embedded in an image.

single check that differs across arms, the information-comprehension question, which control students fail more often; the three symmetric checks show no differential attrition.¹⁹ When we screen only on the three symmetric checks, attrition is balanced across arms ($N = 708$; Table A.38), and our main results on this larger sample, reported in Appendix E, are unchanged.

5.2 Preferences and Prior Beliefs

We ask students about their preferences regarding different job attributes to assess the extent to which they value potential social impact. Figure 2 shows that most students consider their future job's contribution to society either *somewhat important* or *very important*, while only 15% do not consider it important. We also find significant gender differences in these preferences: 90% of women consider contribution to society somewhat or very important, compared with 77% of men ($p < 0.01$). Moreover, 56% of women rate it as very important, against 35% of men ($p < 0.01$), as shown in Figure A.7.

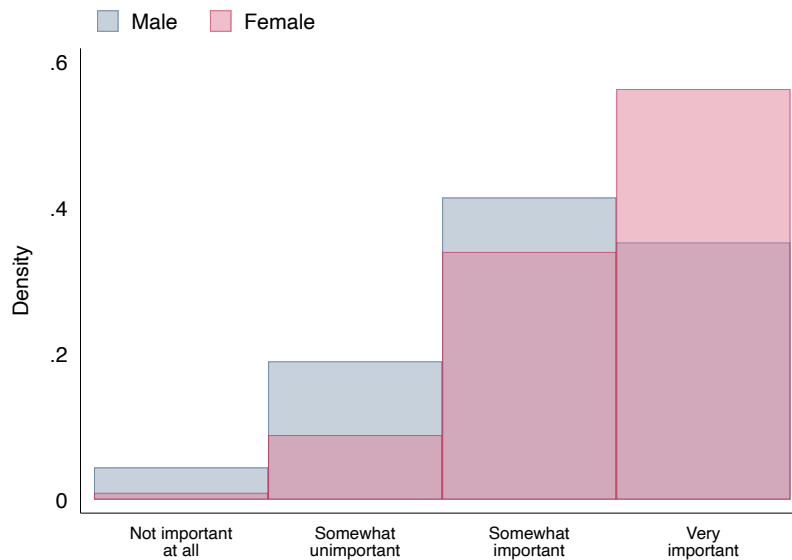


Figure 2: Distribution of Importance for "Contribution to Society"

Figure 3: Preferences for Social Impact

Notes: This Figure shows the distribution of students' answers for the question "When thinking about a job, how important is each of the following factors to you?" when asked about "contribution to society".

Additionally, our measure of willingness to pay (WTP) for social impact, defined as the percentage reduction in earnings students would accept in exchange for a job that makes them feel satisfied with their contribution to society, has a pre-treatment average of 22% (in terms of the minimum salary students would be willing to accept, this amounts to about \$3,551 per year), indicating that students are willing to forgo about one-fifth of their earnings for such a

¹⁹This question was asked after respondents were told what they would see but before any information was displayed, so failing it reflects baseline inattention rather than a reaction to the treatment, and excluding these respondents does not condition on a post-treatment outcome.

job. Figure A.7 shows gender differences for this measure as well, using only students who were asked prior to the information intervention. The difference in the percentage measure is about 2 p.p. (23% for women versus 21% for men) and is not statistically significant. Expressed in dollars of the minimum acceptable salary declared by students, the gap is about \$1,300 per year (women \$4,007 versus men \$2,672) but is likewise not statistically significant at conventional levels.²⁰ We also note this measure is quite noisy, ranging over the full 0–100 scale with a standard deviation of about 21 on a mean of 24.

The focus of our survey is on understanding students’ beliefs about the potential sense of contribution associated with careers in different fields. As a first step, we want to see whether students mention this job characteristic when not primed to think about it. The responses to the top-of-mind (or extensive-margin) question introduced in Section 4 are reported in Figure A.8, where the share of students mentioning something related to social impact is represented for each major. A large language model (Claude Opus 4.6) coded answers as mentioning social impact if they refer to a positive impact on society, such as helping people or communities, improving others’ well-being, addressing social problems, or contributing to society. This figure reveals that most respondents think about social impact as a motive to choose Nursing & Health Sciences (66%), Education (45%) and Social Sciences & Psychology (41%). On the other hand, less than 10% mention something related to contributing as a reason to pursue Business & Economics, Computer Science or Physics & Math.

To quantify more precisely the perceptions of potential social impact after graduating in different majors, we look at the answers to the intensive-margin question, where for each major students are asked how likely they are to be satisfied with their job’s societal contribution and to estimate the share of previous graduates who are satisfied with their current job’s contribution. Figure 4 reports the answers to these questions together with the true numbers from the national survey. First, self and population beliefs are closely related: Table A.9 confirms that the two are significantly correlated. The believed probability of being satisfied after graduating in a major is also correlated with the believed probability that a random individual would be satisfied if they were to successfully pursue that major.²¹ However, students seem to internalize a form of selection for the majors perceived as less socially impactful: they guess that graduates who chose those fields are more satisfied with their contribution than they themselves would be. Table A.11 shows that this gap is larger in the most underestimated fields (those where the difference between students’ population beliefs about graduates’ sat-

²⁰The equal-variance two-sample t -test gives $p = 0.14$. Because women’s dollar WTP is considerably more dispersed than men’s and the distribution is right-skewed, a Welch t -test allowing for unequal variances yields $p \approx 0.10$, indicating only marginal significance at the 10% level.

²¹In Table A.9 we also try to understand if being interested in that major changes the relationship between own self-beliefs and how other people would feel about impact. Column (2) shows a negative coefficient on the interaction with an indicator for being interested in the major (a positive prior probability of pursuing it), and Column (4) shows a negative but insignificant coefficient. We read this as suggestive evidence that the correlation with others’ satisfaction is weaker for majors students are already interested in. The positive and significant coefficient on the interest indicator itself suggests a higher baseline for self-beliefs among interested students.

isfaction and the true numbers from the national survey is higher than average) and that it is more pronounced among students who report that “contribution to society” is important.²² This result is consistent with our model in Section 3, where students and previous graduates may have different standards for which kind of contribution would make them satisfied, and it is an empirical question whether giving information about the population will affect their self-beliefs. We address this question in the next subsection, when analyzing treatment effects.

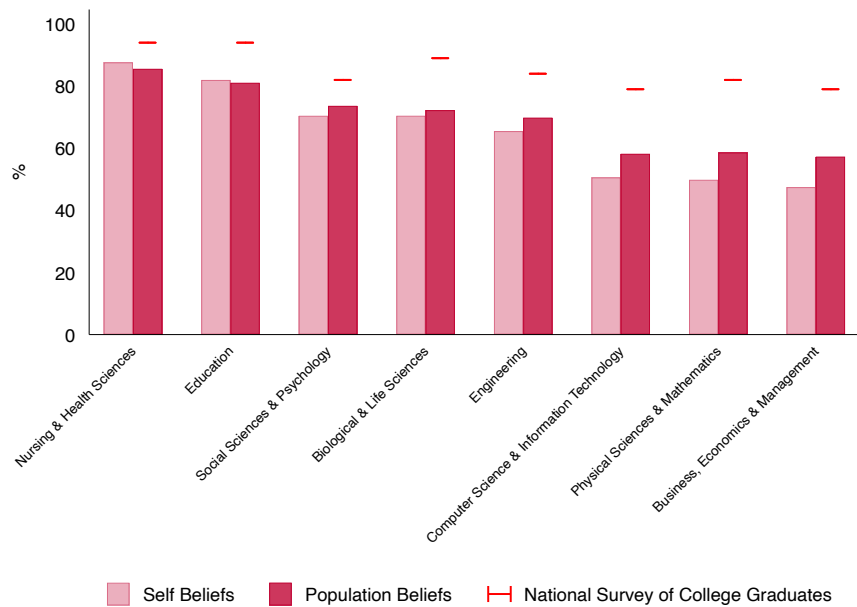


Figure 4: Self and Population Beliefs

Notes: Each bar represents the average beliefs, self and population, across respondents for each major group. The numbers from the 2023 NSCG are reported with the red line: they indicate the correct answer to the question about previous graduates (population beliefs). The difference between the red line and the red bar is the underestimation gap.

Most importantly, Figure 4 reveals how students underestimate previous graduates’ satisfaction with contribution across all fields, but they do so most strongly for three fields: Computer Sciences & IT, Business, Economics & Management and Physics & Mathematics. Indeed, while students roughly get the ranking right—they correctly see graduates in Nursing & Health Sciences as the most satisfied with their job’s societal contribution—they exaggerate the gap between the most- and least-satisfying fields in terms of contribution relative to the true data. Figure 5 plots the believed differences among majors against the true ones. The x-axis indicates the difference between the share of graduates who are satisfied with contribution in each field and the average share across all graduates, according to the NSCG data. On the other hand, on the y-axis we indicate the same difference for students’ second-order beliefs. The plot is useful to evaluate whether students hold stereotypes on this dimension:

²²Moreover, Table A.10 shows that the most underestimated majors are also those where students who care about this dimension hold lower self-beliefs, an effect that is significant for those who consider contribution to society very important.

a slope greater than the 45-degree line indicates that students exaggerate differences between majors in terms of social impact as experienced by previous graduates. This is the case for our OSU sample, and it is mainly driven by students underestimating the reported social impact of fields as Business, Economics & Management, Physics & Math and Computer Science, and particularly their difference with other majors. Table A.12 formalizes the scatter. Regressing students' believed differences on the true ones gives a slope of 1.58 (SE 0.04), well above the value of one that beliefs would take if they simply mirrored the data; the test of a unit slope is rejected ($p < 0.001$). Students do not just reproduce the ordering of fields, they amplify the true gaps by close to 60%²³.

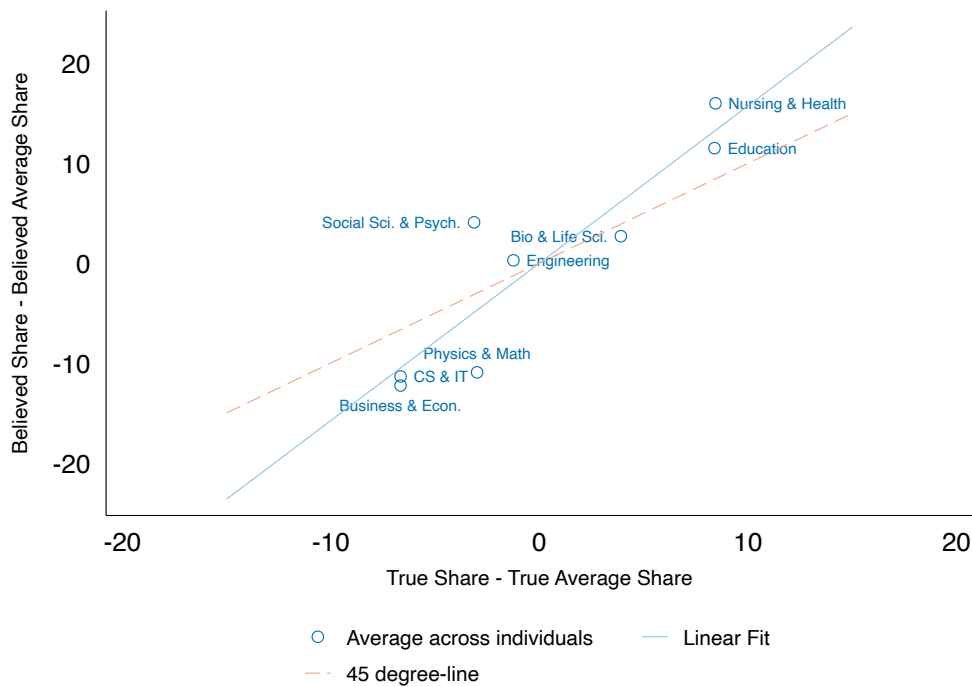


Figure 5: Believed Differences vs Real Differences

Notes: Each dot represents the average across respondents, marking the difference between the believed social impact for each major (graduates' satisfaction with contribution) with the believed overall average against the difference in the NSCG data between the share of graduates satisfied with contribution for each major and the overall share. The blue line indicates the linear fit for these points. A slope greater than one, indicated by the 45 degree-line, denotes a perceived exaggeration of differences.

We read this exaggeration through the stereotype framework introduced in Bordalo et al. (2016), which is based on representativeness. When thinking about the satisfaction with contribution in a field, students overweight the satisfaction levels that are most representative of that field, that is, the levels relatively more common in that field than across the other majors. For the three fields they underestimate the most (Business, Economics & Management, Physics & Mathematics, and Computer Science), the representative type is the small group of graduates who are *very dissatisfied* with their contribution: this group is tiny in absolute terms (around 5

²³In Figure A.9 we report the same plot for salary expectations, noticing that there students do not exaggerate differences between majors, on the contrary they reduce them (slope=0.60).

to 6% in Business and Computer Science, close to zero in Nursing & Health Sciences), yet it is exactly what is distinctive of these fields when compared to others. A major as Social Sciences & Psychology sits in between: its very dissatisfied minority is moderate (between 3% and 4%) and students still regard the field as more impactful, so the downward distortion is more muted than for Business or Computer Science. Table A.13 tests how population beliefs are related to representativeness of the group in the "tail", i.e. the very dissatisfied ones. Holding the true satisfaction share fixed (which still enters positively, confirming the kernel of truth), a field's believed satisfaction decreases the more its graduates are over-represented among the very dissatisfied (a coefficient of -10.8 , significant at the 1% level).

5.3 Model Structural Estimation

Ultimately, our aim is to assess to which extent the perceptions of future social impact influence students' major choices. In Section 3, we described a model of college major choice that accounts for social impact concerns. With the data collected in the survey on prior intentions and beliefs, we are able to provide structural estimates of the model. Even if ultimately we are going to test model's predictions with the experiment, by estimating the model, we can simulate students' behavior under counterfactual beliefs. In the survey, we ask students for the probability of choosing each major m (q_m^i), their beliefs about their future job's social impact ($\tilde{\pi}_m^i$), their expected wage ($E^i[w_m]$), and their expected performance in major m ($E^i[GPA_m]$). We use maximum likelihood to estimate the vector of parameters $\gamma = (\alpha_1, \alpha_2, \theta, \mu_m, \sigma)$, where θ is the vector comprehending all individual θ^i , namely students' individual weight on social impact expectations. We obtain standard errors from a Bayesian bootstrap clustered at the student level.

Table 1 reports the estimates of all the relevant parameters in the model. Salary, expected performance, and beliefs about social impact all contribute significantly to major choice. This holds across all the winsorization bounds (of zero probabilities) shown in the three columns. The average preference for social impact, $\bar{\theta}$ in the table, is reassuringly correlated with our preferences measure elicited in the survey, and it is substantially larger for women than for men: Tables A.16 and A.15 report the differences in the estimated parameter by gender and by the importance that students attach to "contribution to society" from our survey question. In particular, the social impact parameter estimated by the model is higher for women than for men even within each stated level of importance (i.e., comparing women and men who gave the same importance answer).²⁴

The estimates imply that a one-standard-deviation increase in the perceived probability of a satisfying contribution (about 25 percentage points) raises the model-implied probability of

²⁴We eliminate the student-specific normalization term of the multinomial logit with student fixed effects, so that all eight majors enter symmetrically rather than relative to an arbitrarily chosen base major. Appendix Table A.17 shows the estimates are robust to this choice: the gender difference in $\bar{\theta}$ is positive and significant for the base-free specification and for essentially every base major, with the exception for Engineering.

choosing that major by roughly 7 p.p. for women and 4 p.p. for men, evaluated at a major the student is actively considering.²⁵ This is comparable to the effect of a one-standard-deviation increase in expected GPA (about 6 p.p.) and considerably larger than that of a one-standard-deviation increase in yearly expected salary (about \$36,000; roughly 1 p.p.). Equivalently, the estimates imply a willingness to pay of about \$8,700 in expected annual salary for a one-percentage-point increase in the perceived probability of a satisfying contribution ($\bar{\theta}/\alpha_1$, reported in the last row of Table 1); unlike the individual coefficients, whose level scales with the winsorization of the stated probabilities, the magnitude of this ratio is stable across bounds. Note that these WTP estimates are close to those in [Conlon and Patel \(2026\)](#) for a 1 p.p. increase in the probability of one's preferred career; ours are somewhat larger because wages predict major choice less strongly in our model (a smaller salary coefficient), which mechanically raises the implied WTP.

Table 1: Structural choice-model estimates (individual- θ model, student fixed effects).

	Winsorization of probabilities		
	[0.5, 99.5]	[1, 99]	[2, 98]
α_1 : Salary (\$10k)	0.035*** (0.013)	0.029** (0.011)	0.024** (0.009)
$\bar{\theta}$: Impact belief (avg $\hat{\theta}_i$)	3.019*** (0.217)	2.591*** (0.187)	2.166*** (0.157)
Women	3.527*** (0.253)	3.011*** (0.216)	2.500*** (0.180)
Men	2.054*** (0.296)	1.794*** (0.257)	1.533*** (0.218)
α_2 : E[GPA]	1.040*** (0.062)	0.874*** (0.053)	0.700*** (0.043)
σ^2 : Var(μ_m^i)	2.583 (0.049)	1.928 (0.036)	1.365 (0.025)
Implied WTP: 1 pp impact belief (\$10k)	0.871** (0.350)	0.899** (0.371)	0.919** (0.384)
Median $\hat{\theta}_i$	2.855	2.523	2.162
Students	605	605	605

Notes: Individual- θ model (global $\alpha_1, \alpha_2, \sigma^2$ and a per-student $\hat{\theta}_i$), estimated by maximum likelihood in levels of the log stated choice probabilities with student fixed effects (the logit denominator) and major fixed effects. $\bar{\theta}$ is the cross-student average of $\hat{\theta}_i$. Standard errors (parentheses) from a Bayesian bootstrap with 2000 draws, clustered at the student level. σ^2 is degrees-of-freedom corrected for the estimated parameters (student fixed effects and the per-student $\hat{\theta}_i$). The implied willingness to pay ($\bar{\theta}/\alpha_1$, rescaled) is the salary equivalent, in \$10k per year, of a 1 pp increase in the perceived probability of a satisfying contribution; its SE is delta-method, from the bootstrap variance-covariance of $(\bar{\theta}, \alpha_1)$. Salary in \$10k. Major fixed effects μ_m estimated but omitted. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The estimated model then lets us simulate students' behavior if we could fully manipulate their beliefs. For this exercise, we replace each student's self-beliefs with the values reported

²⁵The marginal effect is the logit slope $\theta^i, q_m^i(1 - q_m^i)$ times the standard deviation of the belief, averaged across students at majors with positive stated probability; it is smaller when averaged over all majors, most of which have a near-zero stated probability (about 2 p.p. for women and 1 p.p. for men for social impact, 2 p.p. for GPA, and 0.3 p.p. for salary).

by previous graduates in the NSCG or, alternatively, shift them 1:1 by the underestimation gap on population beliefs²⁶, and recompute major choice probabilities. Table A.18 reports the resulting change in the aggregate probability of choosing each major under both scenarios, for women and men who report in the survey valuing contribution to society. Correcting beliefs reallocates intentions toward the fields students most underestimate (Business & Economics, Physics & Mathematics, and Computer Science) and away from those they already perceive as impactful, such as Social Sciences & Psychology and Health. The predicted reallocation is markedly larger for women, consistent with their stronger preference for social impact. While these simulations provide only correlational evidence, our field experiment is designed to actively shift beliefs and generate causal estimates of the same effects.

5.4 Treatment Effects

Social Impact Beliefs

We now analyze the causal effects of providing information about graduates' reported contribution, first on self-beliefs, and secondly on our pre-registered choice outcomes: the advice students give to peers interested in socially impactful careers, their own major intentions as reported in the survey, and their actual academic choices in administrative data. The first step is understanding whether the provided information changed social impact expectations.

We first assess whether the treatment affected students' own probability to be satisfied with a job's contribution after pursuing different majors, and the magnitude of such effects. To do so, post-treatment self-beliefs are first regressed on priors and a treatment dummy. Column (1) of Table 2 reports the resulting coefficients. As expected, posteriors are significantly and positively correlated with priors, while the treatment has a positive and significant effect of almost 13 percentage points on the post-treatment probability of being satisfied with contribution on average across all majors. These results point to two main insights. First, students weight the information about other graduates, and this evidence is informative for their own expectations. Referring to Section 3, this implies that students update their perceived distribution of contribution across job opportunities, and not only the extent to which graduates care about this aspect. Second, the positive coefficient is consistent with the fact that students initially underestimate the satisfaction of previous graduates across all fields, relative to the NSCG evidence.

However, to assess whether the treatment reduced the dispersion in social impact expectations, one would want this revision to be different by major. In particular, given that we showed how self and population beliefs are correlated, we expect the shift in self-beliefs to depend on the misperception computed comparing students' believed share of satisfied grad-

²⁶In the second case, we take into account the selection that students internalize in the initial self vs population beliefs: that difference is still there in the second manipulation, but self-beliefs responds 1:1 to the misperception computed on population beliefs.

uates with the share reported in national survey. To this purpose, Column (2) augments the baseline regression by interacting the treatment indicator with the underestimation gap in population prior beliefs. The estimated OLS regression is the following:

$$\begin{aligned} PostSelfBeliefs_{i,m} = & \alpha_0 + \alpha_1 PriorSelfBeliefs_{i,m} + \alpha_2 Treat_i \times UnderestimationGap_{i,m} \\ & + \alpha_3 Treat_i + \alpha_4 UnderestimationGap_{i,m} + \alpha_5 X_i + \epsilon_{i,m}, \end{aligned} \quad (9)$$

where each observation refers to individual i and their beliefs for major m . *UnderestimationGap_{i,m}* captures the prior misperception regarding population satisfaction, and it is positive when students underestimate graduates' satisfaction rates. We include individual controls in X_i , including age and fixed effects for year of enrollment, gender and campus. A positive and significant α_2 indicates that upward revisions in self-beliefs are correlated with the extent of underestimation about graduates in field m : the higher the underestimation of graduates' satisfaction with contribution, the higher is the revision in social impact self-beliefs. Column (2) in Table 2 confirms this pattern, showing that information about graduates leads students to update their own probability of being satisfied with contribution, particularly for fields initially perceived as least impactful.

Table 2: Treatment Effects on Self Beliefs

	(1)	(2)
	Post SB	Post SB
Prior Self Beliefs	0.617*** (0.016)	0.535*** (0.018)
Treatment	12.563*** (0.706)	6.255*** (0.773)
Treatment*Underestimation gap		0.384*** (0.038)
Constant	21.340*** (6.655)	33.554*** (6.167)
FEs	Yes	Yes
Control Mean	66.4	66.4
Observations	5256	5256
Adjusted R^2	0.586	0.626

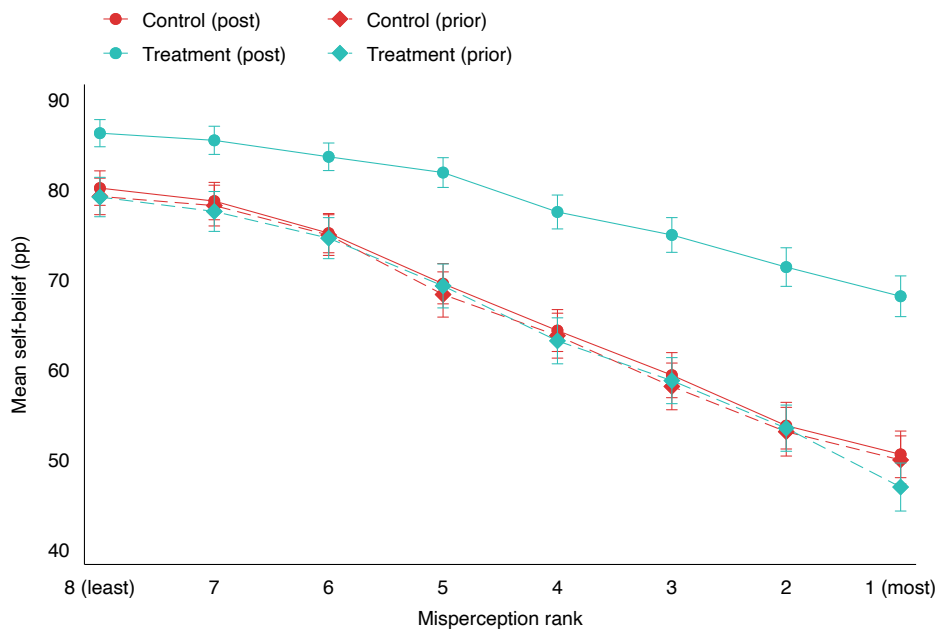
Notes: This table presents OLS estimates for Equation (9). The dependent variable is students' posterior self-beliefs. The "Underestimation gap" refers to the difference between the true share of previous graduates satisfied with their job's contribution and students' believed share. Controls include prior self-beliefs, age, gender, campus and year fixed effects. Each observation is a student-major couple. Standard errors clustered at the student level in parentheses: *, ** and *** indicate significance at 10%, 5% and 1% levels.

In Figure 6, we show more clearly how the intervention reduced stereotyping along this dimension. For each student, we rank majors by their individual (student-level) misperception, from least misperceived (typically Social Sciences & Psychology or Health Sciences) to

most misperceived (for most students, one of Physics & Math, Computer Science, or Business & Economics). We then plot the average prior and posterior self-beliefs at each rank, separately for treated and control students. The figure shows that treated students hold much flatter self-beliefs across majors after the intervention, consistent with reduced stereotyping. The other three series (control prior, control posterior, and treatment prior) overlap almost perfectly along a steeper line; only the treated posterior breaks away and flattens, isolating the effect of the information.

We also collected a social desirability bias (SDB) measure to account for potential experimenter demand effects, using the five-question short form of the [Crowne and Marlowe \(1960\)](#) scale developed by [Reynolds \(1982\)](#) and used in [Costa-Ramón et al. \(2026\)](#). Table A.20 reports estimates of Equation (9) separately for students scoring below and above the median SDB measure in Columns (1) and (2), while Column (3) adds interactions with the continuous SDB score. The results are reassuring: the revision in beliefs is unrelated to social desirability bias. Indeed, the interaction terms are insignificant and the treatment effects are nearly identical across the two subgroups, suggesting that students genuinely update their beliefs rather than responding to experimenter demand.

Figure 6: Prior and Posterior Self-Beliefs



Notes: For each student, majors are ranked from least to most misperceived in terms of the social impact reported by previous graduates. Self-beliefs denote each student's stated probability of being satisfied with the social impact of their future job. Orange represents the control group and green the treatment group; at each rank, diamonds mark pre-intervention self-beliefs and circles mark post-intervention self-beliefs. Error bars are 95% confidence intervals.

Advice to Peers

Given that there are many considerations other than a future sense of impact, students may not change their own major choices after receiving information, even if they now believe that they could find their contribution satisfying in several fields. For this reason, we included another measure in the survey: the advice a student would give to a peer who cares about contribution to society. For each major, students assign a score from 0 to 10 reflecting how strongly they would recommend it to such a peer. Because students know nothing else about these peers and face no trade-off (they could give every major a score of 10), and because the advice is genuinely passed on to a real person, the treatment effect on this measure likely reflects how much the student actually believed the information.

Table 3 reports the effect of the information treatment on this measure; the dependent variable is the 0–10 score indicating how strongly a student would recommend each major to such a peer, and again every observation is a student-major pair. As in the following analysis on choices, we restrict to students who rate contribution to society as at least somewhat important when choosing a job: for them, the peer described in the question shares the same preferences, so their advice reflects their own beliefs about which fields provide the opportunity to contribute. In Column (1), the treatment has a positive and statistically significant effect on average across majors, indicating that treated students recommend all majors more strongly, on average, than control students. Column (2) shows that this effect is heterogeneous across fields in the way we would expect: the positive and significant interaction between treatment and the underestimation gap implies that the advice score rises more for majors that were initially more underestimated in terms of graduates' contribution.

To get the magnitude of such effects, a 10-percentage-point larger underestimation gap raises the treatment effect on the advice score by about 0.31 points, so that moving from the least- to the most-underestimated field (a spread of roughly 15 p.p.) adds about half a point of advice. Relative to the control-group mean of 6.6, this gradient is economically meaningful, about 7% of the average advice score. Consistent with this pattern, the negative and significant coefficient on the underestimation gap reflects lower baseline advice (in the control group) for more underestimated majors. In Figure A.10, we report the aggregate effects on the advice score by major group: the most underestimated fields, such as Physics & Math and Business & Economics, exhibit a larger treatment effect than the least underestimated, meaning Health Sciences and Social Sciences & Psychology. Moreover, in Panel (b), we show these effects are not different by gender. In Table A.21, we show experimenter demand effects do not seem to play a role behind these effects.²⁷

²⁷It shows that the effects are both positive and significant for students with low and high social desirability bias scores in Columns (1) and (2), and that the interactions of the SDB score with the treatment dummy and with the underestimation gap are insignificant in Column (3).

Table 3: Treatment Effects on Advice Score - Preferences for SI

	(1) Scale	(2) Scale
Treatment	0.964*** (0.085)	0.409*** (0.103)
Underestimation gap		-0.084*** (0.004)
Treatment*Underestimation gap		0.031*** (0.006)
Constant	7.370*** (0.754)	8.279*** (0.711)
Control Mean	6.6	6.6
FEs	Yes	Yes
Observations	4496	4496
Adjusted R^2	0.046	0.284

Notes: The table reports OLS estimates of the effect of the information treatment on the advice students give to peers who care about a job's contribution to society. The sample is restricted to students who rate contribution to society as at least somewhat important when choosing a job. The outcome variable is a score from 0 to 10 assigned to each major, with higher values indicating stronger advice to pursue the major. In Column (2), the treatment indicator is interacted with the underestimation gap, the difference between the true share of graduates satisfied with their job's contribution in each field and the student's believed share. Each observation is a student-major pair. All regressions control for age and include gender, campus and year of enrollment fixed effects. Standard errors clustered at the student level in parentheses: *, ** and *** indicate significance at 10%, 5% and 1% levels.

Academic Choices: Major Intentions

Having shown that our intervention shifted the type of advice students give to peers choosing a major, we now ask how it affected their *own* choices. According to the model's predictions, students with a positive θ_i should move towards the majors for which they revised their beliefs the most. The revision itself is post-treatment and hence endogenous, so we instead use each student's initial misperception, elicited before the intervention. Because treated students revise their beliefs the most exactly where they initially underestimated the most (Table 2), this predetermined misperception captures how strongly the treatment corrects their beliefs on that major. The regression we pre-registered for major intentions is the following, which pools all majors:

$$\begin{aligned}
PostP_{i,m} = & \beta_0 + \beta_1 PreP_{i,m} + \beta_2 Treat_i \times DemeanedUndergap_{i,m} \\
& + \beta_3 Treat_i + \beta_4 DemeanedUndergap_{i,m} + \beta_5 Credits_{i,m} + \beta_6 X_i + \epsilon_{i,m},
\end{aligned} \tag{10}$$

where $DemeanedUndergap_{i,m}$ is individual i 's underestimation of the share of satisfied graduates in major m , demeaned by i 's average underestimation across all majors. We use the demeaned value because the probabilities of pursuing the different majors must sum to one

and most students underestimate every major: we therefore expect students to lower the probability of pursuing the least underestimated majors in order to raise the probability of pursuing the most underestimated ones. In regression (10), it implies $\beta_2 > 0$.

Table 4 reports the estimates, for students who report that contribution to society is important. We indeed expect (and observe²⁸) no effect for students who do not value this factor. Column (1) includes all such students, while columns (2) and (3) split them by gender. Motivated by previous literature, we pre-registered this crucial heterogeneity, which is also supported by our findings on the preference measures, both in the survey and in the structural estimates. First, in all columns, the final probability of pursuing major m is highly correlated with the probability reported at the start of the survey, and the number of credits already earned in that major according to the Registrar's data.

Table 4: Treatment Effect by Misperception - Preferences for SI

	Final P(M)		
	(1) All	(2) Women	(3) Men
Initial P(M)	0.949*** (0.012)	0.955*** (0.013)	0.936*** (0.026)
Treatment	0.098 (0.115)	0.217 (0.151)	-0.127 (0.155)
Demeaned Undergap	-0.066*** (0.020)	-0.074*** (0.025)	-0.045 (0.035)
Demeaned Undergap*Treatment	0.042** (0.021)	0.060** (0.024)	0.003 (0.041)
Prior credits in cat. (AU25+SP26)	0.124** (0.050)	0.079 (0.057)	0.219** (0.101)
Constant	0.109 (0.764)	-0.562 (0.886)	3.077 (2.324)
FEs	Yes	Yes	Yes
Observations	4496	3104	1392
Adjusted R^2	0.937	0.944	0.922

Notes: The table reports OLS estimates of the effect of the information treatment on students' major intentions, for students who report that contribution to society is important. The outcome variable is the probability (from 0 to 100) that a student assigns, after the intervention, to graduating in each major; "Initial P(M)" is the corresponding probability elicited at the start of the survey. "Prior credits in cat." measures credits earned in that field over the previous two semesters. The treatment indicator is interacted with the demeaned underestimation gap, individual i 's underestimation of the share of graduates satisfied with their job's contribution in each field, demeaned by i 's average underestimation across all majors. Column (1) includes all such students, while Columns (2) and (3) split them by gender. All regressions control for age, and gender, campus and year of enrollment fixed effects. Each observation corresponds to a student-major pair. Clustered standard errors in parentheses: *, ** and *** indicate significance at 10%, 5% and 1% levels.

²⁸Table A.22 reports the same results as Table 4 for students who report contribution as non-important (either *not important at all* or *somewhat unimportant*). The only marginally significant coefficient, for men, is negative and based on a small sample.

As expected, Column (1) shows that the interaction is positive and significant at the 5% level. However, when we split by gender, as pre-registered, we notice in the second column that this effect is entirely driven by women: treated women who care about social impact, compared to similar control women, increase the probability of pursuing majors they underestimate more. In terms of magnitude, for a treated woman a one-standard-deviation higher underestimation of a major relative to her own average underestimation (about 13 percentage points) raises her stated posterior probability of pursuing that major by almost 1 p.p. On the other hand, Column (3) shows the information had no significant impact for men.

The same result can be seen in Table 5. In this alternative specification, to capture how misperceived each major m is compared to the others, we use a rank measure: a rank of zero corresponds to the major a student most underestimates (in terms of the social impact of previous graduates), and it increases up to seven for the least underestimated. The coefficient on the treatment dummy therefore captures the treatment effect on the probability of pursuing the most underestimated major, while its interaction with the rank captures how this effect changes as the rank increases—i.e., as the individual misperception becomes smaller. Again, Columns (2) and (3) split the sample by gender: the effect is significant and in the predicted direction for women only. Compared with the control group, treated women are 1.3 p.p. more likely to pursue the most underestimated major. The interaction term indicates that the effect is decreasing as the major becomes less misperceived compared to the others ($p < 0.05$ for women)²⁹.

Both Tables 4 and 5 highlight a key fact: among women who care about contribution, those in the control group revise their intentions away from the most misperceived majors and toward the least misperceived ones. This can be seen in the significant, negative coefficient on the demeaned misperception in Table 4, and in the positive, significant coefficient on the rank measure in Table 5. When asked how salient the attribute “contribution to society” had been during the survey, both treated and control students gave high scores (a score of 8.6 out of 10 in the treated group and of 8.5 in the control group), and the difference is not statistically significant (see Figure A.11). Raised salience of this attribute can naturally move students who care about it, but receive no information, toward the majors they already perceive as impactful. Treated students, by contrast, also have their stereotypes corrected, so their revision reflects both forces. Having a control group therefore lets us isolate the effect of receiving information and correcting beliefs, net of this salience channel. To fully confirm it, we re-estimate our model of major choice, as we did in Section 5.3, by using now the control group’s responses on intentions and beliefs at the end of the survey. These students received no information

²⁹Splitting the sample by first and second years, as pre-registered, shows that the effect of the treatment on choice, captured by the interaction with demeaned underestimation, is statistically significant only among first-year students. In Table A.25, the interaction of interest is positive and significant at the 5% level in the first year (0.060 overall, 0.054 for women), while for second-year students it is smaller and insignificant overall (0.024). Among second-year women the estimate is similar in magnitude but imprecisely estimated, so we cannot conclude that their response differs from that of first-year women. The stronger effect in the first year is consistent with students being more responsive to the information earlier in their studies, before they commit to a major.

aimed at correcting social impact beliefs between their priors' and posteriors' elicitation, so any change over the survey reflects the survey itself rather than the treatment. Table A.26 reports controls' average preferences for contribution, i.e. $\bar{\theta}$, separately at the start and the end of the survey. It rises from 2.74 to 3.62 (a change of 0.89, significant at the 1% level), for both genders but more for women (0.99 against 0.69 for men, significant at the 5% and 10% level, respectively), consistent with the survey making contribution to society more salient and hence important: the movement in their stated choices is indeed consistent with a rise in preferences as claimed in hypothesis H2 in Section 3.³⁰

Table 5: Misperception Rank and Treatment - Preferences for SI

	Final P(M)		
	(1) All	(2) Women	(3) Men
Initial P(M)	0.950*** (0.012)	0.956*** (0.012)	0.937*** (0.025)
Treatment	0.825** (0.387)	1.315*** (0.470)	-0.184 (0.634)
Misperception Rank (0=highest)	0.306*** (0.084)	0.383*** (0.110)	0.143 (0.121)
Treatment * Misp. Rank	-0.208* (0.107)	-0.313** (0.123)	0.016 (0.199)
Prior credits in cat. (AU25+SP26)	0.120** (0.049)	0.075 (0.056)	0.214** (0.100)
Constant	-0.958 (0.822)	-1.898* (1.052)	2.592 (2.022)
FEs	Yes	Yes	Yes
Observations	4496	3104	1392
Adjusted R^2	0.937	0.944	0.922

Notes: The table reports OLS estimates of the effect of the information treatment on students' major intentions, for students who report that contribution to society is important. The outcome variable is the probability (from 0 to 100) that a student assigns, after the intervention, to graduating in each major; "Initial P(M)" is the corresponding probability elicited at the start of the survey. "Prior credits in cat." measures credits earned in that field over the previous two semesters. For each student, majors are ranked by how much they initially underestimate the share of graduates satisfied with their job's contribution in each field, from most to least underestimated ("Misperception Rank", with 0 = most underestimated). The treatment indicator is interacted with this rank. Column (1) includes all such students, while Columns (2) and (3) split them by gender. All regressions control for age, and gender, campus and year of enrollment fixed effects. Each observation corresponds to a student-major pair. Clustered standard errors in parentheses: *, ** and *** indicate significance at 10%, 5% and 1% levels.

The revisions of treated and control women can be seen more clearly in Figure A.12, where control women who care about contribution increase the probability of pursuing majors they

³⁰We do not report the analogous estimate for the treatment group. Identification of θ comes from the within-student variation in beliefs about contribution across majors, and the treatment both raises and flattens those beliefs. Once that variation is compressed, the post-treatment weight is no longer separately identified.

perceive as more impactful and decrease the probability of choosing those they perceive as less impactful. Receiving information, by contrast, makes treated women stick to their initial intentions: their revisions are essentially flat across ranks, since they learn that all fields can offer a sense of impact. To see more clearly the differences by treatment status, Figure A.13 plots in Panel (a) the treatment effects by individual rank of misperception. Confirming the same pattern, treated women are significantly more likely to choose their most underestimated major and less likely to choose their least underestimated one, although this latter effect is only marginally significant (at the 10% level). As a further check that these effects on women's reported intentions are not driven by experimenter demand, Panel (b) plots the effects for women with a social desirability bias (SDB) score below and above the median. The pattern is similar across the two subgroups; if anything, the effect at the most underestimated rank is stronger among low-SDB women, the opposite of what a demand story would predict³¹.

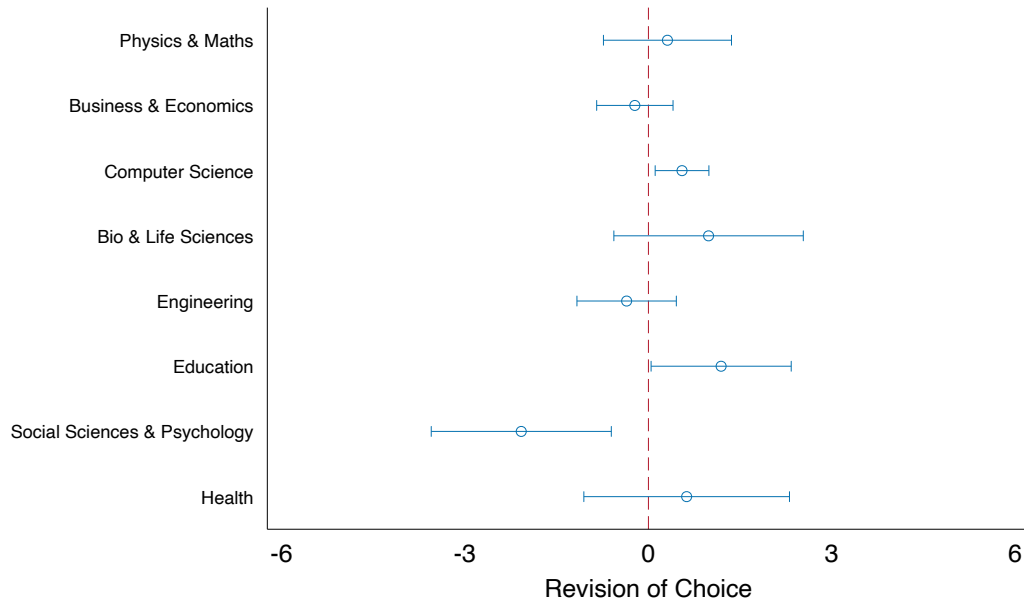
As pre-registered, we finally report the aggregate effects on each major category, i.e. toward which fields our information moved students, to ultimately compare them with the counterfactual exercise in Table A.19. The aggregate treatment effects we find in our intervention are shown in Figure 7, where, for each major group—ordered from the most to the least underestimated on average across all students—we regress the posterior probability of choice on the prior probability, the number of credits accumulated in the previous semesters, the same individual controls as Equation (9) and a treatment dummy; the reported coefficient is the one estimated on the treatment dummy. Panel (a) reports the results for the entire set of students who value contribution, while Panel (b) splits this sample by gender. On aggregate, our intervention raised the probability of pursuing majors such as Computer Science and Education, while it lowered the probability of choosing Social Sciences & Psychology. This is somewhat in line with what was discussed before: Social Sciences & Psychology is one of the least underestimated majors, one of the fields students already consider impactful, whereas Computer Science is among the most underestimated. As shown in Table A.19, the actual effects are positively correlated with the predicted ones from the counterfactual exercises, but more so for women.³²

³¹Our findings are broadly robust to defining the outcome in relative rather than absolute terms, i.e. the revision in the stated probability of each major divided by its prior value, as defined in Section 3 (for majors with a prior of zero, we divide by 0.5). Tables A.23 and A.24 report the equivalent of Tables 4 and 5 with the relative revision as outcome, without controlling for prior intentions. With the rank specification, treated women remain significantly more likely to move toward their most underestimated major; with the demeaned underestimation specification, the interaction keeps its sign and remains larger for women, for whom it is close to marginal significance ($p \approx 0.10$). This loss of precision is expected: dividing by the prior probability makes the relative change mechanically noisier, and its variance inflates for majors with small prior probabilities, where the ratio can become very large.

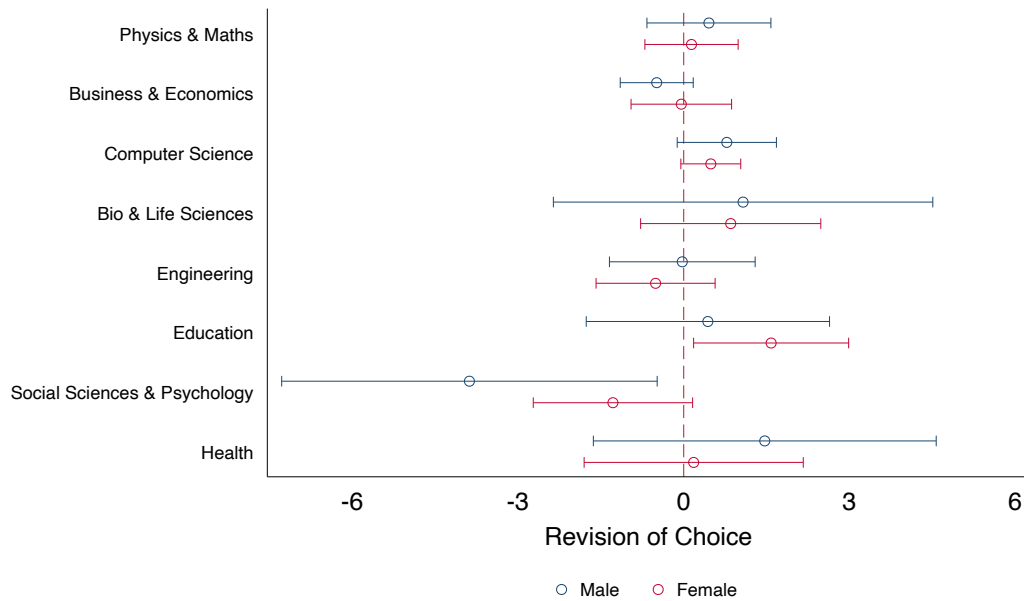
³²The effect on Education is harder to explain, as it is not among the most underestimated majors but, as shown later, it does not persist in actual choices. Looking at the gender split, the effects on Computer Science and Social Sciences & Psychology are common to both genders, significant at least at the 10% level within each cell, while the effect on Education applies only to women.

Figure 7: Revision in Choice Probability – Preferences for SI

(a) All students



(b) By gender



Notes: The plotted coefficients correspond to the aggregate treatment effects on choice probability, obtained by estimating the coefficient on a treatment dummy separately for each major (Panel (a)), and separately by gender (Panel (b)). The dependent variable is the final probability of pursuing that major, and we control for the initial probability (pre-treatment), the prior number of credits in that major, age, and gender, campus and year of enrollment fixed effects. Majors are ordered from the most (Physics & Maths) to the least underestimated (Health) in terms of graduates' perceived impact across all students. The sample is restricted to students who report that contribution to society is important. Error bars reflect 95% confidence intervals.

Academic Choices: Administrative Data

To assess whether the treatment had effects on actual academic choices, we report the effects on the variables we can observe in the OSU administrative data in the semester after our survey and that were pre-registered as primary outcomes: class enrollments, major and minor plans (if declared). We start with the number of classes in each major that a student selected for the fall semester. We observe students' schedules at two points in time. The first is a snapshot from the summer, after students had registered for their fall classes but before the semester started. The second was taken after the add/drop period of the first weeks of classes (where students drop or add courses without penalty). The first snapshot therefore captures planned enrollment, while the second captures the classes students actually take. In the main text we report results using the second snapshot. We measure classes using the number of credits, since each class can carry a different number of credits, reflecting the hours and effort it demands. First, to understand whether the intentions students declared at the end of the survey translate into real enrollment, we report the correlations between the number of credits and the stated intentions. This is only a correlation, but it tells us whether the declared intentions carry any meaning, namely, whether they are predictive of the classes students actually choose. Table 6 reports such associations, regressing at the student-major level the number of credits for Fall 2026 on prior credits earned in the previous two semesters (Autumn 25 and Spring 26) and on the major intentions declared in our survey. Columns (1)–(3) include only the probabilities of pursuing each major after the information provision, while Columns (4)–(6) also add the prior intentions; within each block, we report results for all students and separately by gender. The intentions declared at the end of the survey are strongly correlated with the credits students chose: a 10-point higher stated probability is associated with roughly 0.4 additional credits, and this holds even after controlling for prior enrollments, which is itself a strong predictor (one credit earned in the past in that major is associated with 0.30 additional credits). Enrollment behavior therefore tracks self-reported intentions, and the association holds for both women and men. Moreover, adding prior intentions does not weaken this relationship: if anything, Columns (4)–(6) show that the probabilities declared after the information provision carry essentially all the predictive content, while the prior probability becomes insignificant and close to zero. This is important for interpreting our results: if the posterior intentions merely reflected experimental demand, they should not predict actual choices beyond what prior intentions already capture. Instead, they absorb all of the predictive content.

We next look at aggregate effects by major, as in Figure 7, using the number of credits enrolled as the outcome. Panel (a) of Figure 8 shows that, among students who care about contribution to society, the effects go in the same direction as those on intentions: treated students take more credits in Computer Science (+0.16 credits, $p = 0.13$) and fewer in Social Sciences & Psychology (−0.24 credits, $p = 0.28$), although neither estimate is statistically

significant at any conventional level. The effect on Education, which was significant for intentions, is close to zero for credits. Panel (b) splits the sample by gender. The estimates are less precise, but the negative effect on Social Sciences & Psychology comes entirely from women, as do the positive (but non-significant) effects on the three most underestimated majors³³.

The pattern is stronger in the first snapshot, taken before the semester started and closer to the survey (Figure A.14). There, treated students register for more credits in Computer Science (+0.20, significant at the 10% level) and fewer in Social Sciences & Psychology (−0.43, significant at the 5% level). By gender (Panel (b) of Figure A.14) the drop in Social Sciences & Psychology is driven by women (−0.53, $p = 0.06$), while the estimate for men is smaller and not significant. In Computer Science, the estimate for women is +0.20 ($p = 0.15$), and the estimate for men is also positive but noisier. The fact that these effects are stronger in initial planned enrollments rather than actual course-taking is also aligned with other recent similar interventions with college students (Johnston et al., 2026).

Table 6: Credits (AU26) - Preferences for SI

	Baseline			+ Prior intention		
	(1) All	(2) Women	(3) Men	(4) All	(5) Women	(6) Men
Prior credits in cat. (AU25+SP26)	0.297*** (0.011)	0.307*** (0.013)	0.271*** (0.022)	0.298*** (0.011)	0.306*** (0.014)	0.275*** (0.022)
Final P(M)	0.040*** (0.003)	0.036*** (0.003)	0.049*** (0.005)	0.041*** (0.008)	0.030*** (0.010)	0.061*** (0.013)
Initial P(M)				−0.002 (0.008)	0.006 (0.010)	−0.013 (0.012)
Constant	−0.221 (0.275)	−0.258 (0.306)	−0.036 (0.668)	−0.222 (0.275)	−0.258 (0.305)	−0.045 (0.668)
FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4932	3384	1548	4932	3384	1548
Adjusted R^2	0.573	0.553	0.617	0.573	0.553	0.618

Notes: The table reports OLS estimates of the relationship between students’ survey-declared major intentions and their subsequent course enrollment. The outcome variable is the number of credits a student enrolled in each major group for Fall 2026, “Final P(M)” is the probability (0–100) of pursuing a major declared at the end of the survey, and “Initial P(M)” is the corresponding prior probability reported earlier; “Prior credits in cat.” measures credits earned in that field over the previous two semesters. Columns (1)–(3) include only the post-survey probabilities, while Columns (4)–(6) additionally control for the priors; within each block, results are reported for all students and separately by gender. All specifications control for age and include campus and year fixed effects (in the pooled columns we include also gender fixed effects), and the sample is restricted to students who care about a job’s contribution to society. Each observation corresponds to a student–major pair. Clustered standard errors in parentheses: *, ** and *** indicate significance at 10%, 5% and 1% levels.

However, if we run the misperception regression (Equation (10)), as pre-registered, with credits in each major as the outcome, we find no effect (Table A.35), while the same specification is significant for stated intentions (Table 4). Several features of the outcome make this regression demanding for credits. First, it relies on variation in misperceptions across fields within the same student, which is elicited with noise and attenuates the estimated interaction. Second, course choices are constrained by program requirements, prerequisites, and

³³In Computer Science the estimates are positive although not significant for both genders.

seat availability, and they are made weeks after the survey, even after the beginning of the semester, when only the broad message of the information (“Fields as Computer Science are widely underrated”) is likely to be recalled. Third, and most importantly, credits are coarse. Credits are not as finely assignable as the 0–100 intention scale. A student who, after the information, wants to lean slightly more toward Biology than Health because Biology is slightly more underestimated cannot take half a credit more in one and half a credit less in the other, while she can easily move her stated intentions by a few percentage points. Only a large correction, shared by many students, is enough to move someone into an additional course. The individual-level relationship is therefore harder to detect. When we average across students, however, much of this individual variation cancels out: at the field level, the treatment effects on credits line up with how much each field’s impact is underestimated on average (Figure 9). The points display a positive relationship: treated students who care about contribution tend to add credits in the more underestimated fields, such as Computer Science and Physics & Math, and to cut them in one of the two least underestimated ones, i.e. Social Sciences & Psychology. The association is moderate for the entire set of students who rate contribution as important (correlation +0.48), but it is stronger among women (+0.59) and essentially absent for men (−0.18), suggesting the reallocation after treatment is concentrated among women. Consistent with this pattern, the interaction between the treatment and the field’s average misperception is positive although not significant among women ($p = 0.18$ in Table A.30). Table A.31 reports the same estimates by year of enrollment: the treatment interaction with the category-level misperception is significant only among first-years (0.045 overall, significant at the 5% level, and 0.043 for women, significant at the 10% level).³⁴

To see separately how treated and control women choose their classes differently, Figure A.15 tracks, for women who care about contribution, the share of credits across the three observed semesters in the three most underestimated fields on average (Physics & Math, Business & Economics, Computer Science). In Panel (a) we show the dynamic for the enrollments captured before the semester starts, and in Panel (b) after the add/drop period. In both figures, we can see how control women continue to decrease their enrollments in these three fields from Spring 2026 to Fall 2026, while for treated women the trend is flatter. Pooling credits across these three fields, treated women take about 0.6 more credits in Fall 2026 than control women, around 14% of the control mean, an effect that is marginally significant at the 10% level (Table A.34)³⁵.

Other than credits, we observe students’ declared majors and minors, and whether they change in the semester following our survey.³⁶ Changes in declared plans are rare, so these estimates rest on few students and we read them as suggestive. For majors, the only significant

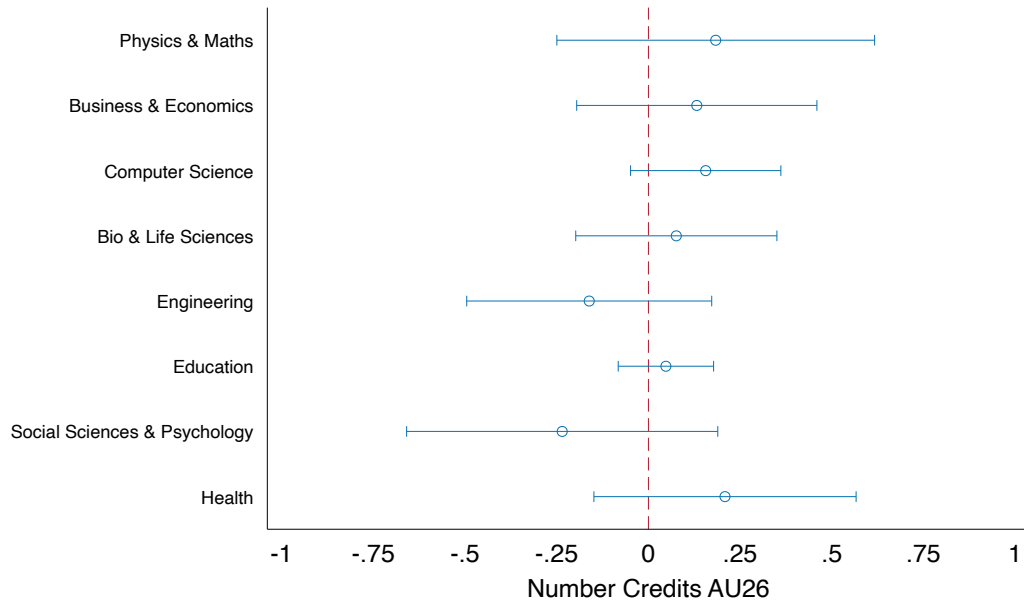
³⁴These associations are again stronger with the first snapshot of data, referring to enrollments before the semester started (Tables A.32 and A.33).

³⁵This regression was not pre-registered.

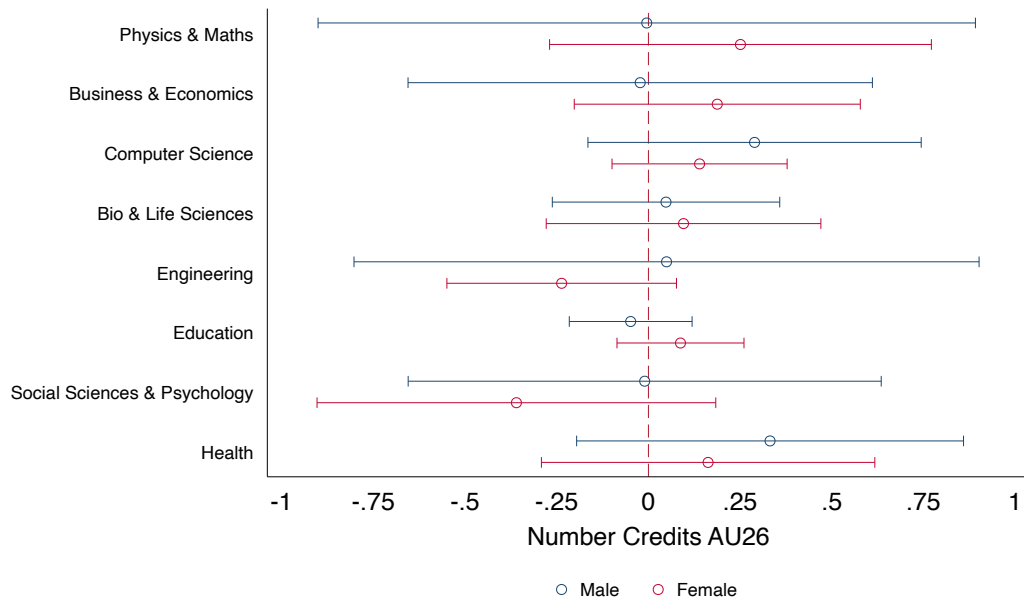
³⁶Because each term’s record reflects plans at the start of the term, we assign plans declared before a student took the survey to the baseline.

Figure 8: Treatment Effects on Credits (AU26) – Preferences for SI

(a) All students



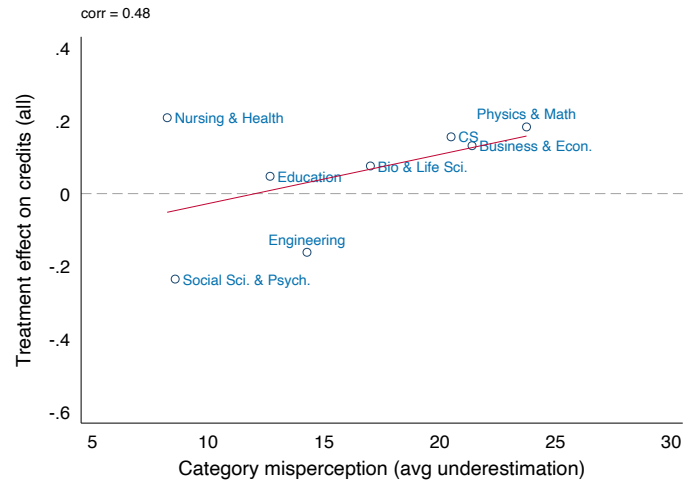
(b) By gender



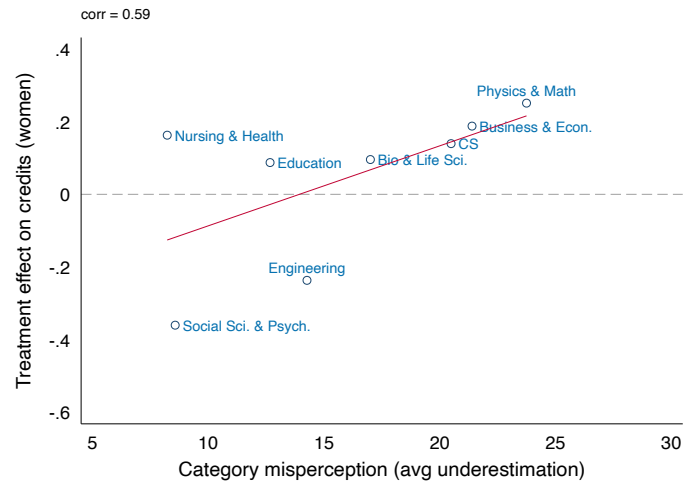
Notes: The plotted coefficients correspond to the aggregate treatment effects on classes enrolled for the Fall semester, obtained by estimating the coefficient on a treatment dummy separately for each major (Panel (a)), and separately by gender (Panel (b)). The dependent variable is the number of credits in that major, and we control for the initial probability (pre-treatment), the prior number of credits in that major, age, and gender, campus and year of enrollment fixed effects. Majors are ordered from the most (Physics & Maths) to the least underestimated (Health) in terms of graduates' perceived impact across all students. The sample is restricted to students who report that contribution to society is important. Error bars reflect 95% confidence intervals.

Figure 9: Treatment Effect on Credits vs. Category Misperception

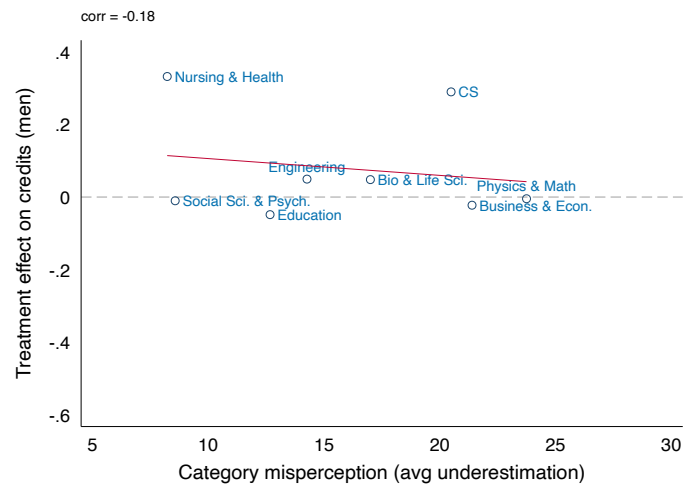
(a) All students



(b) Women



(c) Men



Notes: Each point is one of the eight major categories. The horizontal axis is the category's average underestimation of graduates' satisfaction with contribution, across all students in the sample, and the vertical axis is the estimated treatment effect on the number of credits enrolled in that category for Fall 2026, i.e. the coefficient on the treatment indicator from a per-category regression of AU26 credits on prior credits, the prior intention, age and fixed effects. The red line is a linear fit. The sample is restricted to students who care about a job's contribution to society.

difference is that treated women are less likely to hold a major in Social Sciences & Psychology (−2.9 percentage points, $p < 0.05$; Figure A.17). This reflects three treated women leaving the field, two of them for Business or Neuroscience, and three control women adding it, mostly as a second major. For minors, treated women are more likely to hold a minor in Business & Economics, one of the most underestimated fields (+3.7 percentage points, $p < 0.05$; Figure A.18). This difference also comes from a handful of students. Both patterns are consistent with the changes in intentions and credits, but given how few students change their declared plans in a single semester, we do not place much weight on them.

Other Outcomes

Last, it is worth noting that our treatment could move variables other than beliefs about future satisfaction with contribution. In particular, we want to make sure the information does not affect other factors relevant to major choice. First, Table A.27 shows treatment effects on expected salary. Column (1) shows a positive and significant effect, but Column (2) shows that this effect does not depend on how much the major’s contribution was misperceived (the interaction is essentially zero). Treated students may have become more optimistic about salaries, not only about social impact; but since this shift is homogeneous across majors, it is not a concern for our analysis of major choices.

Second, as discussed above, the survey raised the salience of this job aspect, which could also affect students’ preferences; it is important to check whether this differs by treatment. One of our preference questions—the one eliciting willingness to pay (WTP) for social impact—was administered to both treatment and control groups either before or after the information provision, at random. This lets us test whether preferences are affected by the information. Table A.28 reports the difference-in-differences regression we estimate for the treatment effect on WTP. On aggregate, willingness to pay is essentially the same whether the question is asked at the start or at the end of the survey (23.5% vs. 24.1% of the salary), and this difference does not differ significantly between treatment and control: the interaction (Post $\times$ Treatment) is not significant at any conventional level, so we find no evidence that the information itself shifted preferences for social impact³⁷. It is worth mentioning that willingness to pay is, in any case, a noisy measure, ranging over the full 0–100 scale with a standard deviation of about 21 on a mean of 24, which limits the power of this test. Moreover, willingness to pay measures the value of contribution relative to salary. In our estimated model in Section 5.3, the survey itself raises the weight that students place on contribution (Table A.26), but it also raises, although not significantly, the weight on expected earnings, which remains small, so

³⁷Table A.29 reports the same regressions with willingness to pay measured in dollars, i.e. the minimum acceptable salary multiplied by the share of this salary that students would give up for a socially impactful job. In dollars, willingness to pay is higher when asked at the end of the survey, but neither the change nor the interaction with treatment (Post $\times$ Treatment) is statistically significant. This measure also reflects the minimum acceptable salary itself, which increases for treated students asked after the information, consistent with the treatment effect on expected earnings.

the implied trade-off between the two does not increase—consistent with the absence of a change in willingness to pay³⁸.

6 Conclusions

Previous literature has shown that both workers and students value meaningful work, particularly through its social impact. Understanding which jobs people perceive as most impactful is therefore important. Some stereotypical fields may be seen as especially impactful, while the contribution of others is perceived as little or non-existent. In this paper, we study these perceptions among students choosing their college major, a decision that strongly shapes later career paths.

We administer a survey experiment to first- and second-year students at Ohio State University. We find that students hold stereotypical views on the social impact of different fields. In particular, they most underestimate how satisfied recent graduates are with their job's contribution to society in three fields: Physics & Math; Business & Economics; and Computer Science. Although these figures concern other individuals, exposure to graduates' reported satisfaction, together with social-impact narratives from alumni, leads students to revise their own perceived probability of being satisfied with their contribution across majors. The revisions are largest for the majors that were initially most underestimated, suggesting that once informed students hold fewer stereotypes along this dimension and see contribution as possible in all fields.

As a result of beliefs revision, the treatment significantly affects the advice that contribution-minded students would give to peers with similar preferences: relative to the control group, treated students recommend a more diverse set of majors, not only the stereotypically impactful ones. These belief revisions also translate into some adjustment in students' own intended choices. Students who report contribution as important become more likely to report pursuing the most underestimated majors, although this effect is entirely driven by women, consistent with women holding stronger preferences for this job dimension. In their course choices for the following semester, treated women move in the same direction as their intentions, taking more credits in the three most underestimated fields (Physics & Math, Business & Economics and Computer Science) and fewer in Social Sciences & Psychology. Field by field, these differences are clearest in the schedules students planned before the semester started and become less precise after the add/drop period, although taken together treated women still take about 14% more credits than control women in the three most underestimated fields. Treated women

³⁸Notice that a higher weight on earnings would not drive the reallocation of control students' intentions toward the least misperceived majors: students' expected earnings differences across majors are unrelated to how much they underestimate each field's contribution, so the reallocation we observe in the control group reflects the increase in θ . In the control group, the estimated weight on expected earnings (α_1 , per \$10,000) rises from 0.040 at the start of the survey to 0.077 at the end, a change of 0.037 that is not statistically significant, while θ rises from 2.74 to 3.62, a change of 0.89 significant at the 1% level.

are also more likely to hold a minor in Business & Economics and less likely to hold a major in Social Sciences & Psychology, although these changes involve few students and we read them as suggestive.

Future research should investigate why these stereotypes arise, and whether students, and individuals more broadly, define contribution narrowly as direct impact. Our results suggest this is not the case: students revise their beliefs after receiving information on many kinds of impactful jobs, not only those involving direct impact, such as teachers or doctors. This in turn raises the question of why the effect on choices remains limited. It may be that a specific feature of stereotypically impactful jobs, such as those of social workers or nurses, is what individuals particularly value, for instance direct contact with people or seeing the results of one's work quickly and tangibly. Note, however, that our effects on choice are in line with those of other information interventions on college major choice. [Wiswall and Zafar \(2015\)](#), who provide information on earnings across four major categories, find average revisions in stated probabilities of between 0.4 and 3.9 percentage points by field, similar in magnitude to our aggregate effects in Figure 7. [Ersoy and Speer \(2025\)](#) have a design similar to ours, providing information (on several factors) about all eight major categories in the survey and eliciting prior and posterior beliefs and intentions.³⁹ They find aggregate changes of about one percentage point by field, and for example, a response of 0.42 percentage points to a one-standard-deviation revision in beliefs about the share of female students. Even if this is not exactly the same measure as ours, this is similar magnitude to our estimates in Table 4. [Christian et al. \(2024\)](#), who provide information on the Education majors only, find an increase of about three percentage points in the stated probability of majoring or minoring in Education. [Conlon and Patel \(2026\)](#) find larger effects of a given change in beliefs on intentions and class taking, but their intervention provides information only about each student's two most preferred majors, where intentions have potentially more room to move; even so, the average differences between treated and control students in posterior intentions are generally small and not statistically significant, whereas some of our aggregate effects by major are. Our aggregate effects on major intentions, such as +0.5 percentage points in Computer Science and -2.1 in Social Sciences & Psychology, and the 1.3 percentage-point increase for treated women in their most underestimated major, are of the same order of magnitude as all effects listed in these studies.

Concluding, our findings suggest meaning, and in particular its beneficence dimension, is important not only for workers, but also for students choosing a college major, and particularly female students. It may be one of the reasons that keep women away from, or lead them to leave ([Astorne-Figari and Speer, 2018](#)), some male-dominated fields. Another interesting avenue of future research should explore differences within field in actual career paths, examining whether women and men end up selecting into more impactful careers within the same

³⁹They do not have a control group, so all effects rest on pre/post comparisons.

broad field (e.g. Mathematics, Computer Science). If this is the case, an interesting intervention, aimed to move women toward fields perceived as less socially useful, would be to focus the information only on other women's careers.

References

- ARIELY, D., E. KAMENICA, AND D. PRELEC (2008): "Man's search for meaning: The case of Legos," *Journal of Economic Behavior & Organization*, 67, 671–677.
- ARTEAGA, C. (2018): "The effect of human capital on earnings: Evidence from a reform at Colombia's top university," *Journal of Public Economics*, 157, 212–225.
- ASHRAF, N., O. BANDIERA, E. DAVENPORT, AND S. S. LEE (2020): "Losing prosociality in the quest for talent? Sorting, selection, and productivity in the delivery of public services," *American Economic Review*, 110, 1355–1394.
- ASHRAF, N., O. BANDIERA, V. MINNI, AND L. ZINGALES (2024): "Meaning at work," *Unpublished Working Paper, London School of Economics*.
- ASTORNE-FIGARI, C. AND J. D. SPEER (2018): "Drop out, switch majors, or persist? The contrasting gender gaps," *Economics Letters*, 164, 82–85.
- (2019): "Are changes of major major changes? The roles of grades, gender, and preferences in college major switching," *Economics of Education Review*, 70, 75–93.
- BAYER, A., S. P. BHANOT, AND F. LOZANO (2019): "Does simple information provision lead to more diverse classrooms? Evidence from a field experiment on undergraduate economics," in *AEA Papers and Proceedings*, American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203, vol. 109, 110–114.
- BLEEMER, Z. AND A. MEHTA (2022): "Will studying economics make you rich? A regression discontinuity analysis of the returns to college major," *American Economic Journal: Applied Economics*, 14, 1–22.
- BORDALO, P., K. COFFMAN, N. GENNAIOLI, AND A. SHLEIFER (2016): "Stereotypes," *The Quarterly Journal of Economics*, 131, 1753–1794.
- (2019): "Beliefs about gender," *American Economic Review*, 109, 739–773.
- BOUCHER, K. L., M. A. FUESTING, A. B. DIEKMAN, AND M. C. MURPHY (2017): "Can I work with and help others in this field? How communal goals influence interest and participation in STEM fields," *Frontiers in psychology*, 8, 239640.
- BREDA, T., J. GRENET, M. MONNET, AND C. VAN EFFENTERRE (2023): "How Effective Are Female Role Models in Steering Girls Towards STEM? Evidence from French High Schools," *The Economic Journal*, 133, 1773–1809.
- BRIEF, A. P. AND W. R. NORD (1990): "Meanings of occupational work: A collection of essays," (No Title).

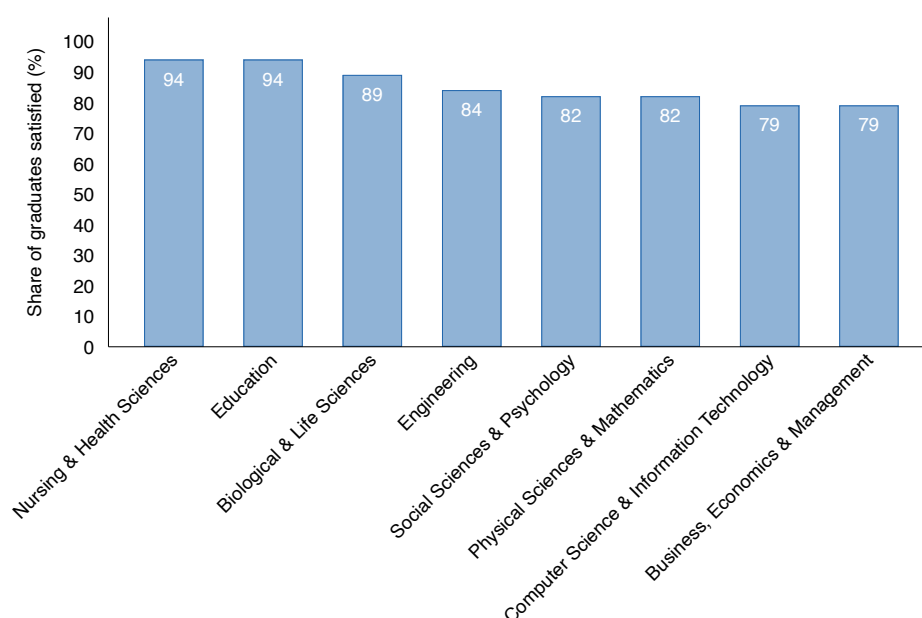
- BURBANO, V., N. PADILLA, AND S. MEIER (2024a): "Gender differences in preferences for meaning at work," *American Economic Journal: Economic Policy*, 16, 61–94.
- BURBANO, V. C. (2016): "Social responsibility messages and worker wage requirements: Field experimental evidence from online labor marketplaces," *Organization Science*, 27, 1010–1028.
- BURBANO, V. C., O. FOLKE, S. MEIER, AND J. RICKNE (2024b): "The gender gap in meaningful work," *Management Science*, 70, 7004–7023.
- BUURMAN, M., J. DELFGAAUW, R. DUR, AND S. VAN DEN BOSSCHE (2012): "Public sector employees: Risk averse and altruistic?" *Journal of Economic Behavior & Organization*, 83, 279–291.
- CARPENTER, J. AND E. GONG (2016): "Motivating agents: How much does the mission matter?" *Journal of Labor Economics*, 34, 211–236.
- CASSAR, L. (2019): "Job mission as a substitute for monetary incentives: Benefits and limits," *Management Science*, 65, 896–912.
- CASSAR, L. AND S. MEIER (2018): "Nonmonetary incentives and the implications of work as a source of meaning," *Journal of Economic Perspectives*, 32, 215–238.
- CHANDLER, D. AND A. KAPELNER (2013): "Breaking monotony with meaning: Motivation in crowdsourcing markets," *Journal of Economic Behavior & Organization*, 90, 123–133.
- CHRISTIAN, A., M. RONFELDT, AND B. ZAFAR (2024): "College students and career aspirations: Nudging student interest in teaching," Tech. rep., National Bureau of Economic Research.
- CONLON, J. J. (2021): "Major malfunction: A field experiment correcting undergraduates' beliefs about salaries," *Journal of Human Resources*, 56, 922–939.
- CONLON, J. J. AND D. PATEL (2026): "What jobs come to mind? Stereotypes about fields of study," *The Quarterly Journal of Economics*, qjag031.
- CORTES, P. AND J. PAN (2018): "Occupation and gender," *The Oxford handbook of women and the economy*, 425–452.
- COSTA-RAMÓN, A., M. SLOTWINSKI, U. SCHAEDE, AND A. A. BRENØE (2026): "(Not) Thinking About the Future: Financial Information and Maternal Labor Supply," *The Quarterly Journal of Economics*, 141, 1335–1382.
- CROWNE, D. P. AND D. MARLOWE (1960): "A new scale of social desirability independent of psychopathology," *Journal of consulting psychology*, 24, 349.
- DEL CARPIO, L. AND M. GUADALUPE (2022): "More women in tech? Evidence from a field experiment addressing social identity," *Management Science*, 68, 3196–3218.
- DIEKMAN, A. B., E. K. CLARK, A. M. JOHNSTON, E. R. BROWN, AND M. STEINBERG (2011): "Malleability in communal goals and beliefs influences attraction to stem careers: evidence for a goal congruity perspective," *Journal of personality and social psychology*, 101, 902.
- DUR, R. AND M. VAN LENT (2019): "Socially useless jobs," *Industrial Relations: A Journal of Economy and Society*, 58, 3–16.
- ERSOY, F. AND J. D. SPEER (2025): "Opening the black box of college major choice: Evidence from an information intervention," *Journal of Economic Behavior & Organization*, 231, 106800.

- FEHR, E. AND G. CHARNES (2025): "Social preferences: fundamental characteristics and economic consequences," *Journal of Economic Literature*, 63, 440–514.
- GENNAIOLI, N. AND A. SHLEIFER (2010): "What comes to mind," *The Quarterly journal of economics*, 125, 1399–1433.
- GRAEBER, T., C. ROTH, AND F. ZIMMERMANN (2024): "Stories, statistics, and memory," *The Quarterly Journal of Economics*, 139, 2181–2225.
- GREGG, P., P. A. GROUT, A. RATCLIFFE, S. SMITH, AND F. WINDMEIJER (2011): "How important is pro-social behaviour in the delivery of public services?" *Journal of public economics*, 95, 758–766.
- GROVE, W. A., A. HUSSEY, AND M. JETTER (2011): "The gender pay gap beyond human capital: Heterogeneity in noncognitive skills and in labor market tastes," *Journal of Human Resources*, 46, 827–874.
- HAALAND, I., C. ROTH, AND J. WOHLFART (2023): "Designing information provision experiments," *Journal of economic literature*, 61, 3–40.
- HASTINGS, J. S., C. A. NEILSON, AND S. D. ZIMMERMAN (2013): "Are some degrees worth more than others? Evidence from college admission cutoffs in Chile," Tech. rep., National Bureau of Economic Research.
- JOHNSTON, K., J. MEER, AND D. SERRA (2026): "Shaping Major Choice: The Role of High School Counselors," Tech. rep., National Bureau of Economic Research.
- KAHN, S. AND D. GINTHER (2017): "Women and science, technology, engineering, and mathematics (STEM): Are differences in education and careers due to stereotypes, interests, or family?" .
- KIRKEBOEN, L. J., E. LEUVEN, AND M. MOGSTAD (2016): "Field of study, earnings, and self-selection," *The quarterly journal of economics*, 131, 1057–1111.
- KUGLER, A. D., C. H. TINSLEY, AND O. UKHANEVA (2021): "Choice of majors: Are women really different from men?" *Economics of Education Review*, 81, 102079.
- LEE, M. AND L. HUANG (2018): "Gender bias, social impact framing, and evaluation of entrepreneurial ventures," *Organization Science*, 29, 1–16.
- LI, H.-H. (2018): "Do mentoring, information, and nudge reduce the gender gap in economics majors?" *Economics of Education Review*, 64, 165–183.
- NIKOLOVA, M. AND F. CNOSSEN (2020): "What makes work meaningful and why economists should care about it," *Labour economics*, 65, 101847.
- PATNAIK, A., M. WISWALL, AND B. ZAFAR (2021): "College majors 1," *The Routledge handbook of the economics of education*, 415–457.
- PUGATCH, T. AND E. SCHROEDER (2021): "Promoting female interest in economics: Limits to nudges," in *AEA Papers and Proceedings*, American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203, vol. 111, 123–127.

- REYNOLDS, W. M. (1982): "Development of reliable and valid short forms of the Marlowe-Crowne Social Desirability Scale," *Journal of clinical psychology*, 38, 119–125.
- SCHNEIDER, F. H., F. BRUN, AND R. A. WEBER (2024): "Sorting and wage premiums in immoral work," *Review of Economics and Statistics*, 1–46.
- SU, R. AND J. ROUNDS (2015): "All STEM fields are not created equal: People and things interests explain gender disparities across STEM fields," *Frontiers in psychology*, 6, 189.
- SU, R., J. ROUNDS, AND P. I. ARMSTRONG (2009): "Men and Things, Women and People: A Meta-Analysis of Sex Differences in Interests," *Psychological Bulletin*, 135, 859–884.
- WISWALL, M. AND B. ZAFAR (2015): "Determinants of college major choice: Identification using an information experiment," *The Review of Economic Studies*, 82, 791–824.
- (2018): "Preference for the workplace, investment in human capital, and gender," *The Quarterly Journal of Economics*, 133, 457–507.
- ZAFAR, B. (2013): "College major choice and the gender gap," *Journal of Human Resources*, 48, 545–595.

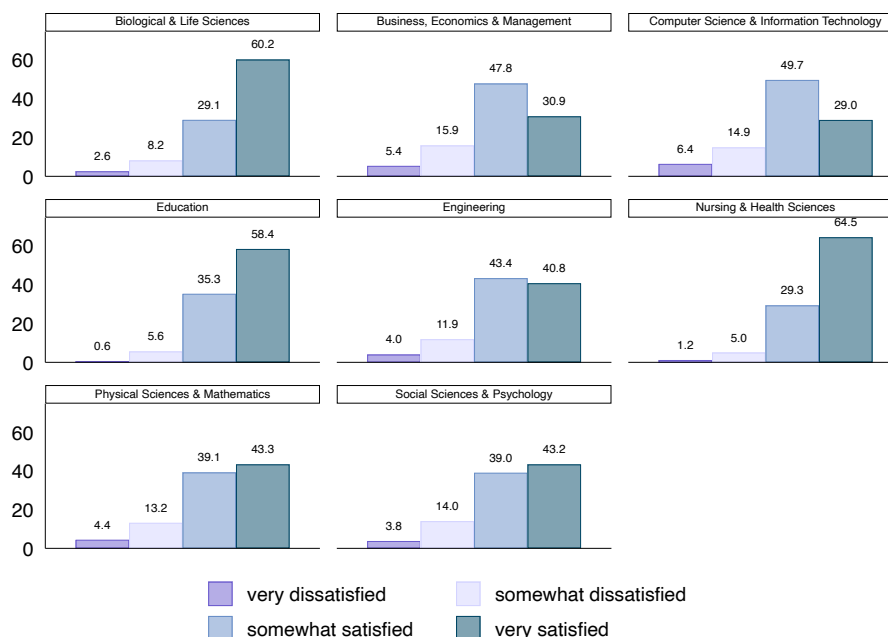
A Appendix: Supplementary Figures and Tables

Figure A.1: Share of Graduates Satisfied with Contribution to Society



Notes: For each major group, the figure displays the average share of previous graduates aged 30 to 35 currently full-time employed who are satisfied with their current job's contribution, meaning they are either *somewhat satisfied* or *very satisfied*, according to the last National Survey of College Graduates in 2023.

Figure A.2: Distribution of Satisfaction with Contribution to Society



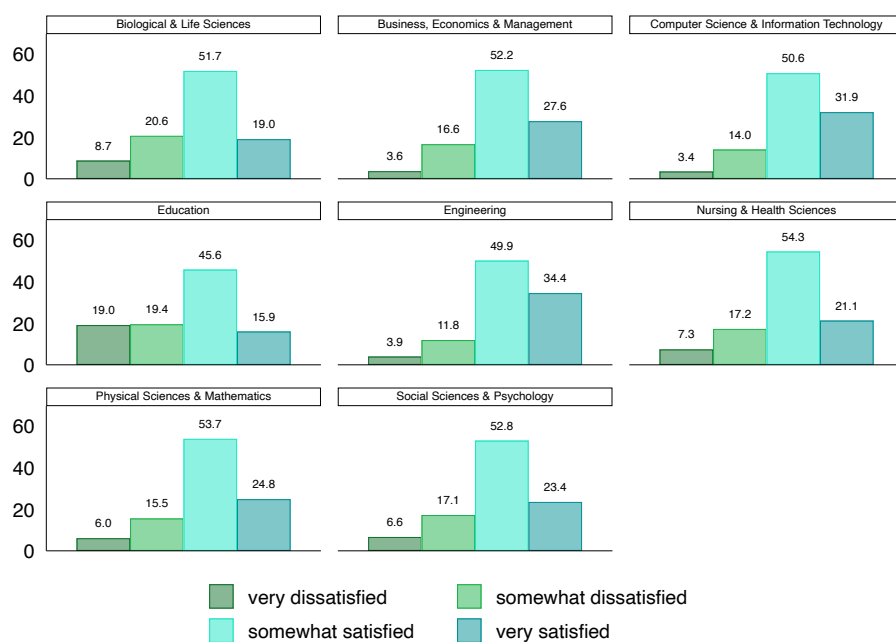
Notes: For each major group, the figure displays the share of previous graduates in percentage points, aged 30 to 35 currently full-time employed who answered different levels of satisfaction with their current job's contribution to society, according to the last National Survey of College Graduates in 2023.

Figure A.3: Examples of Jobs which Contribute to Society



Notes: The figure displays a word cloud of the most frequently cited terms in response to the open-ended question in our main survey "Think about the kinds of jobs you can get with a Bachelor's degree or higher. Can you think of one or more examples of such jobs that you would personally consider to contribute to society?". Word size is proportional to the frequency with which each term appears in students' answers.

Figure A.4: Distribution of Satisfaction with Salary

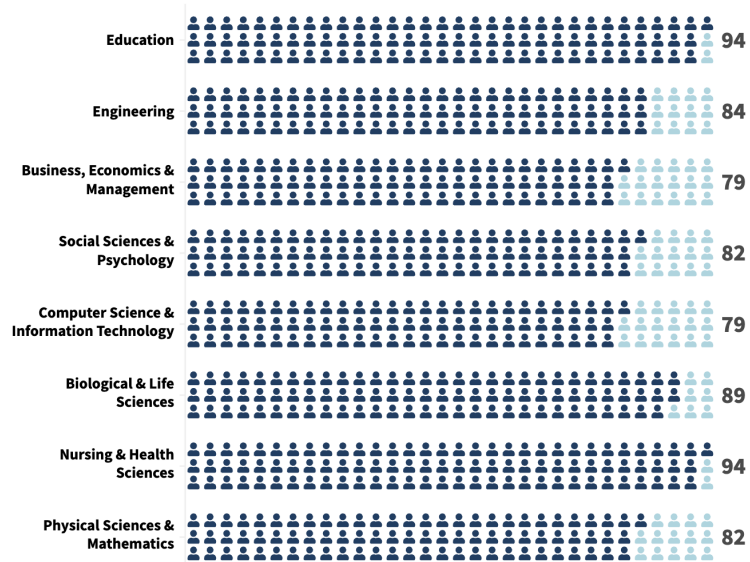


Notes: For each major group, the figure displays the share of previous graduates, in percentage points, aged 30 to 35 currently full-time employed who answered different levels of satisfaction with their current job's salary, according to the last National Survey of College Graduates in 2023.

Figure A.5: Information Graphic - Statistics

1

Share of graduates satisfied with job's contribution



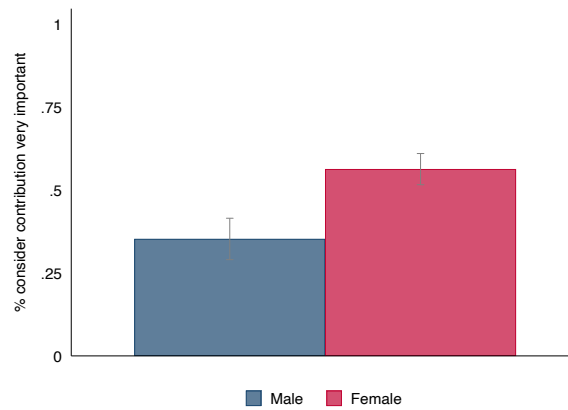
Notes: Students are shown the following intro: "Below you can see the correct answers to the questions we asked you before, according to the last National Survey of Graduates. As you can see, most people feel satisfied with their job's contribution across all fields."

Figure A.6: Information Graphic - Stories

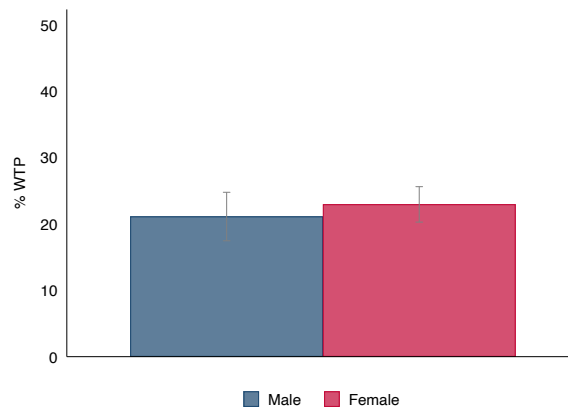


Notes: Students are shown the following intro: "Every field has its own ways of making a positive difference. Sometimes students are not aware of the contribution they can have by pursuing different majors. Below you'll find short summaries of reflections from Ohio State University alumni in each field. They describe what they do in their job and how they feel it positively contributes to society. Click on each card to discover the kinds of impact different fields can have. You must open all cards before continuing."

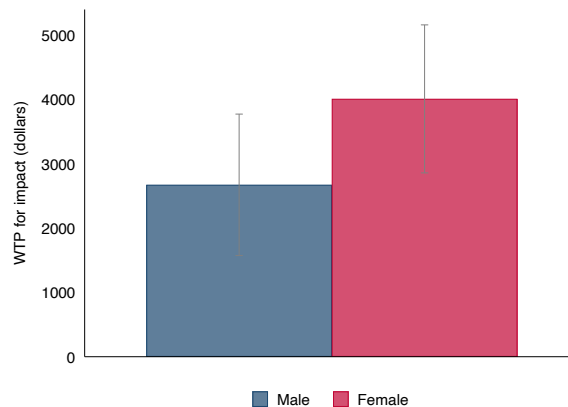
Figure A.7: Preferences - Gender Differences



(a) Share of Students Considering "Contribution to Society" Very Important



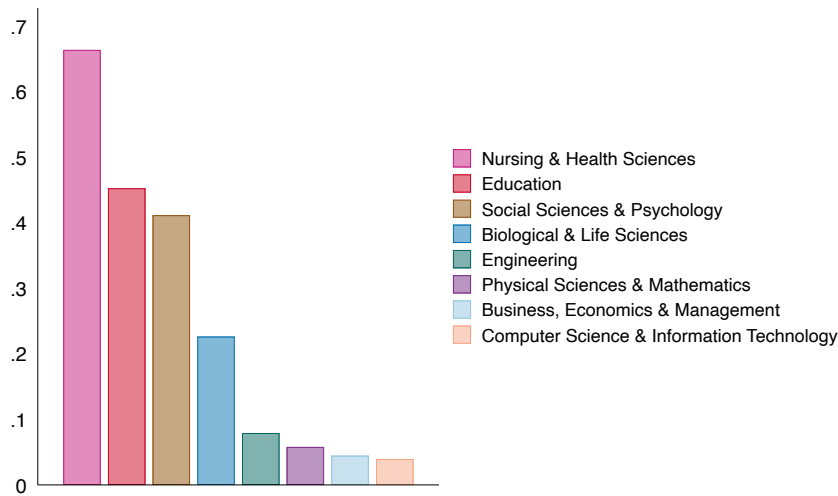
(b) WTP for Job's Contribution to Society



(c) WTP for Job's Contribution to Society

Notes: Panels (a), (b) and (c) show gender differences in two different measures for preferences in the main survey. Panel (a) shows the share of male and female students declaring "contribution to society" as very important as future job attribute, while panel (b) shows students' willingness to pay for a socially impactful job, measured as the percentage reduction in wage they would accept after stating their minimum net monthly salary when considering an otherwise identical job that provides satisfaction with its contribution to society. Panel (c) plot the same measure in terms of dollars, computed with the minimum minimum net monthly salary.

Figure A.8: Mentioning Social Impact - Top of Mind Priors



Notes: For each major group, the figure displays the average share of students whose responses to the question "Write a few short reasons about what job's aspects might make you choose that field as your major" include references to social impact (for example "helping other people", "contributing to the community"). This question was asked before the information provision (priors). A response is coded as mentioning social impact if it refers to a positive impact on society—such as helping people or communities, improving others' well-being, addressing social problems, or contributing to society. The coding is carried out by a large language model (Claude Opus 4.6) following a fixed rule applied uniformly to all responses; answers that merely name an occupation, without describing any job aspect, are treated as missing.

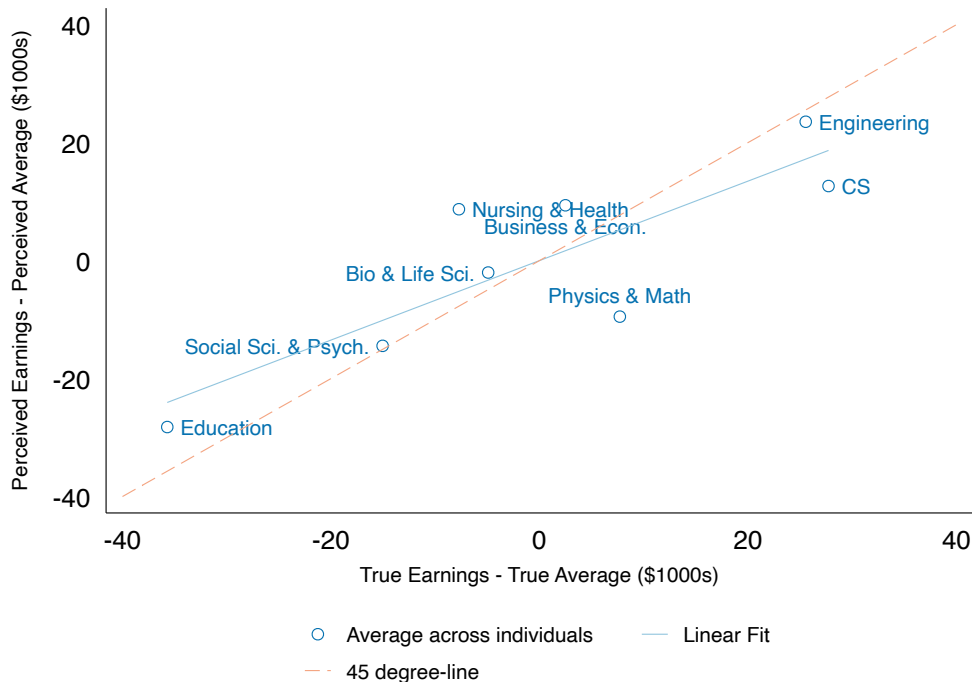
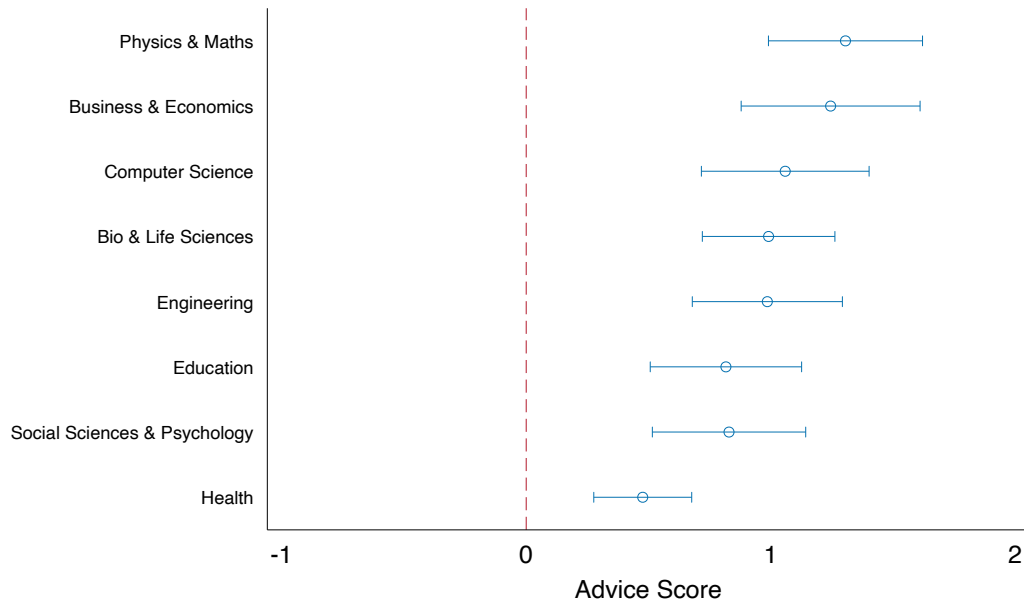


Figure A.9: Believed Differences vs Real Differences in Yearly Salary

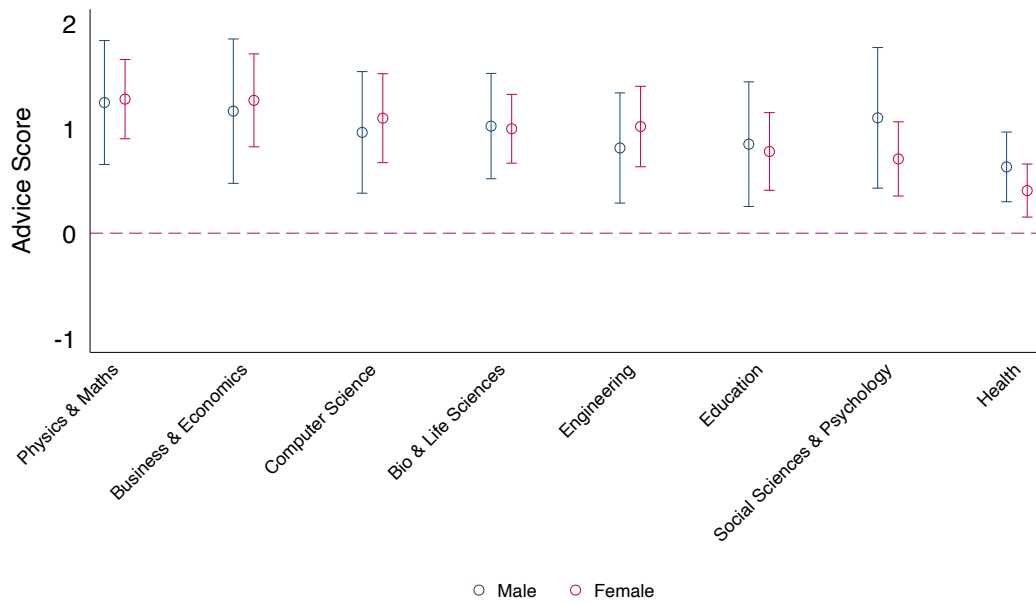
Notes: Each dot represents the average across respondents, marking the difference between the believed yearly salary for each major with the believed overall average against the true difference in the NSCG data. The blue line indicates the linear fit for these points. A slope smaller than one, indicated by the 45-degree-line, denotes a perceived shrinking of differences.

Figure A.10: Treatment Effects on Advice Score – Preferences for SI

(a) All students

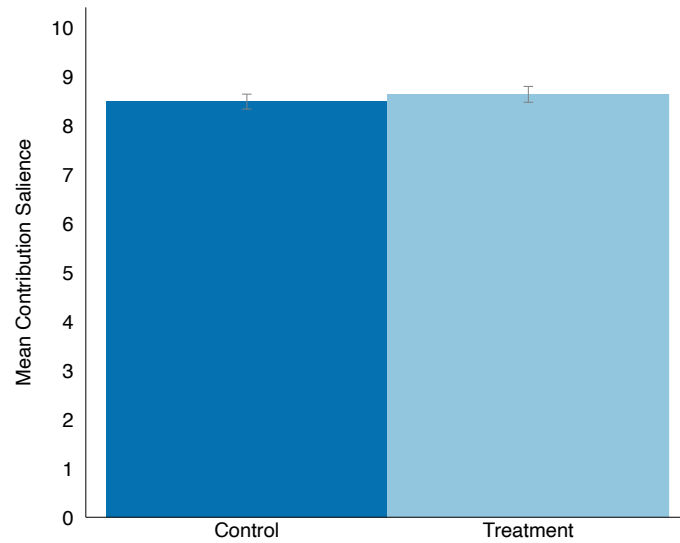


(b) By gender



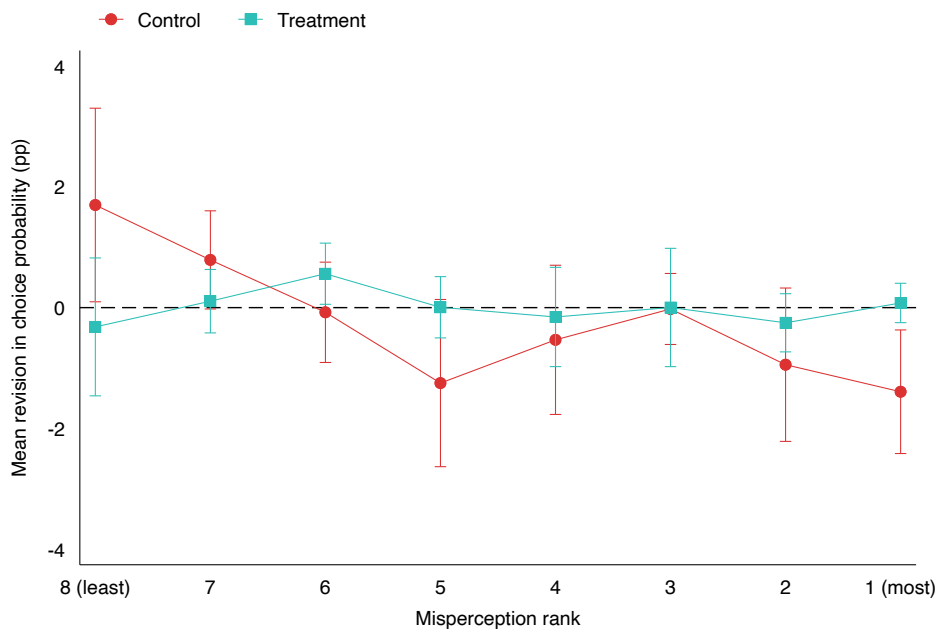
Notes: The plotted coefficients correspond to the aggregate treatment effects on the advice score given to peers for each major, obtained by estimating the coefficient on a treatment dummy separately for each major (Panel (a)), and separately by gender (Panel (b)). The dependent variable is a score from 0 to 10, and we control for age, gender, year of enrollment and campus FEs. Majors are ordered from the most (Physics & Math) to the least underestimated (Health) in terms of graduates' perceived impact across all students. The sample is restricted to students who report that contribution to society is important. Error bars reflect 95% confidence intervals.

Figure A.11: Salience "Contribution to Society" - Preferences for SI



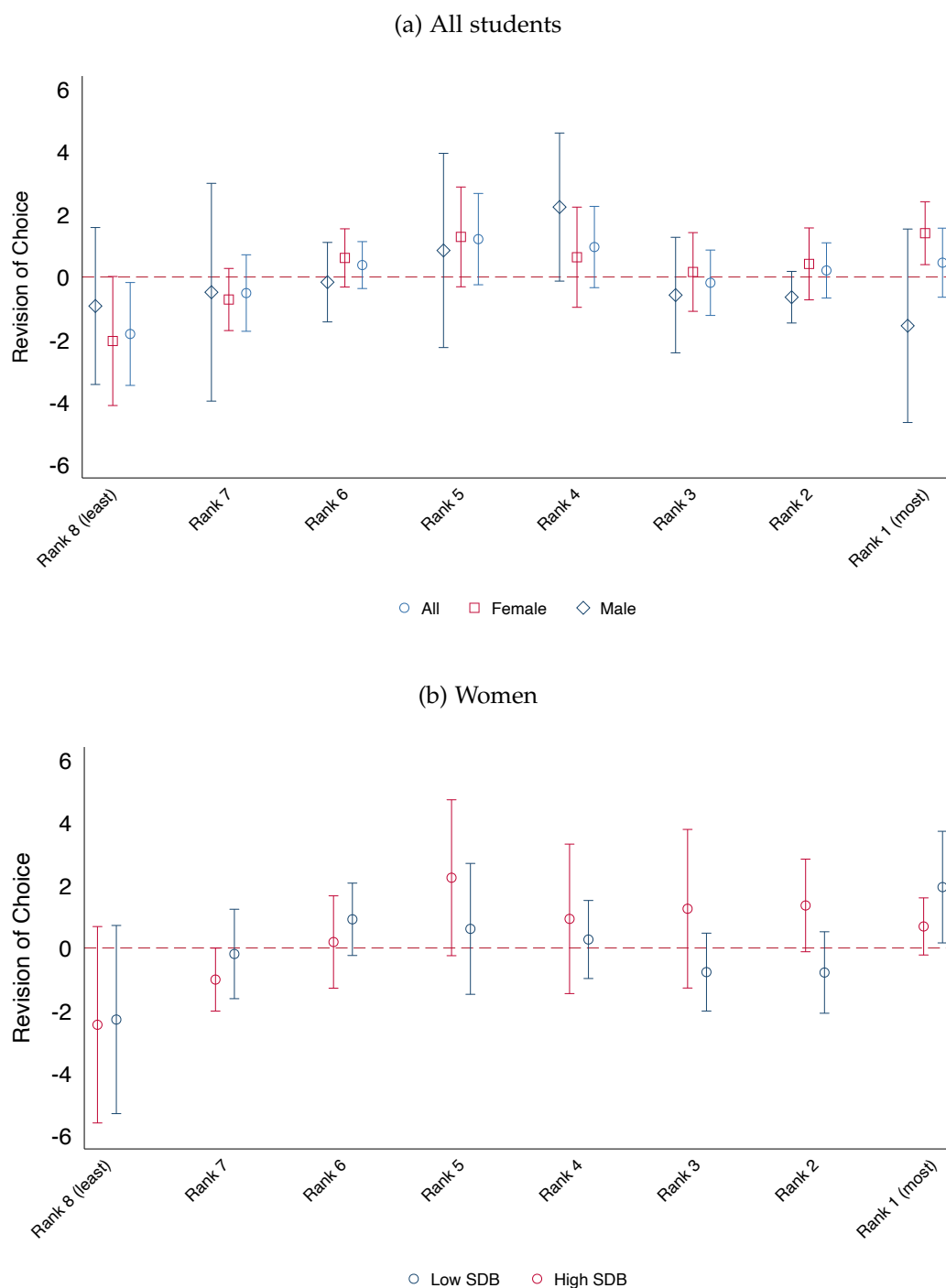
Notes: This figure reports the average score students gave, at the end of the survey, to the question: "On a scale from 0 to 10, how much was the idea of contributing to society on your mind during the survey?" The sample is restricted to students who report that contribution to society is important, and the bars show the means for treated and control students separately, with 95% confidence intervals.

Figure A.12: Revision in Choice Probability - Preferences for SI, Women



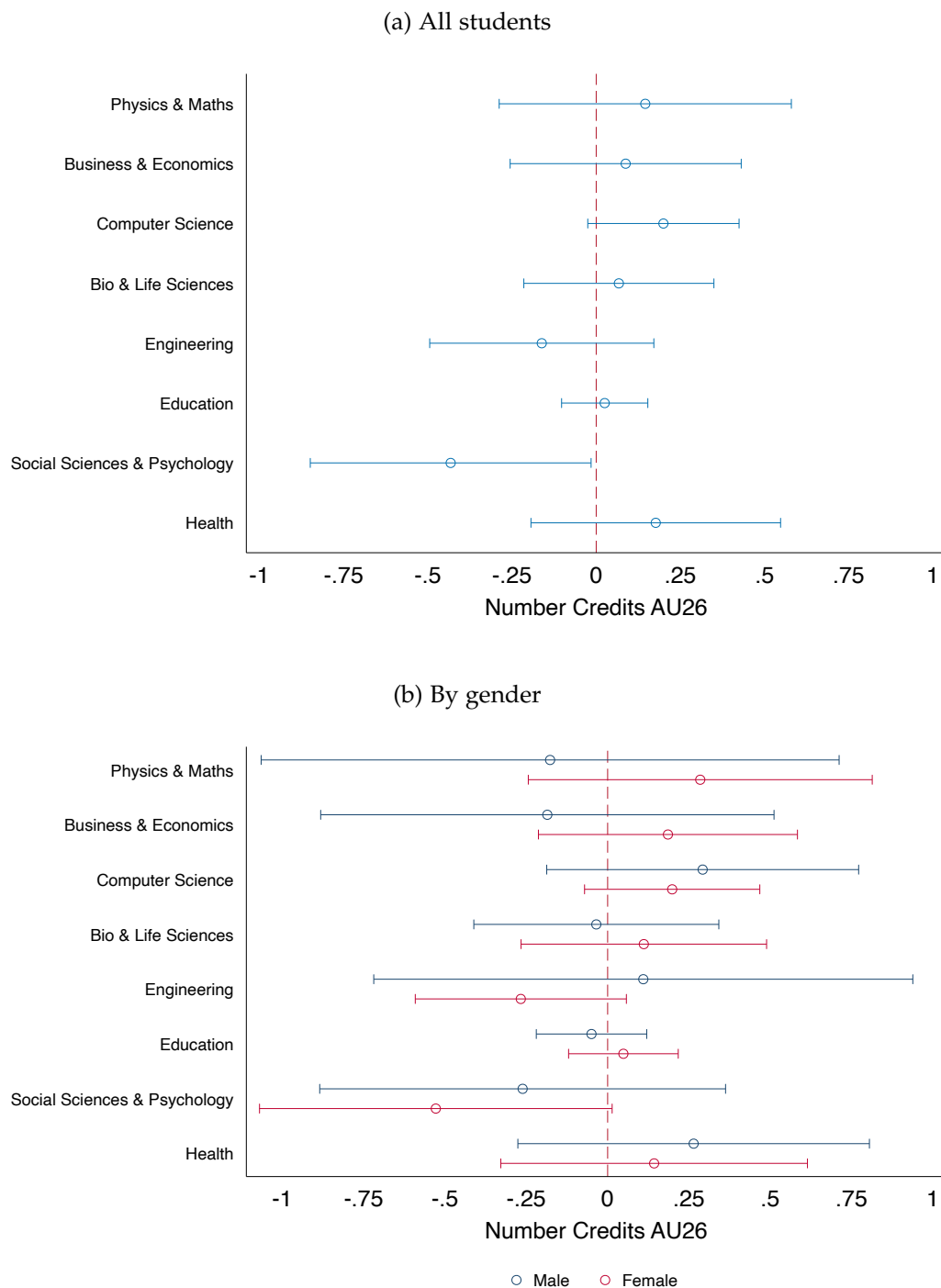
Notes: For each student, majors are ranked by how much she initially underestimates the social impact of previous graduates, from the least to the most underestimated. The figure plots the average revision in the probability of pursuing each major – the posterior minus the prior probability, in percentage points – at each rank, separately for treated (green) and control (orange) women who report that contribution to society is important. Error bars are 95% confidence intervals.

Figure A.13: Revision in Choice Probability by Individual Rank of Misperception – Preferences for SI



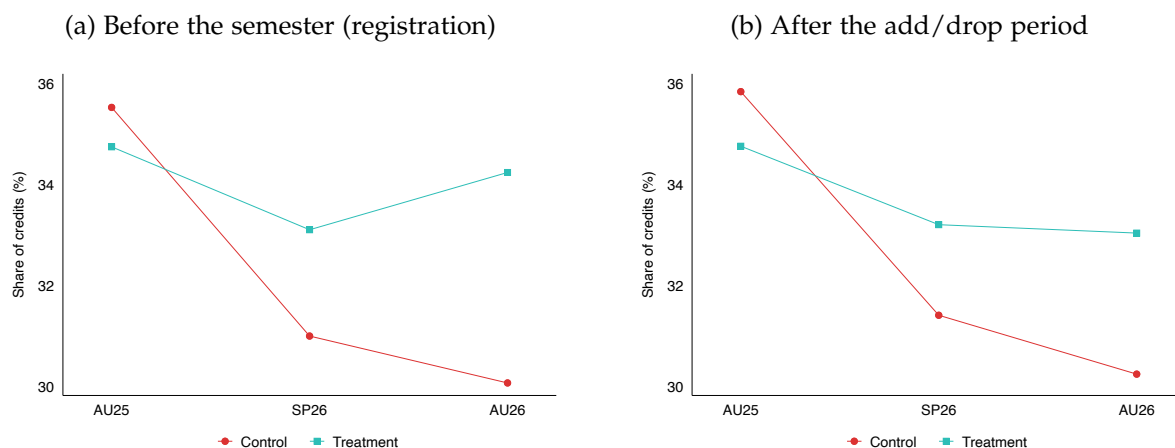
Notes: The plotted coefficients are the treatment effects on choice probability, obtained by estimating the coefficient on a treatment dummy separately for each individual rank of misperception—each student's majors are ranked from the least to the most underestimated at the individual level. Panel (a) shows the coefficients for all students who care about contribution, and separately by gender; Panel (b) restricts to women and plots the coefficients for low- and high-SDB women. The dependent variable is the final probability of pursuing the major at that rank, and we control for the initial (pre-treatment) probability and the prior number of credits in that major. The sample is restricted to students who report that contribution to society is important. Error bars reflect 95% confidence intervals.

Figure A.14: Treatment Effects on Registered Credits Before the Semester (AU26) – Preferences for SI



Notes: The figure replicates Figure 8 using the first snapshot of the administrative data, taken in early July 2026, after students had registered for their Fall classes and before the add/drop period. The plotted coefficients correspond to the aggregate treatment effects on classes registered for the Fall semester, obtained by estimating the coefficient on a treatment dummy separately for each major (Panel (a)), and separately by gender (Panel (b)). The dependent variable is the number of credits in that major, and we control for the initial probability (pre-treatment) and the prior number of credits in that major. Majors are ordered from the most (Physics & Maths) to the least underestimated (Health) in terms of graduates' perceived impact across all students. The sample is restricted to students who report that contribution to society is important. Error bars reflect 95% confidence intervals.

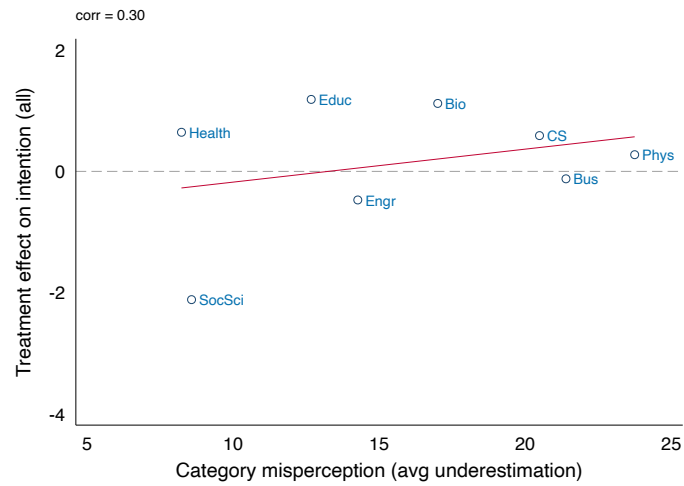
Figure A.15: Credit Shares in the Most Underestimated Fields Across Semesters – Preferences for SI, Women



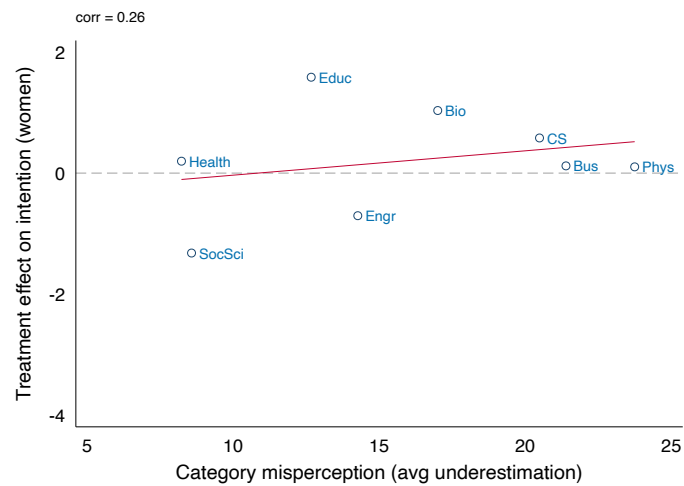
Notes: The figure plots, for women who report caring about contribution to society, the mean share of enrolled credits in the three most underestimated fields (Business & Economics, Computer Science, and Physics & Maths) across the three observed semesters (Autumn 2025, Spring 2026, Autumn 2026), separately for the control and treated groups. The survey took place in Spring 2026, so Autumn 2026 is the semester after the survey. Panel (a) measures Autumn 2026 credits with the first snapshot of the administrative data, taken in early July 2026 after students had registered for their classes; Panel (b) uses the snapshot taken after the add/drop period. Autumn 2025 and Spring 2026 are the same in both panels. Shares are computed at the student level and averaged within each arm. Because course-taking follows a curriculum sequence, the absolute levels partly reflect standard progression; the control-vs-treated comparison nets out this common trend.

Figure A.16: Treatment Effect on Intentions vs. Category Misperception

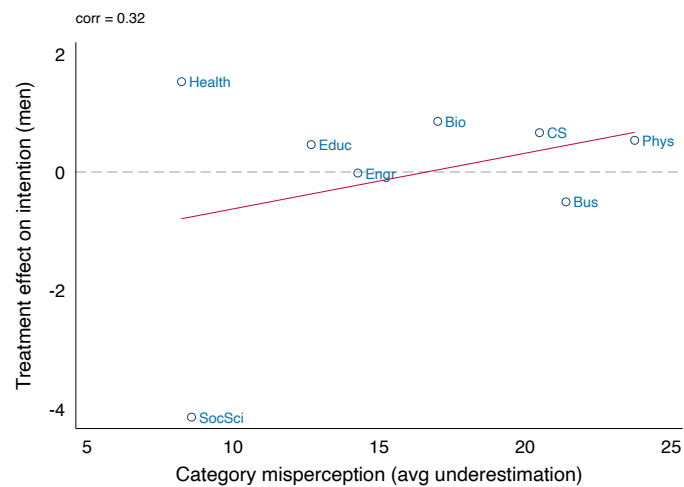
(a) All students



(b) Women



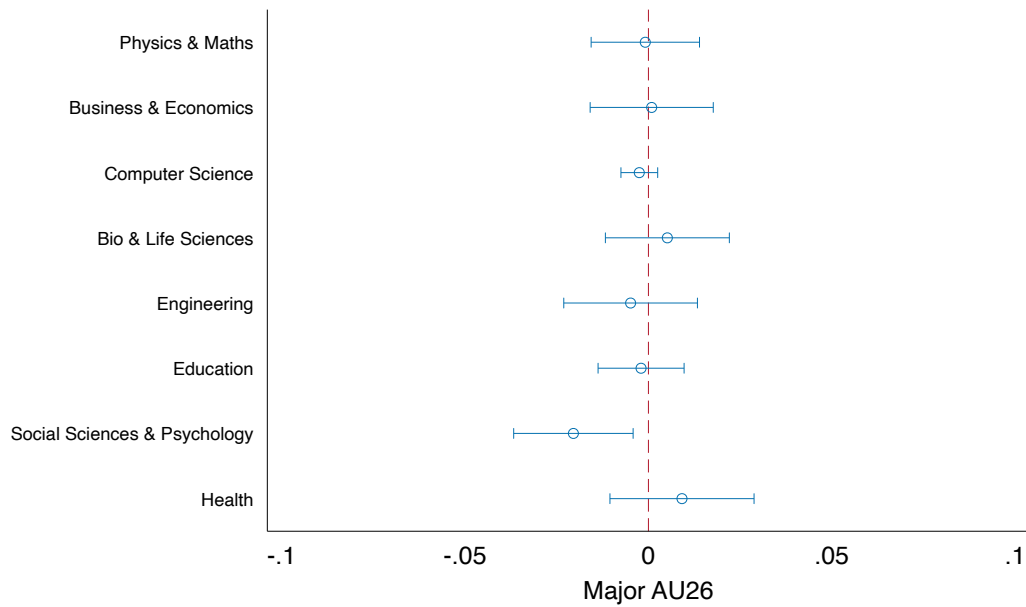
(c) Men



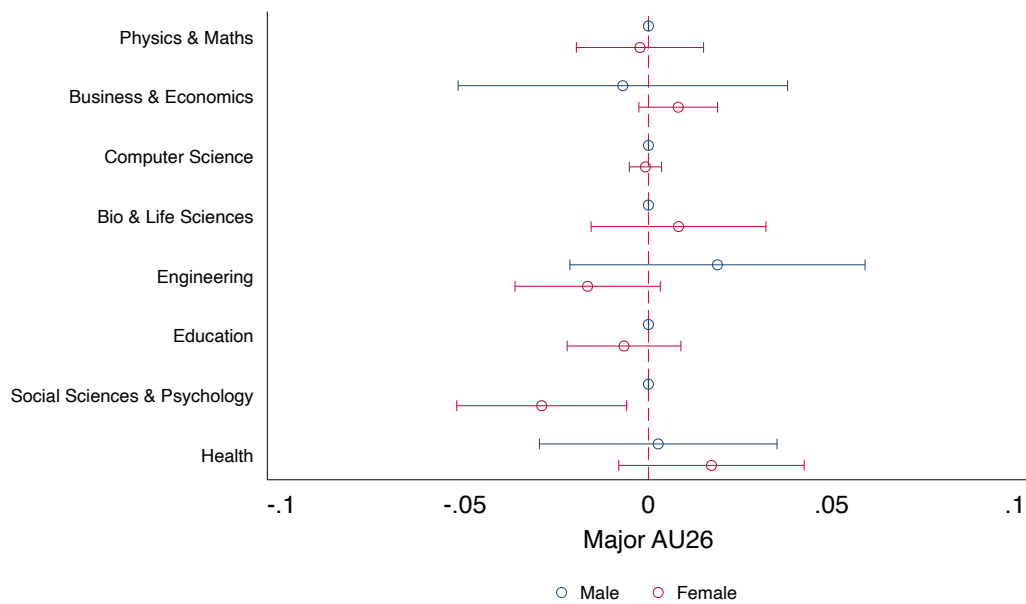
Notes: Each point is one of the eight major categories. The horizontal axis is the category's average misperception on population and the vertical axis is the estimated treatment effect on major intentions, i.e. the coefficient on the treatment indicator from a per-category regression of posterior probability on prior credits, the prior intention, and fixed effects. The red line is a linear fit. The sample is restricted to students who care about a job's contribution to society.

Figure A.17: Treatment Effects on Major Declarations (AU26) – Preferences for SI

(a) All students



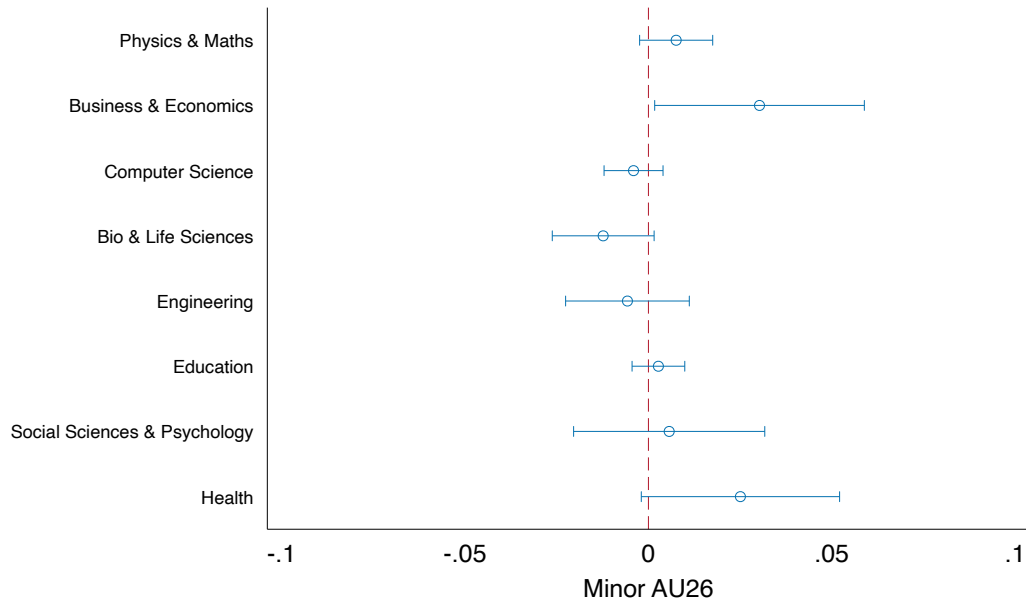
(b) By gender



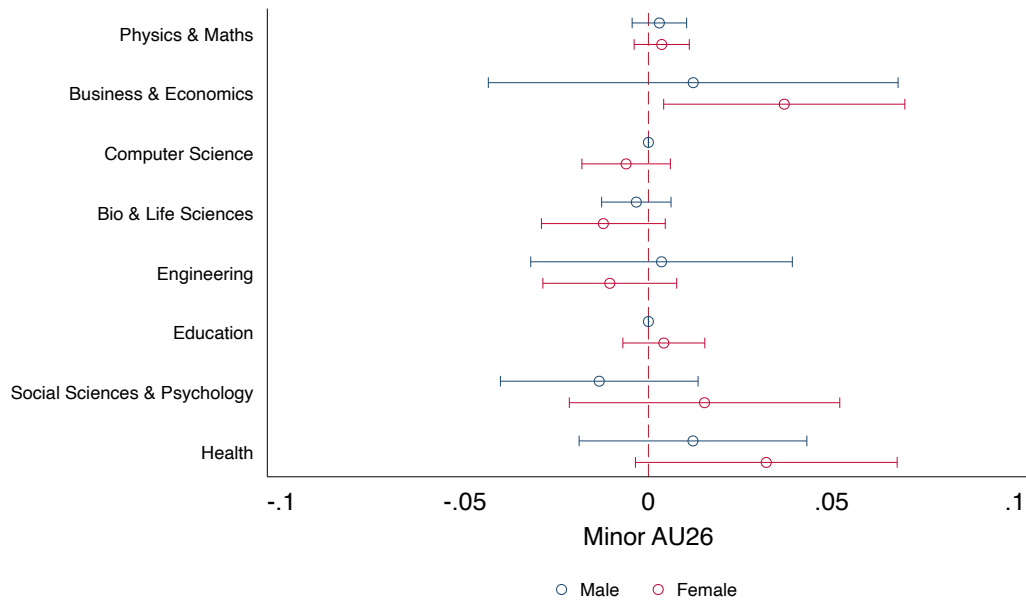
Notes: The plotted coefficients correspond to the aggregate treatment effects on major declarations for the Fall semester, obtained by estimating the coefficient on a treatment dummy separately for each major (Panel (a)), and separately by gender (Panel (b)). The dependent variable is a dummy for declaring that major, and we control for the major declared at the term before, the initial stated probability (pre-treatment), the prior number of credits in that major. Majors are ordered from the most (Physics & Maths) to the least underestimated (Health) in terms of graduates' perceived impact across all students. The sample is restricted to students who report that contribution to society is important. Error bars reflect 95% confidence intervals.

Figure A.18: Treatment Effects on Minor Declarations (AU26) – Preferences for SI

(a) All students



(b) By gender



Notes: The plotted coefficients correspond to the aggregate treatment effects on minor declarations for the Fall semester, obtained by estimating the coefficient on a treatment dummy separately for each major (Panel (a)), and separately by gender (Panel (b)). The dependent variable is a dummy for declaring a minor in that field, and we control for the minor declared at the term before, the stated initial probability (pre-treatment) and the prior number of credits in that field. Majors are ordered from the most (Physics & Maths) to the least underestimated (Health) in terms of graduates' perceived impact across all students. The sample is restricted to students who report that contribution to society is important. Error bars reflect 95% confidence intervals.

Table A.1: Majors Groups from the National Survey of College Graduates

Group Name	Nationally Representative Survey Major Names
Biological & Life Sciences	Biochemistry and Biophysics; Biology, General; Botany; Cell and Molecular Biology; Ecology; Genetics, Animal and Plant; Microbiological Sciences and Immunology; Pharmacology, Human and Animal; Physiology and Pathology, Human and Animal; Zoology, General; OTHER Biological Sciences.
Business, Economics & Management	Accounting; Business Administration and Management; Business, General; Business and Managerial Economics; Financial Management; OTHER Business Management/Administrative Services; Business Marketing/Marketing Management; Marketing Research; Economics.
Computer Science & Information Technology	Computer and Information Sciences, General; Computer Science; Computer Systems Analysis; Information Services and Systems; OTHER Computer and Information Sciences; Computer Programming; Data Processing.
Education	Education Administration; Counselor Education and Guidance Services; Elementary Teacher Education; Physical Education and Coaching; Pre-school/Kindergarten/Early Childhood Teacher Education; Secondary Teacher Education; Special Education; OTHER Education; Computer Teacher Education; Mathematics Teacher Education; Science Teacher Education; Social Science Teacher Education.
Engineering	Aerospace, Aeronautical and Astronautical Engineering; Chemical Engineering; Architectural Engineering; Civil Engineering; Computer and Systems Engineering; Electrical, Electronics and Communications Engineering; Industrial and Manufacturing Engineering; Mechanical Engineering; Agricultural Engineering; Bioengineering and Biomedical Engineering; Engineering Sciences, Mechanics and Physics; Environmental Engineering; Engineering, General; Materials Engineering, including Ceramics and Textiles; Metallurgical Engineering; Nuclear Engineering; Other Engineering (including Geophysical, Geological, Mining, Mineral, Naval Architecture, Marine, and Petroleum); Electrical and Electronic Technologies; Industrial Production Technologies; Mechanical Engineering-Related Technologies; OTHER Engineering-Related Technologies.
Nursing & Health Sciences	Audiology and Speech Pathology; Health Services Administration; Health/Medical Assistants; Health/Medical Technologies; Medical Preparatory Programs (e.g., Pre-Dentistry, -Medical, -Veterinary); Medicine (Dentistry, Optometry, Osteopathic, Podiatry, Veterinary); Nursing (4 Years or Longer Program); Pharmacy; Physical Therapy and Other Rehabilitation/Therapeutic Services; Public Health (including Environmental Health and Epidemiology); OTHER Health/Medical Sciences; Nutritional Sciences.
Physical Sciences & Mathematics	Chemistry, Except Biochemistry; Atmospheric Sciences and Meteorology; Earth Sciences; Geology; Geological Sciences, Other (including Oceanography); Astronomy and Astrophysics; Physics; OTHER Physical Sciences; Applied Mathematics; Mathematics, General; Operations Research; Statistics; OTHER Mathematics; Actuarial Science.
Social Sciences & Psychology	Educational Psychology; Clinical Psychology; Counseling Psychology; Experimental Psychology; General Psychology; Industrial/Organizational Psychology; Social Psychology; OTHER Psychology; Anthropology and Archaeology; Criminology; Sociology; Area and Ethnic Studies; Philosophy of Science; OTHER Social Sciences, including History of Science; OTHER Philosophy, Religion, Theology; Social Work; History, other; Public Policy Studies; International Relations; Political Science and Government; Public Administration; Geography; OTHER Public Affairs.
Others	OTHER Agricultural Business and Production; OTHER Agricultural Sciences; Environmental Science or Studies; Forestry Sciences; Criminal Justice/Protective Services; Home Economics; Library Science; Parks, Recreation, Leisure, and Fitness Studies; OTHER Natural Resources and Conservation; OTHER Fields (Not Listed); Animal Sciences; Food Sciences and Technology; Plant Sciences; Agricultural Economics; Architecture/Environmental Design; Communications, general; Journalism; OTHER communications; English Language, Literature and Letters; OTHER Foreign Languages and Literature; Liberal Arts/General Studies; Dramatic Arts; Fine Arts, all fields; Music, all fields; OTHER Visual and Performing Arts; Linguistics; Law/Prelaw/Legal Studies.

Table A.2: Alumni Stories by Major Group

Group Name	Story (Graduate Perspective)
Biological & Life Sciences	Graduates in the biological and life sciences drive progress in medicine, working to develop treatments and technologies that directly improve and save lives. • An alumnus who studied Biochemistry works as a Scientist at a pharmaceutical company producing vaccines for diseases including influenza, malaria, and cancer. “We recently received FDA allowance to proceed with clinical trials, which was a huge milestone,” they share about their ongoing work. • A Molecular Genetics graduate serves as a Senior Scientist at a cancer immunotherapy company, working as a computational biologist to develop next-generation therapeutics for patients with solid tumors, with a clinical trial beginning in the coming months. • A graduate who studied Biochemistry works as an Assistant Director of Research and Development in oligonucleotide manufacturing, designing production methods for components used in biological and clinical research. “Every sequence we perfect is a tool handed directly to researchers who are revolutionizing human health.”
Business, Economics & Management	Graduates in business, economics, and management apply analytical skills to address challenges ranging from environmental sustainability to making financial markets more trustworthy. • An alumnus who studied Economics works as an Electric Vehicle Strategy Senior Analyst in the automotive industry, developing ways to keep electric vehicles viable amid changing regulations. “I went into this industry because I believe that electric vehicles are paramount to the energy transition,” they explain. • A graduate with a degree in Economics serves as an Environmental Economist at an engineering consultancy, performing early-stage assessment for renewable-focused projects and quantifying natural capital so companies make better choices for the environment. • An Accounting graduate works as a Senior Associate at a public accounting firm, helping clients navigate complex financial reporting and ensuring that the accounting information available to investors is accurate and reliable.

Group Name	Story (Graduate Perspective)
Computer Science & Information Technology	Graduates in computer science and information technology shape the systems that millions of people rely on, improving efficiency, strengthening security, and protecting consumers. • An alumnus who studied Computer Science and Engineering works as a Software Engineer in automation solutions for manufacturing. “Hundreds of people use these applications each day to aid in their work,” they explain, noting the tools they build help operators monitor stations across the country. • A Data Analytics graduate works as an Analytic Engineer in the insurance industry, developing testing methods and deploying fraud detection systems. “By preventing financial mistakes through software, defecting fraud, and ensuring audit compliance, the software I work with contributes to the financial security of millions of Americans.” • Another alumnus who studied Computer and Information Science conducts research in computer security and privacy, contributing to changes in how organizations handle password policies and authentication practices that affect users worldwide.
Education	Graduates with education degrees support learning and well-being in settings that extend well beyond the traditional classroom. • An alumnus who studied Special Education works as an Intervention Specialist, supporting students with disabilities by accommodating their needs and teaching skills to address learning gaps. “I prepare students for college readiness, shaping the next generation,” they share. • A graduate with a degree in Education now serves as President of an executive coaching firm, helping senior leaders develop strategic clarity and communication skills. They also do pro bono coaching for military service members transitioning to civilian careers, giving them confidence to succeed. • Another Education graduate works as a Director of Operations at a therapy practice, organizing administrative decisions to support the work of therapists. “Good mental health is an important part of being a happy and healthy human being,” they reflect about the mission behind their role.

Group Name	Story (Graduate Perspective)
Engineering	Graduates in engineering apply problem-solving skills to design systems that improve quality of life, from ensuring clean drinking water to advancing life-saving medicines. • An alumnus who studied Civil Engineering works as an Environmental Engineer at a consulting firm, leading projects focused on water and wastewater treatment. “My work involves the treatment of water and wastewater to produce potable and boutique water for municipalities and private industry,” they explain, including efforts to remove harmful compounds from drinking water. • A Biomedical Engineering graduate serves as a Principal Scientist at a pharmaceutical company, conducting early-stage research on new targets to treat heart failure, work that can lead to therapeutics prolonging patients’ quality of life. • A graduate who studied Industrial and Systems Engineering works as a Data Scientist in biopharma, improving the efficiency of plasma collection and optimizing therapies used to treat immune deficiencies and bleeding disorders.
Nursing & Health Sciences	Graduates in nursing and health sciences work at the frontlines of public health, improving nutrition, food safety, and access to innovative therapies. • An alumnus who studied Nutrition and Dietetics works as a Registered Dietitian and researcher, counseling patients with neurological diseases in an outpatient clinic. “Helping those struggling with chronic diseases with their nutrition isn’t about having them change to the picture perfect diet but rather coming up with creative ideas to help with quality of life.” • A graduate in Environmental Public Health works as a Research Scientist in food safety, studying foodborne disease in Ethiopia to reduce illness and build local capacity. “Our work informed decision-making for the Ethiopian government related to hospital care, food production and processing, and community education.” • A Public Health graduate serves as a Program Manager in gene therapy development, coordinating analytical testing for potentially life-changing treatments so patients receive timely care.
Physical Sciences & Mathematics	Graduates in physical sciences and mathematics contribute to society in many ways, from ensuring the safety of medications to making healthcare more affordable. • One alumnus who studied Chemistry works as a Scientist in pharmaceutical manufacturing, determining the purity and potency of medications before they reach markets worldwide. “I never expected when earning my chemistry degree that I would be in a role to protect the public in such a way.” • An Actuarial Science graduate serves as a Senior Associate in benefits consulting, helping employers navigate complex healthcare decisions so employees receive proper care at an affordable price. Their work helped a client implement targeted support for employees with musculoskeletal conditions, reducing the need for costly surgeries. • A graduate who studied Math Biology works as a Manager of Data Engineering at a consultancy, helping major corporations build out their data capabilities to better understand and serve their customers.

Group Name	Story (Graduate Perspective)
Social Sciences & Psychology	Graduates in the social sciences and psychology apply their understanding of human behavior to improve lives across healthcare, education, and public policy. • An alumnus who studied Psychology works as a Campus Engagement Librarian in higher education, teaching college students about information literacy and helping them evaluate credible sources. "There is so much misinformation out there, and I help provide students with tools to determine what information is credible." • A graduate in Anthropology works as a Behavioral Health Parity Analyst in insurance regulation, ensuring that insurance companies comply with laws requiring equitable coverage for behavioral health services. Their work often results in corrective actions that expand access to care for people who need it most. • A Psychology graduate works as a Licensed Professional Counselor in mental health services, providing individual therapy to adults and teens and helping people navigate challenges such as anxiety and depression.

Table A.4: Correlation Satisfaction with Salary and Contribution

	(1)	(2)	(3)
	Satisfaction Salary	Satisfaction Salary	Satisfaction Salary
Satisfaction Contribution	0.094*** (0.030)	0.129*** (0.029)	
Biological*Contribution			0.149*** (0.055)
Business*Contribution			0.074 (0.082)
Computer Science*Contribution			0.156*** (0.046)
Education*Contribution			−0.013 (0.196)
Engineering*Contribution			0.164*** (0.037)
Nursing*Contribution			0.193** (0.079)
Physics Maths*Contribution			0.164** (0.069)
Social Sciences*Contribution			0.143*** (0.054)
Major FEs	No	Yes	Yes
Observations	11699	11699	11699
Adjusted R^2	0.009	0.042	0.043

Notes: This table reports OLS estimates of the relationship between graduates' satisfaction with their salary and their satisfaction with their job's contribution to society, using the 2023 National Survey of College Graduates (NSCG). Both measures are reported on a four-point scale from 1 (very dissatisfied) to 4 (very satisfied); the dependent variable is satisfaction with salary. Column (1) pools all graduates; Column (2) adds field-of-study (major) fixed effects; Column (3) interacts satisfaction with contribution with field-of-study indicators, so each coefficient is the within-field slope of salary satisfaction on contribution satisfaction, and includes field-of-study fixed effects. The sample consists of college graduates aged 30–35 employed full time (at least 35 hours per week and 45 weeks per year), and all specifications are weighted by NSCG sampling weights. Robust standard errors in parentheses: *, ** and *** indicate significance at the 10%, 5% and 1% levels.

Table A.3: Representativeness of Majors across Job Attributes

	Contribution	Salary	Advancement	Challenge	Benefits	Independence	Location	Responsibility	Security
Biological & Life Sciences	1.59	0.70	1.04	1.12	1.04	1.52	0.88	1.04	1.30
Business, Economics & Management	0.71	1.15	0.80	0.77	0.87	1.09	0.98	0.87	1.12
Computer Science & IT	0.71	1.37	1.27	1.28	1.13	1.23	1.16	1.04	0.72
Education	2.88	0.46	2.27	2.10	0.50	1.45	2.15	1.19	0.95
Engineering	1.01	1.55	1.22	1.20	1.36	1.15	0.69	1.02	0.91
Nursing & Health Sciences	2.90	0.89	1.01	1.62	0.96	1.27	1.22	1.24	1.47
Physical Sciences & Mathematics	0.89	1.06	1.09	0.87	1.42	1.30	1.17	1.23	0.76
Social Sciences & Psychology	0.89	0.93	0.90	0.82	1.09	0.59	1.06	0.95	0.88

Notes: This table reports representativeness ratios for every job attribute listed in the 2023 National Survey of College Graduates (NSCG). Each ratio measure how representative is major m of that attribute, using the group of graduates who is satisfied (very or somewhat satisfied) vs unsatisfied (very or somewhat satisfied) with that attribute.

Table A.5: Correlation Overall Satisfaction and Job Features

	(1) Overall Satisfaction	(2) Overall Satisfaction
Satisfaction Advancement	0.103** (0.047)	0.101** (0.045)
Satisfaction Benefits	−0.009 (0.061)	−0.004 (0.056)
Satisfaction Challenge	0.092** (0.036)	0.089** (0.035)
Satisfaction Independence	0.161*** (0.026)	0.155*** (0.026)
Satisfaction Location	0.066*** (0.017)	0.067*** (0.017)
Satisfaction Responsibility	0.122*** (0.046)	0.125*** (0.045)
Satisfaction Salary	0.280*** (0.045)	0.274*** (0.040)
Satisfaction Security	0.096*** (0.027)	0.094*** (0.026)
Satisfaction Contribution	0.154*** (0.024)	0.166*** (0.027)
Major FEs	<i>No</i>	<i>Yes</i>
Observations	11699	11699
Adjusted R^2	0.541	0.547

Notes: This table reports OLS estimates from regressing graduates' overall satisfaction with their current job on their satisfaction with each of nine job attributes—advancement, benefits, challenge, independence, location, responsibility, salary, security, and contribution to society—using the 2023 National Survey of College Graduates (NSCG). All variables are reported on a four-point scale from 1 (very dissatisfied) to 4 (very satisfied); the dependent variable is overall job satisfaction. Column (1) includes no controls; Column (2) adds field-of-study (major) fixed effects. The sample consists of college graduates aged 30–35 employed full time (at least 35 hours per week and 45 weeks per year), and all specifications are weighted by NSCG sampling weights. Robust standard errors in parentheses: *, ** and *** indicate significance at the 10%, 5% and 1% levels.

Table A.6: Attrition: Attentive (N=657) vs Inattentive (N=320)

	Inattentive	Attentive	Difference
Treatment	0.450	0.533	-0.083**
1st Year	0.519	0.478	0.041
2nd Year	0.450	0.463	-0.013
3rd Year	0.031	0.059	-0.028**
Columbus	0.875	0.904	-0.029
Lima	0.009	0.009	0.000
Mansfield	0.028	0.015	0.013
Marion	0.022	0.015	0.007
Newark	0.050	0.052	-0.002
Wooster	0.016	0.005	0.011
Female	0.603	0.654	-0.051
Age	19.141	19.167	-0.027
Contribution Important	0.856	0.855	0.001
P(Biology & Life Sciences)	11.711	12.270	-0.559
P(Business & Economics)	23.947	21.214	2.733
P(Computer Science)	5.244	5.276	-0.033
P(Education)	4.303	4.241	0.062
P(Engineering)	15.606	18.193	-2.587
P(Health Sciences)	15.488	12.400	3.087
P(Physics & Maths)	2.211	5.170	-2.960***
P(Social Sciences)	12.384	13.137	-0.753
P(Other)	7.906	6.927	0.979

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Difference = Inattentive – Attentive.

Notes: The table compares the baseline characteristics of respondents who passed all four attention checks (“Attentive”, our final sample of $N = 657$) with those who failed at least one and are dropped (“Inattentive”, $N = 320$). It reports the mean of each characteristic in the two groups and their difference, with stars from a two-sample t -test with unequal variances. The “Treatment” row is the key differential-attrition check: a significant difference would indicate that retention depends on treatment assignment. Indicator variables are shares (0–1); P(major) is the stated prior probability of choosing each major (0–100). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: Baseline sample characteristics

	Mean	SD
Female	0.65	0.48
<i>Year of enrollment</i>		
1st year	0.48	0.50
2nd year	0.46	0.50
3rd year	0.06	0.24
<i>Campus</i>		
Columbus	0.90	0.29
Lima	0.01	0.10
Mansfield	0.02	0.12
Marion	0.02	0.12
Newark	0.05	0.22
Wooster	0.00	0.07
<i>Ethnicity</i>		
White	0.59	0.49
Black or African American	0.05	0.22
American Indian or Alaska Native	0.00	0.04
Asian	0.19	0.39
Hispanic	0.02	0.14
Other	0.01	0.11
Prefer not to say	0.02	0.13
Two or more races	0.12	0.32
<i>Undecided</i>		
Unsure	0.71	0.45
Entropy of major intentions (Normalized Shannon Entropy)	0.19	0.21

Notes: Baseline characteristics of the final sample ($N = 657$); the two columns report the mean and the standard deviation of each variable. We report gender (share of female), the distribution of students across years of enrollment, campuses and their ethnicity, the share of undecided students (defined as those assigning positive probability to more than one major), the entropy of stated major intentions (a normalized measure of dispersion ranging from 0, all probability on a single major, to 1, uniform across majors). Indicator variables are reported as shares (0–1).

Table A.8: Balance Table: Baseline Characteristics

	Control	Treatment	Difference
1st Year	0.446	0.506	-0.059
2nd Year	0.482	0.446	0.036
3rd Year	0.072	0.049	0.023
Columbus	0.899	0.909	-0.010
Lima	0.007	0.011	-0.005
Mansfield	0.013	0.017	-0.004
Marion	0.020	0.011	0.008
Newark	0.059	0.046	0.013
Wooster	0.003	0.006	-0.002
Female	0.651	0.657	-0.006
Age	19.277	19.071	0.205**
Unsure	0.733	0.697	0.036
Contribution Important	0.857	0.854	0.002
P(Biology & Life Sciences)	11.770	12.708	-0.938
P(Business & Economics)	23.565	19.151	4.414
P(Computer Science)	5.515	5.067	0.448
P(Education)	5.090	3.497	1.593
P(Engineering)	14.129	21.759	-7.630***
P(Health Sciences)	12.498	12.314	0.184
P(Physics & Maths)	5.311	5.047	0.264
P(Social Sciences)	13.282	13.011	0.271
P(Other)	7.349	6.557	0.791
White	0.629	0.563	0.066*
Black or African American	0.055	0.051	0.004
American Indian or Alaska Native	0.003	0.000	0.003
Asian	0.150	0.217	-0.067**
Hispanic	0.023	0.017	0.006
Other	0.020	0.006	0.014
Prefer not to say	0.013	0.020	-0.007
Two or more races	0.107	0.126	-0.018

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: Means for the final sample ($N = 657$) are reported for all variables, separately for treatment and control groups. We report age, gender, the distribution of students across campuses and enrollment years, and their ethnicity. We also report the share of students who are unsure about their major, defined as those assigning positive probability to more than one major, the share of students reporting “contribution to society” as important, and the initial major intentions defined as the probabilities of pursuing each major ($P(\text{major})$ is the stated prior probability of choosing each major (0–100)). Indicator variables are reported as shares (0–1).

Table A.9: Correlations between Beliefs

	(1) Self Beliefs	(2) Self Beliefs	(3) Self Beliefs	(4) Self Beliefs
Population Beliefs	0.888*** (0.020)	0.910*** (0.024)		
Population Beliefs*Interested		-0.081** (0.034)		
Interested		11.829*** (2.578)		7.046*** (2.183)
Average Individual Beliefs			0.763*** (0.018)	0.769*** (0.020)
AI Beliefs*Interested				-0.038 (0.028)
Constant	3.953** (1.616)	0.241 (1.861)	15.787*** (1.636)	13.840*** (1.824)
FEs	Yes	Yes	Yes	Yes
Observations	5256	5256	5256	5256
Adjusted R^2	0.430	0.443	0.538	0.545

Notes: This Table presents OLS regressions where the dependent variable is students' prior self-beliefs about social impact, measured as the probability of being satisfied with job's contribution to society after each major. An observation is a student-major couple. In Column (1) the independent variable is students' prior beliefs about previous graduates' satisfaction with social impact in each major ("Population Beliefs"), while in Column (3) the independent variable is students' prior beliefs about the satisfaction of an average individual randomly assigned to each major ("Average Individual Beliefs"). In Column (2) and (4) we add an interaction with a dummy equal to one when the student is interested in that major, meaning they assign a positive probability to pursue it. Clustered standard errors in parentheses: *, ** and *** indicate significance at 10%, 5% and 1% levels.

Table A.10: Prior Self-Beliefs and Preferences for SI

	(1) Self Bel.	(2) Self Beliefs	(3) Self Beliefs	(4) Self Bel.
Contribution Importance	1.189 (1.359)	1.189 (1.360)		
Category misperception (avg)		-2.054*** (0.152)		-2.066*** (0.074)
Contr. Importance*Category misp.		-0.255 (0.165)		
Very important			1.186 (0.965)	1.186 (0.965)
Very imp.*Category misp.				-0.420*** (0.115)
Constant	64.654*** (1.455)	64.654*** (1.455)	65.145*** (1.062)	65.145*** (1.062)
FEs	Yes	Yes	Yes	Yes
Observations	5256	5256	5256	5256
Adjusted R^2	0.001	0.246	0.001	0.248

Notes: This table presents OLS regressions where the dependent variable is students' prior self-beliefs about social impact, measured as the probability of being satisfied with their job's contribution to society after graduating in each major. An observation is a student-major pair. In Column (1) the independent variable is "Contribution Importance", a dummy variable for saying contribution to society is *important* or *very important*. In Column (2) "Category misperception (avg)" is how much students underestimate the true share of satisfied graduates in that major (demeaned by the average underestimation across all majors and all students). In Column (3) "Very important" is a dummy for saying contribution to society is *very important*. Columns (2) and (4) also include the interaction between the importance dummy and category misperception. Clustered standard errors in parentheses: *, ** and *** indicate significance at 10%, 5% and 1% levels.

Table A.11: Self-Population Gap and Preferences for SI

	(1) Self-Pop	(2) Self-Pop	(3) Self-Pop	(4) Self-Pop
Contribution Importance	−0.820 (1.344)	−0.820 (1.345)		
Category misperception (avg)		−0.332*** (0.121)		−0.513*** (0.068)
Contr. Importance*Category misp.		−0.352*** (0.133)		
Very important			0.513 (0.890)	0.513 (0.890)
Very imp.*Category misp.				−0.244** (0.102)
Constant	−3.196** (1.407)	−3.196** (1.408)	−4.017*** (0.950)	−4.017*** (0.950)
FEs	Yes	Yes	Yes	Yes
Observations	5256	5256	5256	5256
Adjusted R^2	0.004	0.038	0.004	0.038

Notes: This table presents OLS regressions where the dependent variable is the difference between students' prior self-beliefs about social impact and their population beliefs. An observation is a student-major pair. In Column (1) the independent variable is "Contribution Importance", a dummy variable for saying contribution to society is *important* or *very important*. In Column (2) "Category misperception (avg)" is how much students underestimate the true share of satisfied graduates in that major (demeaned by the average underestimation across all majors and all students). In Column (3) "Very important" is a dummy for saying contribution to society is *very important*. Columns (2) and (4) also include the interaction between the importance dummy and category misperception. Clustered standard errors in parentheses: *, ** and *** indicate significance at 10%, 5% and 1% levels.

Table A.12: Exaggeration of Differences

	(1) Believed Difference
True Difference	1.576*** (0.039)
Constant	−0.000*** (0.000)
p(slope=1)	0.000
Observations	5256
R ²	0.350

Notes: This table presents an OLS regression where the dependent variable is “Believed Difference”, the difference between a student’s population belief about a given major and the average of their population beliefs about the other majors. An observation is a student-major pair. “True Difference” is the corresponding difference in the data, the actual share of graduates satisfied with contribution in that major minus the average share across the other majors (NSCG). “p(slope=1)” reports the *p*-value of the test that the slope equals one. Clustered standard errors (student level) in parentheses: *, ** and *** indicate significance at 10%, 5% and 1% levels.

Table A.13: Population Beliefs and Representativeness

	(1) Population Beliefs
True Share	0.490*** (0.093)
Repr. very dissatisfied	−10.847*** (1.012)
Constant	39.079*** (8.961)
Observations	5256
R ²	0.249

Notes: This table presents an OLS regression where the dependent variable is “Population Beliefs”, students’ beliefs about the share of previous graduates who report being satisfied with the societal contribution of their job in a given major. An observation is a student-major pair. “True Share” is the actual share of graduates satisfied with contribution in that major, measured in the NSCG. “Repr. very dissatisfied” is the representativeness of the *very dissatisfied* type in that major, defined as the share of very dissatisfied graduates in the major divided by the average share across the other majors. Clustered standard errors (student level) in parentheses: *, ** and *** indicate significance at 10%, 5% and 1% levels.

Table A.14: Predicting Prior Major Intentions

	(1) P(M)	(2) P(M)	(3) P(M)	(4) P(M)
Prior Self Beliefs	0.182*** (0.013)		0.015 (0.040)	0.004 (0.039)
Population Beliefs		0.061*** (0.018)		
Contribution Importance*Self Beliefs			0.197*** (0.042)	0.188*** (0.041)
Contribution Importance			-12.529*** (2.683)	-12.911*** (2.564)
Self Beliefs Log(Salary)				8.825*** (0.966)
Expected GPA				6.023*** (0.434)
Constant	-0.412 (0.853)	7.329*** (1.267)	10.273*** (2.573)	-109.492*** (11.441)
FEs	Yes	Yes	Yes	Yes
Observations	5256	5256	5256	5022
Adjusted R^2	0.026	0.000	0.029	0.069

Notes: This Table presents OLS regressions where the dependent variable is students' prior major intentions, measured with the probability they assign to pursue and get a degree in each major at the start of the survey. An observation is a student-major couple. "Contribution Importance" is a dummy variable for saying contribution to society is *important* or *very important*. Clustered standard errors in parentheses: *, ** and *** indicate significance at 10%, 5% and 1% levels.

Table A.15: Impact preference $\bar{\theta}$ by gender (individual- θ model, student fixed effects).

	Winsorization of probabilities		
	[0.5, 99.5]	[1, 99]	[2, 98]
$\bar{\theta}$ Women	3.527 (0.253)	3.011 (0.216)	2.500 (0.180)
$\bar{\theta}$ Men	2.054 (0.296)	1.794 (0.257)	1.533 (0.218)
Difference (Women – Men)	1.473*** (0.331)	1.217*** (0.285)	0.967*** (0.240)
Students	605	605	605

Notes: Mean individual $\hat{\theta}_i$ (impact preference) for women and men and their difference (stars on the difference), from the individual- θ model. Standard errors (parentheses) from a Bayesian bootstrap with 2000 draws, clustered at the student level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.16: Structural impact preference θ_i by gender and stated contribution importance.

Contribution to society is. . .	[0.5, 99.5]			[1, 99]			[2, 98]		
	W	M	W–M	W	M	W–M	W	M	W–M
Not important	-0.93	1.49	-2.42	-0.78	1.44	-2.22	-0.63	1.10	-1.74
Somewhat unimportant	2.10	1.15	+0.95	1.84	1.03	+0.81	1.54	0.90	+0.65
Somewhat important	2.90	1.84	+1.06	2.49	1.62	+0.87	2.08	1.40	+0.68
Very important	4.19	2.88	+1.31	3.56	2.47	+1.09	2.95	2.10	+0.84

Notes: Cells are mean individual $\hat{\theta}_i$ (impact-preference) for women (W) and men (M) at each level of stated importance of “contribution to society”, for three winsorization bounds. $\hat{\theta}_i$ from the individual- θ model (student fixed effects, all majors symmetric). Cell sizes (constant across bounds): Not important: 3W/9M; Somewhat unimportant: 35W/38M; Somewhat important: 135W/91M; Very important: 223W/71M.

Table A.17: Robustness of the gender gap in $\bar{\theta}$ to the choice of base major.

Specification	$\bar{\theta}$ Women	$\bar{\theta}$ Men	Gap (W–M)	(SE)
Student fixed effects (main, base-free)	3.53	2.05	1.47***	(0.331)
Bio & Life Sci.	4.02	1.69	2.33***	(0.464)
Business & Econ.	4.05	2.56	1.49**	(0.607)
Computer Science	2.69	1.32	1.37***	(0.423)
Education	2.70	1.65	1.06***	(0.358)
Engineering	3.34	3.24	0.10	(0.511)
Health	4.00	1.37	2.64***	(0.424)
Physics & Maths	3.43	2.24	1.19***	(0.385)
Social Sci. & Psych.	3.37	1.95	1.42***	(0.417)

Notes: The first row is the main specification, which removes the student-specific logit normalization with student fixed effects, so all eight majors enter symmetrically (base-free). Each remaining row instead estimates the individual- θ model on log choice-probability ratios against the indicated base major (primary winsorization [0.5,99.5]). The gender gap is not exactly invariant to the base: unobserved taste for the base major enters all of a student's ratios and partially loads on $\hat{\theta}_i$, so whichever gender has a stronger taste for the base sees its $\bar{\theta}$ inflated. Consistent with this, the extremes occur at the most gender-segregated bases (Health and Bio inflate the gap; Engineering, the most male field, collapses it), while the base-free estimate lies at the centre of the range with the smallest standard error. The gap is positive and significant at the 5% level for the main specification and for seven of the eight bases. Bootstrap SEs (400 draws, clustered by student) in parentheses, on the gap. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.18: Belief-correction counterfactual: model-implied shift in major-choice probability.

	Women		Men	
	Nat.	Misp.	Nat.	Misp.
Bio & Life Sci.	-0.14	+0.92	+0.25	+0.14
Business & Econ.	+2.39	+1.08	+1.24	+0.70
Computer Science	+1.42	+0.40	+0.66	+0.53
Education	+0.08	+0.30	-0.14	-0.12
Engineering	-0.29	-0.46	-2.04	-1.08
Health	-1.83	-0.85	-0.52	-0.23
Physics & Maths	+2.07	+1.04	+1.11	+0.78
Social Sci. & Psych.	-2.01	-1.27	-0.27	-0.28
Other	-1.69	-1.16	-0.29	-0.44

Notes: Each entry is the average model-implied change in the choice probability (percentage points) for the major when students' social-impact beliefs are corrected to the true values, computed using the gender-average impact preference ($\bar{\theta}_W = 3.70$, $\bar{\theta}_M = 2.30$) over the 520 students in the estimation sample who rate contribution to society as at least somewhat important. "Nat." sets each belief to the national-survey satisfaction rate; "Misp." adds the elicited underestimation gap one-for-one to self-beliefs.

Table A.19: Belief-correction counterfactual: shift in major-choice probability, versus the actual treatment effect.

	Women			Men		
	Nat.	Misp.	Actual	Nat.	Misp.	Actual
Bio & Life Sci.	-0.14	+0.92	+1.01	+0.25	+0.14	+1.29
Business & Econ.	+2.39	+1.08	+0.13	+1.24	+0.70	-0.44
Computer Science	+1.42	+0.40	+0.55	+0.66	+0.53	+0.88
Education	+0.08	+0.30	+1.60	-0.14	-0.12	+0.44
Engineering	-0.29	-0.46	-0.73	-2.04	-1.08	-0.05
Health	-1.83	-0.85	+0.74	-0.52	-0.23	+1.47
Physics & Maths	+2.07	+1.04	+0.22	+1.11	+0.78	+0.65
Social Sci. & Psych.	-2.01	-1.27	-1.68	-0.27	-0.28	-4.25
Other	-1.69	-1.16	-0.71	-0.29	-0.44	+1.14
Corr. with actual (Nat/Misp)	0.37 / 0.61			0.09 / 0.14		

Notes: Each entry is the average model-implied change in the choice probability (percentage points) for the major when students' social-impact beliefs are corrected to the true values, computed on the individual- θ model using the gender-average impact preference over this sample; predicted patterns are nearly identical across the two. "Nat." sets each belief to the national-survey satisfaction rate shown in the treatment; "Misp." adds the elicited underestimation gap one-for-one. Choice probabilities are the model's softmax over all nine majors ("Other" has no contribution belief and is held fixed), so the shifts sum to zero within each column. Because this is a *complete* correction it is larger in magnitude than the (partial) experimental effect, so the comparison to "Actual" is one of pattern. "Actual" is the reduced-form treatment effect on the stated post-intervention probability (same specification as Figure 7). Both the counterfactual and "Actual" are computed on the same 520 students: the estimation sample restricted to those who rate contribution to society as at least somewhat important. The last row reports the across-major correlation between each counterfactual and the actual effects.

Table A.20: Revision of Self Beliefs by Social Desirability Bias

	(1) Low SDB	(2) High SDB	(3) Interaction
Treatment	6.507*** (1.046)	5.878*** (1.163)	7.755*** (1.529)
Treatment*Underestimation gap	0.368*** (0.051)	0.392*** (0.056)	0.294*** (0.082)
Treatment*SDB			−0.642 (0.575)
Treatment*Misp*SDB			0.040 (0.031)
Prior Self Beliefs	0.541*** (0.021)	0.527*** (0.031)	0.535*** (0.018)
Constant	25.705** (10.547)	35.402*** (9.070)	31.969*** (6.269)
FEs	Yes	Yes	Yes
Observations	2976	2280	5256
Adjusted R^2	0.617	0.640	0.626

Notes: This table presents OLS estimates of Equation 9. The dependent variable is students' posterior self-belief about the share of previous graduates satisfied with their job's contribution to society. The "Underestimation gap" is the difference between that true share and the share a student initially believed, so a positive value means the student underestimates it. Column (1) restricts to students with a low social desirability bias (SDB), i.e. at or below the median SDB score; Column (2) to students with a score above the median; and Column (3) uses the full sample and adds interactions with the (continuous) SDB measure. All specifications control for prior self-beliefs and include fixed effects. Each observation is a student-major pair. Clustered standard errors in parentheses: *, ** and *** indicate significance at 10%, 5% and 1% levels.

Table A.21: Advice by Social Desirability Bias - Preferences for SI

	(1) Low SDB	(2) High SDB	(3) Interaction
Treatment	0.526*** (0.149)	0.308** (0.147)	0.537** (0.230)
Treatment*Underestimation gap	0.022*** (0.008)	0.039*** (0.007)	0.014 (0.013)
Treatment*SDB			−0.051 (0.080)
Treatment*Misp*SDB			0.007 (0.004)
Constant	8.772*** (1.154)	7.064*** (0.809)	8.072*** (0.747)
Control Mean	6.6	6.6	6.6
FEs	Yes	Yes	Yes
Observations	2464	2032	4496
Adjusted R^2	0.238	0.345	0.285

Notes: The table reports OLS estimates of the effect of the information treatment on the advice students give to peers who care about a job's contribution to society. The outcome variable is a score from 0 to 10 assigned to each major, with higher values indicating stronger advice to pursue the major. The treatment indicator is interacted with the underestimation gap, which measures the initial misperception regarding graduates' satisfaction with contribution in each field. Column (1) restricts to students with a low social desirability bias (SDB), i.e. at or below the median SDB score; Column (2) to students with a score above the median; and Column (3) uses the full sample and adds interactions with the (continuous) SDB measure. Each observation corresponds to a student-major pair. Clustered standard errors in parentheses: *, ** and *** indicate significance at 10%, 5% and 1% levels.

Table A.22: Treatment Effect by Misperception - No preferences for SI

	Final P(M)		
	(1) All	(2) Women	(3) Men
Initial P(M)	0.889*** (0.046)	0.847*** (0.079)	0.916*** (0.056)
Treatment	0.045 (0.137)	0.005 (0.224)	0.008 (0.193)
Demeaned Undergap	-0.036 (0.023)	-0.055 (0.045)	-0.012 (0.016)
Demeaned Undergap*Treatment	-0.001 (0.025)	0.043 (0.042)	-0.054* (0.027)
Prior credits in cat. (AU25+SP26)	0.421** (0.194)	0.456* (0.236)	0.419 (0.286)
Constant	-1.949 (1.726)	-1.235 (3.168)	-3.430 (3.029)
FEs	Yes	Yes	Yes
Observations	760	336	424
Adjusted R^2	0.878	0.826	0.915

Notes: The table reports OLS estimates of the effect of the information treatment on students' major intentions, for students who report that contribution to society is unimportant. The outcome variable is the probability (from 0 to 100) that a student assigns, after the intervention, to graduating in each major; "Initial P(M)" is the corresponding probability elicited at the start of the survey. "Prior credits in cat." measures credits earned in that field over the previous two semesters. The treatment indicator is interacted with the demeaned underestimation gap, individual i 's underestimation of the share of graduates satisfied with their job's contribution in each field, demeaned by i 's average underestimation across all majors. Column (1) includes all such students, while Columns (2) and (3) split them by gender. Each observation corresponds to a student-major pair. Clustered standard errors in parentheses: *, ** and *** indicate significance at 10%, 5% and 1% levels.

Table A.23: Treatment Effect by Misperception - Preferences for SI (Relative Revision)

	(1) All	(2) Women	(3) Men
Treatment	0.025 (0.227)	0.027 (0.216)	0.052 (0.528)
Demeaned Undergap	−0.055* (0.029)	−0.051* (0.031)	−0.066 (0.066)
Demeaned Undergap*Treatment	0.038 (0.031)	0.052 (0.032)	0.013 (0.071)
Prior credits in cat. (AU25+SP26)	0.007 (0.026)	−0.005 (0.024)	0.031 (0.060)
Constant	1.659 (1.534)	0.146 (1.189)	11.739 (8.211)
FEs	Yes	Yes	Yes
Observations	4496	3104	1392
Adjusted R^2	0.003	0.003	−0.000

Notes: The table reports OLS estimates of the effect of the information treatment on the relative revision of students' major intentions, for students who rate contribution to society as at least somewhat important. The outcome variable is the change in the probability that a student assigns to graduating in each major between the start and the end of the survey, divided by the initial probability (for majors with an initial probability of zero, the change is divided by 0.5). The treatment indicator is interacted with the demeaned underestimation gap, individual i 's underestimation of the share of graduates satisfied with their job's contribution in each field, demeaned by i 's average underestimation across all majors. Column (1) includes all such students, while Columns (2) and (3) split them by gender. Each observation corresponds to a student-major pair. All regressions control for prior credits in the field (AU25 and SP26), age, and gender, campus and year of enrollment fixed effects, but not for initial intentions. Standard errors clustered at the student level in parentheses: *, ** and *** indicate significance at 10%, 5% and 1% levels.

Table A.24: Misperception Rank and Treatment - Preferences for SI (Relative Revision)

	(1) All	(2) Women	(3) Men
Treatment	0.474 (0.304)	0.701** (0.346)	-0.013 (0.634)
Misperception Rank (0=highest)	0.194** (0.095)	0.191* (0.099)	0.204 (0.217)
Treatment * Misp. Rank	-0.128 (0.112)	-0.192* (0.113)	0.019 (0.258)
Prior credits in cat. (AU25+SP26)	0.007 (0.026)	-0.004 (0.025)	0.031 (0.060)
Constant	0.977 (1.547)	-0.526 (1.361)	11.030 (7.895)
FEs	Yes	Yes	Yes
Observations	4496	3104	1392
Adjusted R^2	0.000	-0.000	-0.003

Notes: The table reports OLS estimates of the effect of the information treatment on the relative revision of students' major intentions, for students who rate contribution to society as at least somewhat important. The outcome variable is the change in the probability that a student assigns to graduating in each major between the start and the end of the survey, divided by the initial probability (for majors with an initial probability of zero, the change is divided by 0.5). For each student, majors are ranked by how much they initially underestimate the share of graduates satisfied with their job's contribution in each field, from most to least underestimated ("Misperception Rank", with 0 = most underestimated). The treatment indicator is interacted with this rank. Column (1) includes all such students, while Columns (2) and (3) split them by gender. Each observation corresponds to a student-major pair. All regressions control for prior credits in the field (AU25 and SP26), age, and gender, campus and year of enrollment fixed effects, but not for initial intentions. Standard errors clustered at the student level in parentheses: *, ** and *** indicate significance at 10%, 5% and 1% levels.

Table A.25: Choice Heterogeneity by Class Year - Preferences for SI

	All		Women		Men	
	(1)	(2)	(3)	(4)	(5)	(6)
	1st yr	2nd yr	1st yr	2nd yr	1st yr	2nd yr
Treatment	0.113 (0.221)	0.154 (0.118)	0.299 (0.268)	0.200 (0.180)	-0.334 (0.301)	0.028 (0.077)
Demeaned Undergap	-0.079*** (0.026)	-0.057 (0.035)	-0.073*** (0.025)	-0.083* (0.049)	-0.102 (0.075)	0.001 (0.020)
Demeaned Undergap*Treatment	0.060** (0.026)	0.024 (0.039)	0.054** (0.025)	0.073 (0.048)	0.078 (0.071)	-0.061 (0.046)
FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2152	2088	1544	1368	608	720
Adjusted R^2	0.943	0.926	0.937	0.947	0.960	0.890

Notes: The table reports OLS estimates of the effect of the information treatment on students' major intentions, for students who report that contribution to society is important, split by class year. The outcome variable is the probability (from 0 to 100) that a student assigns, after the intervention, to graduating in each major. All specifications control for "Initial P(M)", the corresponding probability elicited at the start of the survey, and for "Prior credits in cat.", the credits earned in that field over the previous two semesters. The treatment indicator is interacted with the demeaned underestimation gap, individual i 's underestimation of the share of graduates satisfied with their job's contribution in each field, demeaned by i 's average underestimation across all majors. Columns (1)–(2) include all such students, Columns (3)–(4) women, and Columns (5)–(6) men; within each group, the first column restricts to first-year students and the second to second-year students. Each observation corresponds to a student-major pair. Clustered standard errors in parentheses: *, ** and *** indicate significance at 10%, 5% and 1% levels.

Table A.26: Impact preference $\bar{\theta}$ before and after the survey: control group.

	Pre	Post	Δ
All	2.74 (0.31)	3.62 (0.36)	0.89*** (0.33)
Women	3.31 (0.36)	4.30 (0.43)	0.99** (0.39)
Men	1.65 (0.44)	2.34 (0.51)	0.69* (0.37)

Notes: Mean individual impact preference $\hat{\theta}_i$ in the control group (no information), before (Pre) and after (Post) the survey, and the change. Individual- θ model (student fixed effects) estimated on pre- and post-survey stated choices and beliefs; $\bar{\theta}$ is the mean $\hat{\theta}_i$. Expected GPA is not re-elicited at the end of the survey, so the same pre-survey GPA responses are used in both periods, with the GPA coefficient held at its pre-estimated value. Bootstrap SEs (clustered by student) in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.27: Revision Salary - Preferences for SI

	(1)	(2)
	Post Earnings	Post Earnings
Self Beliefs Log(Salary)	0.616*** (0.048)	0.614*** (0.048)
Treatment	0.061*** (0.017)	0.060** (0.024)
Treatment*Underestimation gap		−0.000 (0.001)
Underestimation gap		−0.001** (0.001)
Constant	4.093*** (0.568)	4.129*** (0.567)
FEs	Yes	Yes
Observations	4496	4496
Adjusted R ²	0.404	0.406

Notes: The table reports OLS estimates of the effect of the information treatment on salary expectations. Each observation corresponds to a student-major pair. Clustered standard errors in parentheses: *, ** and *** indicate significance at 10%, 5% and 1% levels.

Table A.28: Willingness to Pay - Preferences for SI

	(1)	(2)
	WTP	WTP
Treatment	−1.092 (2.536)	−1.118 (2.537)
Post	−0.445 (2.608)	−0.450 (2.609)
Post*Treatment	1.959 (3.555)	1.967 (3.556)
Contribution Salience		0.137 (0.663)
Constant	17.465 (19.105)	16.708 (19.537)
Control Mean	24.2	24.2
FEs	Yes	Yes
Observations	562	562
Adjusted R ²	−0.008	−0.009

Notes: The Table reports estimates from a difference-in-differences specification examining the effect of the information treatment on willingness to pay for social impact. "Post" is an indicator equal to one for observations collected after the information provision, and "Treatment" indicates assignment to the treatment group. The interaction term captures the treatment effect. The dependent variable is the percentage reduction in monthly earning students are willing to accept for a socially impactful job. Robust standard errors in parentheses: *, ** and *** indicate significance at 10%, 5% and 1% levels.

Table A.29: Willingness to Pay - Preferences for SI

	(1) WTP	(2) WTP
Treatment	570.1 (1011.2)	591.7 (1013.9)
Post	815.2 (1009.5)	819.0 (1010.5)
Post*Treatment	2279.8 (1675.5)	2273.5 (1669.9)
Contribution Salience		-114.7 (406.5)
Constant	-558.1 (7430.6)	77.9 (8518.7)
Control Mean	3325.1	3325.1
FEs	Yes	Yes
Observations	562	562
Adjusted R^2	0.010	0.009

Notes: The Table reports estimates from a difference-in-differences specification examining the effect of the information treatment on willingness to pay (in dollars, given students' reservation wage) for social impact. "Post" is an indicator equal to one for observations collected after the information provision, and "Treatment" indicates assignment to the treatment group. The interaction term captures the treatment effect. The dependent variable is the percentage reduction in monthly earning students are willing to accept for a socially impactful job. Robust standard errors in parentheses: *, ** and *** indicate significance at 10%, 5% and 1% levels.

Table A.30: Treatment Effects on Credits (AU26) by between-category misperception - Preferences for SI

	(1) All	(2) Women	(3) Men
Prior credits in cat. (AU25+SP26)	0.258*** (0.014)	0.257*** (0.016)	0.257*** (0.024)
Initial P(M)	0.045*** (0.003)	0.042*** (0.004)	0.051*** (0.005)
Treatment	-0.129 (0.206)	-0.265 (0.247)	0.169 (0.374)
Treatment*Category Undergap	0.012 (0.013)	0.020 (0.015)	-0.008 (0.023)
Category Undergap (avg)	0.006 (0.009)	0.003 (0.011)	0.009 (0.016)
FEs	Yes	Yes	Yes
Observations	4384	3008	1376
Adjusted R ²	0.590	0.567	0.635

Notes: The Table reports OLS estimates of the effect of the information treatment on students' enrolled credits in Autumn 2026 for students who report that contribution to society is important. The outcome variable is the number of credits, "Initial P(M)" is the corresponding prior probability reported earlier, "Prior credits in cat." measures credits earned in that field over the previous two semesters. "Category misperception" is the average underestimation of that major category contribution. Each observation corresponds to a student-major pair. Clustered standard errors in parentheses: *, ** and *** indicate significance at 10%, 5% and 1% levels.

Table A.31: Credits (AU26) Heterogeneity by Class Year - Preferences for SI

	All		Women		Men	
	(1) 1st yr	(2) 2nd yr	(3) 1st yr	(4) 2nd yr	(5) 1st yr	(6) 2nd yr
Treatment	-0.759** (0.311)	0.436 (0.302)	-0.704* (0.379)	0.148 (0.361)	-0.794 (0.560)	0.900* (0.540)
Category Misp.	-0.006 (0.015)	0.015 (0.013)	-0.007 (0.018)	0.008 (0.016)	-0.005 (0.025)	0.021 (0.022)
Category Misp.*Treatment	0.045** (0.019)	-0.021 (0.019)	0.043* (0.024)	-0.004 (0.022)	0.047 (0.035)	-0.048 (0.034)
FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2080	2048	1480	1336	600	712
Adjusted R ²	0.537	0.626	0.521	0.601	0.577	0.669

Notes: The Table reports OLS estimates of the effect of the information treatment on students' enrolled credits in Autumn 2026 for students who report that contribution to society is important, split by class year. The outcome variable is the number of credits a student enrolls in each field; all specifications control for "Initial P(M)", the corresponding prior probability reported earlier, and for "Prior credits in cat.", the credits earned in that field over the previous two semesters. "Category Misp." is the average underestimation of that major category's contribution, which we also interact with the treatment. Columns (1)–(2) include all such students, Columns (3)–(4) women, and Columns (5)–(6) men; within each group, the first column restricts to first-year students and the second to second-year students. Each observation corresponds to a student-major pair. Clustered standard errors in parentheses: *, ** and *** indicate significance at 10%, 5% and 1% levels.

Table A.32: Treatment Effects on Registered Credits Before the Semester (AU26) by between-category misperception - Preferences for SI

	(1) All	(2) Women	(3) Men
Prior credits in cat. (AU25+SP26)	0.275*** (0.014)	0.269*** (0.017)	0.283*** (0.024)
Initial P(M)	0.044*** (0.003)	0.043*** (0.004)	0.049*** (0.006)
Treatment	-0.260 (0.203)	-0.434* (0.248)	0.109 (0.351)
Treatment*Category Undergap	0.017 (0.013)	0.029* (0.015)	-0.009 (0.022)
Category Undergap (avg)	0.005 (0.009)	0.001 (0.011)	0.009 (0.015)
FEs	Yes	Yes	Yes
Observations	4368	3008	1360
Adjusted R^2	0.596	0.568	0.648

Notes: The Table reports OLS estimates of the effect of the information treatment on students' enrolled credits in Autumn 2026 (using the first snapshot of the administrative data, taken in early July 2026) for students who report that contribution to society is important. The outcome variable is the number of credits, "Initial P(M)" is the corresponding prior probability reported earlier, "Prior credits in cat." measures credits earned in that field over the previous two semesters. "Category misperception" is the average underestimation of that major category contribution. Each observation corresponds to a student-major pair. Clustered standard errors in parentheses: *, ** and *** indicate significance at 10%, 5% and 1% levels.

Table A.33: Registered Credits Before the Semester (AU26) Heterogeneity by Class Year - Preferences for SI

	All		Women		Men	
	(1)	(2)	(3)	(4)	(5)	(6)
	1st yr	2nd yr	1st yr	2nd yr	1st yr	2nd yr
Treatment	-0.902*** (0.292)	0.364 (0.309)	-0.883** (0.368)	0.031 (0.370)	-0.852* (0.478)	0.939* (0.549)
Category Misp.	-0.011 (0.014)	0.018 (0.013)	-0.010 (0.018)	0.011 (0.016)	-0.014 (0.021)	0.029 (0.023)
Category Misp.*Treatment	0.053*** (0.018)	-0.020 (0.019)	0.053** (0.023)	0.001 (0.023)	0.047 (0.030)	-0.055 (0.035)
FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2080	2032	1480	1336	600	696
Adjusted R ²	0.546	0.631	0.518	0.610	0.607	0.666

Notes: The Table reports OLS estimates of the effect of the information treatment on students' enrolled credits in Autumn 2026 (using the first snapshot of the administrative data, taken in early July 2026) for students who report that contribution to society is important, split by class year. The outcome variable is the number of credits a student enrolls in each field; all specifications control for "Initial P(M)", the corresponding prior probability reported earlier, and for "Prior credits in cat.", the credits earned in that field over the previous two semesters. "Category Misp." is the average underestimation of that major category's contribution, which we also interact with the treatment. Columns (1)–(2) include all such students, Columns (3)–(4) women, and Columns (5)–(6) men; within each group, the first column restricts to first-year students and the second to second-year students. Each observation corresponds to a student–major pair. Clustered standard errors in parentheses: *, ** and *** indicate significance at 10%, 5% and 1% levels.

Table A.34: Admin Credits (AU26) in the Most Underestimated Fields - Preferences for SI

	(1) All	(2) Women	(3) Men
Treatment	0.428 (0.277)	0.625* (0.324)	-0.080 (0.563)
Prior credits in 3 fields (AU25+SP26)	0.235*** (0.027)	0.246*** (0.031)	0.210*** (0.058)
Initial P(3 fields)	0.050*** (0.005)	0.048*** (0.006)	0.056*** (0.010)
Constant	-2.213 (2.738)	-3.023 (2.886)	-1.136 (9.861)
Control Mean	5.13	4.59	6.30
FEs	Yes	Yes	Yes
Observations	548	376	172
Adjusted R^2	0.511	0.505	0.486

Notes: The table reports OLS estimates of the effect of the information treatment on the total number of credits students enrolled in for Fall 2026, after the add/drop period, in the three fields that are most underestimated on average: Business & Economics, Computer Science, and Physics & Maths. The sample is restricted to students who rate contribution to society as important. Each observation is a student: credits, prior credits and initial intentions are summed over the three fields. "Prior credits in 3 fields" measures credits earned in these fields over the previous two semesters (AU25 and SP26), and "Initial P(3 fields)" is the sum of the probabilities of pursuing each of the three fields reported at the start of the survey. Column (1) includes all such students, while Columns (2) and (3) split them by gender. All regressions control for age, and gender, campus and year of enrollment fixed effects. "Control Mean" reports the average number of credits in the three fields among control students. Robust standard errors in parentheses: *, ** and *** indicate significance at 10%, 5% and 1% levels.

Table A.35: Admin Credits (AU26) by Misperception - Preferences for SI

	(1) All	(2) Women	(3) Men
Prior credits in cat. (AU25+SP26)	0.261*** (0.013)	0.260*** (0.016)	0.260*** (0.024)
Initial P(M)	0.044*** (0.003)	0.041*** (0.004)	0.051*** (0.005)
Treatment	0.054 (0.036)	0.057 (0.043)	0.045 (0.071)
Demeaned Undergap	−0.000 (0.004)	0.003 (0.005)	−0.009 (0.007)
Demeaned Undergap*Treatment	−0.002 (0.005)	−0.006 (0.006)	0.007 (0.010)
FEs	Yes	Yes	Yes
Observations	4384	3008	1376
Adjusted R^2	0.590	0.566	0.635

Notes: The Table reports OLS estimates of the effect of the information treatment on students' enrolled credits, for students who report that contribution to society is important. The outcome variable is the number of credits students enrolled in the semester after our survey; "Initial P(M)" is the corresponding probability elicited at the start of the survey. The treatment indicator is interacted with the demeaned underestimation gap – individual i 's underestimation of the share of graduates satisfied with their job's contribution in each field, demeaned by i 's average underestimation across all majors. Column (1) includes all such students, while Columns (2) and (3) split them by gender. Each observation corresponds to a student–major pair. Clustered standard errors in parentheses: *, ** and *** indicate significance at 10%, 5% and 1% levels.

B Appendix: Additional Model Results

B.1 Predictions for a Shift in Preferences

Suppose: $\theta^i \uparrow$. This is going to have a direct impact through preferences and an indirect one through beliefs. For the first one, we can apply a reasoning very similar to that for the belief changes described in Section 3. Given Equation (3), the relative probability of pursuing m instead of m' will increase as long as the prior probability of being satisfied with contribution after majoring in m is larger than the same probability for m' . Everything else the same:

$$\text{if } \tilde{\pi}_m^i > \tilde{\pi}_{m'}^i \Rightarrow \log \frac{q_m^i}{q_{m'}^i} \uparrow.$$

As a consequence, if we suppose priors are such that:

$$\tilde{\pi}_M^i > \tilde{\pi}_{M-1}^i > \dots > \tilde{\pi}_1^i,$$

the probability of choosing the major with the lowest social-impact expectations will decrease:

$$\Delta q_1^i < 0 \tag{A.1}$$

For all other majors $m = 2, \dots, M$:

$$\text{if } \tilde{\pi}_m^i > \tilde{\pi}_1^i \Rightarrow \frac{\Delta q_m^i}{q_m^i} > \frac{\Delta q_1^i}{q_1^i} \tag{A.2}$$

Therefore, an upward shift in preferences, with everything else staying the same, moves students towards majors with a higher prior probability of contribution.

However, notice that a change in preferences for contribution has also an indirect impact through the perceived probability of being satisfied with contribution. Indeed, if individual i now cares more about impact, they can be more demanding in terms of how much contribution would make them feel satisfied. Specifically, if θ^i changes, $\bar{c}^i$ is also affected. In particular, since the threshold $\bar{c}^i$ is an increasing function of θ^i :

$$\theta^i \uparrow \Rightarrow \bar{c}(\theta^i) \uparrow$$

Given Equation (5), the effect of a change in preferences on beliefs for major m is negative:

$$\frac{\partial \tilde{\pi}_m^i}{\partial \theta^i} = -\phi\left(\frac{\tilde{\lambda}_m^i - \bar{c}^i}{\tilde{\sigma}_m^i}\right) \frac{1}{\tilde{\sigma}_m^i} \frac{\partial \bar{c}^i}{\partial \theta^i} < 0. \tag{A.3}$$

This downward revision of social-impact beliefs about major m is proportional to how much of its perceived contribution sits right at the threshold, namely $\frac{1}{\tilde{\sigma}_m^i} \phi\left(\frac{\tilde{\lambda}_m^i - \bar{c}^i}{\tilde{\sigma}_m^i}\right)$. This density is

largest when when perceived contribution is centered near the threshold, and small when it lies far from it on either side. Imagine three cases:

1. High contribution expectations (e.g. Nursing & Health Sciences): almost all perceived mass is above the threshold, meaning the probability of being satisfied is very high. If the threshold increases, it barely moves the expected probability of being satisfied with contribution; these majors are essentially untouched by the indirect channel.
2. Middle contribution expectations (e.g. around 50% chance of being satisfied): the mass is concentrated around the threshold, where small changes flip students between satisfied and dissatisfied, i.e. the margin is crowded: this is the case where beliefs decrease the most.
3. Very low contribution expectations: almost all mass is below the threshold, so again little sits at the margin. The belief is already low, and a higher threshold leaves it basically unchanged.

As a result, the indirect channel hits the middle hardest and leaves both extremes nearly fixed. For the lowest-contribution majors it can even partly compensate the direct effect. For the highest-contribution majors the two channels point the same way: preferences favor them through the direct channel and the belief channel does not touch them.

Given our assumptions on $\bar{c}^i(\theta^i)$ (increasing, concave, and bounded above by $\bar{c}_{\max}$ ⁴⁰), we conclude the direct effect dominates, so the net effect still moves students toward majors with a higher prior probability of contribution. And one conclusion holds regardless of this assumption: high-contribution majors gain, since they are favored by the stronger preferences and they are not affected by an increase in the threshold $\bar{c}^i$.

⁴⁰We assume that $\bar{c}^i$ cannot go above a certain value $\bar{c}_{\max}$ and its first derivative with respect to θ^i is positive and decreasing:

$$\frac{\partial \bar{c}^i}{\partial \theta^i} > 0 \quad \wedge \quad \frac{\partial^2 \bar{c}^i}{\partial (\theta^i)^2} < 0.$$

C Appendix: Prompt to Build Vignettes

I'm working on a research project that involves an experiment with college students. In particular, we conduct a survey at a large U.S. state university to measure students' preferences regarding future job's social impact and their beliefs about how different majors can lead to careers that provide a sense of fulfillment through contributing to society. We then implement an information intervention designed to highlight how graduates from all fields can make meaningful contributions to society.

As part of our treatment, we want to include some information about different career options that students can pursue after each major that allow them to positively contribute to society. With that in mind, we have been surveying alumni at the same university to get to know their experiences with their current job. I'm attaching the data. There, you can find the following columns:

A. Major B. Field (groups of majors) C. What is your current job title? D. What is your primary employer's main business or industry - that is, what does that employer make or do? E. In 1-2 sentences, please describe what you do in your current role. In your own words, how does your work contribute to society or help improve people's lives? F. Can you describe a moment, project, or example that illustrates the positive impact of your work? G. Many students may not be aware of how careers in your field contribute to society. If you were advising a student who is thinking about majoring in your field, what would you tell them about the ways work in this field makes a difference in people's lives or in society more broadly?

We would like to have a concise vignette/information brochure for each FIELD. Could you try to put all of this information together and create an output that puts together all the relevant information for each field? It is important that you keep the information vignette for each field relatively similar in terms of:

- Length (between 130 and 150 words)
- Structure: an opening statement mentioning the diverse impactful applications in the field and 3 alumni examples per field that have a positive impact on society. Mention the job title, the industry and the major of each person. Use bullet points but writing in flowing prose rather than listing attributes with commas. For each example, make sure you convey just what is the content of their job and its contribution to society. You can use direct quotes from the alumni: in that case reproduce the full sentence exactly as written, no manipulation, and use quotation marks. Avoid quoting anything motivational or abstract — only include quotes where the alumni is describing what they actually do, also through examples. Aim to 2 or 3 quotes per field. Avoid mentioning examples of jobs or quoting wording that could be perceived as violent or controversial and could make some students feel uncomfortable. Keep the gender neutral.

- Clarity of language: Flesch-Kincaid Grade around 10, no abbreviations or acronyms but keep a smooth flow avoiding short sentences (less than 5 words).
- Informativeness - quantity of content
- Engagement - how interesting and engaging is the vignette

In the information we give to students, the vignettes you will create will be prefaced by the following introduction: "Every field has its own ways of making a positive difference. Sometimes students are not aware of the contribution they can have by pursuing different majors. Below you'll find short summaries of reflections from Ohio State University alumni in each field. They describe what they do in their job and how they feel it positively contributes to society."

Give me an excel sheet with the final vignettes per field.

D Appendix: Validation Survey on Prolific

To ensure that the alumni-story vignettes are of comparable quality across fields—so that any treatment effect cannot be attributed to some fields being presented with more compelling stories—we ran a validation survey on Prolific. Each of the 321 respondents was shown the vignette for a single, randomly assigned field and rated it on three dimensions — clarity, informativeness, and engagement — each on a 0–10 scale. Table A.36 reports the mean ratings by field, Figure A.19 plots them with 95% confidence intervals, and Table A.37 reports one-way ANOVA tests of equality across fields. Ratings are uniformly high and statistically indistinguishable across fields, confirming that the vignettes are standardized.

Table A.36: Validation survey: mean ratings of the alumni-story vignettes by field

Field	Clarity	Informativeness	Engagement	Overall	N
Biological & Life Sciences	7.85	7.41	6.32	7.20	41
Business, Economics & Management	7.70	7.22	5.90	6.94	40
Computer Sciences & Information Technology	8.27	7.66	5.88	7.27	41
Education	8.26	7.46	6.15	7.29	39
Engineering	7.76	7.97	5.95	7.23	38
Nursing & Health Sciences	7.90	7.51	6.46	7.29	41
Physical Sciences & Mathematics	7.97	7.72	6.78	7.49	40
Social Sciences & Psychology	8.10	7.44	6.05	7.20	41

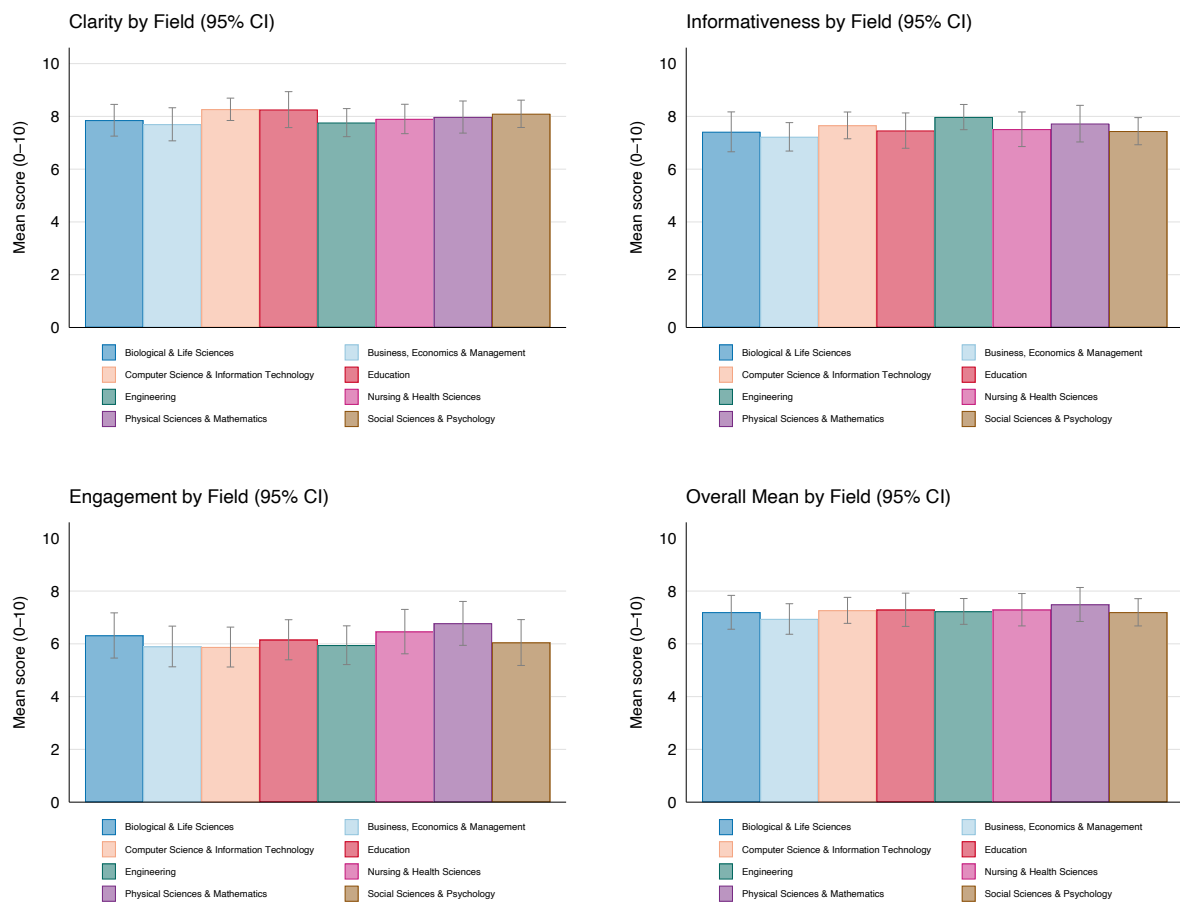
Notes: The table reports mean ratings of the alumni-story vignettes from a validation survey of 321 respondents recruited on Prolific. Each respondent was shown the vignette for a single, randomly assigned field and rated it on clarity, informativeness, and engagement, each on a 0–10 scale; “Overall” is the average of the three dimensions. *N* is the number of respondents who rated each field. Ratings are uniformly high and similar across fields; formal tests of equality are reported in Table A.37.

Table A.37: Validation survey: one-way ANOVA of mean ratings across fields

Dimension	<i>F</i> -statistic	df (between, within)	<i>p</i> -value
Clarity	0.54	(7, 313)	0.806
Informativeness	0.53	(7, 313)	0.811
Engagement	0.59	(7, 313)	0.763
Overall	0.27	(7, 313)	0.966

Notes: Each row reports a one-way ANOVA testing the null hypothesis that the mean rating is equal across all eight fields, using the 321 respondent-level ratings (each respondent rated the vignette of one randomly assigned field). “Overall” is the average of clarity, informativeness, and engagement. None of the tests rejects equality of means (all $p > 0.76$), indicating that the vignettes are rated similarly across fields.

Figure A.19: Validation survey: mean ratings by field with 95% confidence intervals



Notes: Each panel plots the mean rating of the alumni-story vignettes by field (bars) with 95% confidence intervals, on a 0–10 scale.

E Appendix: Robustness symmetric-attention sample

This section in the Appendix reproduces our main results on the larger sample of $N = 708$ respondents obtained when we screen only on the three attention checks that are identical across treatment arms, as discussed in Section 5.1. Because that check is the only source of differential attrition, this sample is balanced across treatment and control (Table ??). The estimates below are very close to those in the main text, confirming that our pre-registered exclusion criterion does not drive the main results.

Table A.38: Attrition: Attentive (N=708) vs Inattentive (N=269)

	Inattentive	Attentive	Difference
Treatment	0.506	0.506	-0.000
1st Year	0.502	0.487	0.015
2nd Year	0.465	0.456	0.008
3rd Year	0.033	0.056	-0.023
Columbus	0.881	0.900	-0.019
Lima	0.007	0.010	-0.002
Mansfield	0.026	0.017	0.009
Marion	0.022	0.016	0.007
Newark	0.048	0.052	-0.004
Wooster	0.015	0.006	0.009
Female	0.591	0.655	-0.064*
Age	19.156	19.160	-0.003
Contribution Important	0.851	0.857	-0.006
P(Biology & Life Sciences)	11.578	12.280	-0.702
P(Business & Economics)	23.252	21.674	1.578
P(Computer Science)	4.844	5.426	-0.582
P(Education)	4.729	4.084	0.645
P(Engineering)	16.855	17.532	-0.677
P(Health Sciences)	14.706	12.919	1.787
P(Physics & Maths)	2.426	4.876	-2.450***
P(Social Sciences)	13.041	12.834	0.207
P(Other)	7.309	7.225	0.084

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Difference = Inattentive – Attentive.

Notes: As in Table A.6, but a respondent is counted as “Attentive” (708) if they passed the three attention checks that are identical across treatment and control, excluding the arm-specific information-comprehension check. Dropping that one check removes the only source of differential attrition, so the Treatment row is balanced.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.39: Balance Table: Baseline Characteristics

	Control	Treatment	Difference
1st Year	0.463	0.511	-0.048
2nd Year	0.471	0.441	0.030
3rd Year	0.066	0.047	0.018
Columbus	0.894	0.905	-0.011
Lima	0.006	0.014	-0.008
Mansfield	0.014	0.020	-0.005
Marion	0.020	0.011	0.009
Newark	0.060	0.045	0.015
Wooster	0.006	0.006	0.000
Female	0.651	0.659	-0.008
Age	19.257	19.064	0.193**
Unsure	0.709	0.687	0.021
Contribution Important	0.860	0.855	0.005
P(Biology & Life Sciences)	11.876	12.675	-0.800
P(Business & Economics)	23.564	19.827	3.737
P(Computer Science)	5.909	4.954	0.955
P(Education)	4.764	3.419	1.346
P(Engineering)	13.696	21.284	-7.588***
P(Health Sciences)	13.220	12.626	0.594
P(Physics & Maths)	4.816	4.934	-0.119
P(Social Sciences)	12.664	12.999	-0.335
P(Other)	8.057	6.411	1.647
White	0.617	0.567	0.050
Black or African American	0.051	0.053	-0.002
American Indian or Alaska Native	0.003	0.000	0.003
Asian	0.160	0.215	-0.055*
Hispanic	0.031	0.017	0.015
Other	0.020	0.006	0.014*
Prefer not to say	0.014	0.020	-0.005
Two or more races	0.103	0.123	-0.020

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: Means for the attrition-robust sample ($N = 708$) are reported for all variables, for treatment and control groups. We report age, gender, the distribution of students across campuses and enrollment years, and their ethnicity. We also report the share of students who are unsure about their major, defined as those assigning positive probability to more than one major and the share of students reporting "contribution to society" as important.

Table A.40: Treatment Effects on Self Beliefs

	(1) Post SB	(2) Post SB
Prior Self Beliefs	0.618*** (0.015)	0.535*** (0.018)
Treatment	12.121*** (0.680)	5.589*** (0.737)
Treatment*Underestimation gap		0.399*** (0.037)
Constant	25.980*** (1.308)	38.660*** (1.676)
FEs	Yes	Yes
Control Mean	67.1	67.1
Observations	5664	5664
Adjusted R^2	0.584	0.628

Notes: This table presents OLS estimates for Equation (9). The dependent variable is students' posterior self-beliefs. The "Underestimation gap" refers to the difference between the true share of previous graduates satisfied with their job's contribution and students' believed share. Each observation is a student-major couple. FEs include year, gender, ethnicity and campus. Clustered standard errors in parentheses: *, ** and *** indicate significance at 10%, 5% and 1% levels.

Table A.41: Treatment Effects on Advice Score - Preferences fo SI

	(1) Scale	(2) Scale
Treatment	0.938*** (0.084)	0.359*** (0.096)
Underestimation gap		-0.084*** (0.004)
Treatment*Underestimation gap		0.032*** (0.005)
Constant	6.565*** (0.097)	7.969*** (0.106)
Control Mean	6.6	6.6
FEs	Yes	Yes
Observations	4856	4856
Adjusted R^2	0.045	0.289

Notes: The table reports OLS estimates of the effect of the information treatment on the advice students give to peers who care about a job's contribution to society. The outcome variable is a score from 0 to 10 assigned to each major, with higher values indicating stronger advice to pursue the major. In Column (2), the treatment indicator is interacted with the underestimation gap, which measures the initial misperception regarding graduates' satisfaction with contribution in each field. Each observation corresponds to a student-major pair. FEs include year, gender, ethnicity and campus. Clustered standard errors in parentheses: *, ** and *** indicate significance at 10%, 5% and 1% levels.

Table A.42: Treatment Effect by Misperception - Preferences for SI

	Final P(M)		
	(1) All	(2) Women	(3) Men
Initial P(M)	0.951*** (0.011)	0.956*** (0.012)	0.938*** (0.024)
Treatment	0.117 (0.104)	0.227* (0.137)	-0.113 (0.141)
Demeaned Undergap	-0.063*** (0.018)	-0.072*** (0.022)	-0.038 (0.032)
Demeaned Undergap*Treatment	0.039** (0.020)	0.057*** (0.022)	-0.004 (0.038)
Prior credits in cat. (AU25+SP26)	0.112** (0.047)	0.073 (0.053)	0.200** (0.096)
Constant	0.221 (0.876)	-0.524 (0.968)	3.721 (2.763)
FEs	Yes	Yes	Yes
Observations	4856	3352	1504
Adjusted R^2	0.940	0.946	0.927

Notes: The table reports OLS estimates of the effect of the information treatment on students' major intentions, for students who report that contribution to society is important. The outcome variable is the probability (from 0 to 100) that a student assigns, after the intervention, to graduating in each major; "Initial P(M)" is the corresponding probability elicited at the start of the survey. "Prior credits in cat." measures credits earned in that field over the previous two semesters. The treatment indicator is interacted with the demeaned underestimation gap, individual i 's underestimation of the share of graduates satisfied with their job's contribution in each field, demeaned by i 's average underestimation across all majors. Column (1) includes all such students, while Columns (2) and (3) split them by gender. Each observation corresponds to a student-major pair. Clustered standard errors in parentheses: *, ** and *** indicate significance at 10%, 5% and 1% levels.