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Tightening the Leaky Pipeline(s): The Role of Beliefs About Ability in STEM Major Choice

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Tightening the Leaky Pipeline(s): The Role of Beliefs About Ability in STEM Major Choice

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Abstract

To study beliefs about ability and STEM major choice, I conduct a field experiment where I provide students with information that they are above average in their top fields of study. I find that STEM students are more likely to switch out of their major and that non-STEM students fail to switch into STEM at the same rates as other fields. I also find that learning you are above average in your top field of study increases STEM major choice by almost a third, as STEM students appear more like to persist and non-STEM students increase their switching into STEM fields.

Key Words: Beliefs, STEM, Human Capital, College Major
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1 Introduction

Despite a growing demand for STEM-capable workers in the U.S. workforce, college students intending to major in science, technology, engineering and mathematics (STEM) fields fail to do so at extremely high rates (Olson and Riordan, 2012; Xue and Larson, 2015; Chen and Soldner, 2014). STEM students also are more likely to switch majors or drop out entirely when compared to students of other fields (Stinebrickner and Stinebrickner, 2013). This phenomenon is one version of what is often referred to the STEM "leaky pipeline", in which students initially interested in completing a STEM degree either switch majors or drop out altogether.

So far, the research on the causes of this leaky pipeline out of STEM is decidedly thin. Economists studying major choice more broadly have predominantly focused on students expectations of post-graduation returns to majors, with an emphasis on pecuniary returns (Zafar, 2011; Wiswall and Zafar, 2015a, 2018, 2015b; Conlon, 2020). Relatively little attention, however, has been paid to students' beliefs about their ability to do well in different majors. Beliefs about ability are likely to be relevant in studying the leaky pipeline as STEM fields are often considered some of the most academically demanding majors. Also, while incoming college students may have a sense of the overall ability distribution within an institution, they importantly have imperfect information about how they compare academically to successful STEM graduates[1].

In an important study of this topic, Stinebrickner and Stinebrickner (2013) conclude that aspiring STEM students fail to graduate with a degree in the those fields ultimately because they enter college with incorrect beliefs about their ability. The authors argue that, as students progress through the science curriculum, they receive negative shocks to their beliefs via grades in science courses, which tend to be lower compared to non-science fields, ultimately leading them to switch majors. For educators and policy-makers hoping to increase interest and persistence in STEM tracks, a natural question that arises in light of this is; if students were to receive a positive shock to their beliefs about their ability to complete a STEM degree, would we see a corresponding increase in STEM persistence?

[1]Using data provided to me from the UC Davis registrar on the average HS GPA, SAT and ACT scores of recent graduates in different majors, I see that graduates of STEM fields have average scores that are higher than either biology, social science or humanities graduates across all the measures just mentioned.

To study this question, I conduct a field experiment in which I first elicit college students' top choices of major and then randomly provide them with information they are above average in those fields. I then measure how this information influences their decision to major in STEM. In my descriptive analyses, I show that students are indeed more likely to leave their preferred field of study if that field is a STEM field compared to students whose top field is non-STEM. Specifically, STEM students are four times as likely to leave their top choice of major compared to non-STEM students. I also show that this is not due to STEM students placing less likelihood on graduating in that field compared to non-STEM students. STEM students believe they are just as likely to graduate in their top field as non-STEM students. When studying beliefs about ability, I also find that over one in four STEM students who are actually above average in their top field believe they are "below average" in that field. Focusing on those students who switch out of STEM, they are more likely to be female, believe that their peers are of higher ability relative to their own ability as well as overestimate the actual ability of their peers.

In addition, my data allow me to identify a leaky pipeline *into* STEM fields, as students are less likely to switch into STEM majors if they are originally interested in a non-STEM field. This second "pipeline" into STEM is rarely discussed, if even mentioned, in the STEM major choice literature, although my results show that getting students to switch into STEM fields is likely as important to increasing STEM major choice overall as increasing persistence in those fields.

In my experimental results, I find that the information I provide to students increases persistence in STEM by 40 percent among marginal *out* STEM students, those whose top choice of major is a STEM field, but who are also considering majoring in fields other than STEM. Focusing on marginal *into* STEM students, those who are considering majoring in STEM but do not select it as their top choice, I find my intervention also increased switching into STEM by a significant amount. Looking across the entire sample, I find that my treatment increased STEM major choice overall by five percentage points, representing close to 30 percent of the control mean. I also find that treatment effects on STEM major choice are strongest for first-generation students.

Using unique data on beliefs that I elicit as part of my intervention, I find that the information I provide does not provide any differential impact for students based on the beliefs they held about *mean* ability ex-ante. This implies that, similar to effects of learning about returns to majors (Conlon, 2020), learning you are above average compared to recent STEM graduates likely induces changes in STEM major choice through reducing uncertainty rather than shifting mean beliefs about ability. Taken together, these results show that beliefs about ability are an important feature of STEM major choice. Learning you are above average in your top choice of major can help alleviate uncertainty about those beliefs and meaningfully inform subsequent decisions about which fields to major in and whether to continue on and ultimately graduate in that field.

This paper contributes to several literatures. The first is the literature studying the determinants of college major choice. Most papers in this literature use structural modeling techniques to untangle the magnitudes of different determinants of students' college major decisions, including expected earnings, productivity and academic ability (Arcidiacano et al., 2012; Arcidiacano, 2004; Gong et al., 2019; Zafar, 2011). Another branch in this literature studies the major choice decision by providing information to students about characteristics of majors and measuring changes in students' major choice behavior (Conlon, 2020; Li, 2018; Carrell et al., 2020; Owen, 2020). Other work examines the effect of role models in major choice (Carrell et al., 2010; Porter and Serra, 2019)

Despite the various focuses, approaches and methods used, one commonality among these papers is that each describe perceptions of ability as an important feature of the major choice decision. Surprisingly, however, there has been little work studying this mechanism directly. In one of the few papers addressing this, Li (2018) finds that female students in an introductory economics course respond positively to learning about their ability. In this paper, the author finds a 50 percent increase in economics major choice as a result of their information and nudge treatment. In a similar study using information derived from introductory STEM courses, Owen (2020) finds that low-performing male students are likely to leave STEM as a result of learning how they compare to other students in their class, effectively reducing the gender persistence gap in STEM. I add to this line of literature by estimating causal effects on STEM major choice that arise from shocks to beliefs about ability across a large set of majors. This allows me to study both rates of persistence in as well as *switching* into STEM fields that may derive from beliefs about ability in non-STEM fields.

Secondly, this paper contributes to the study of beliefs in education (Bobba and Frasinco, 2019a,b; Zafar, 2011; Bleemer and Zafar, 2018; Dizon-Ross, 2019; Kaufman, 2014; Attanasio and Kaufman, 2014; Rury and Carrell, 2020; Ersoy, 2019; Conlon, 2020). Papers in this literature highlight the important role of beliefs in student decision-making across a range of outcomes, including study effort, college-going and major choice. As such, in order to fully understand the casual factors behind academic decision making, researchers must collect and analyze students' expectations as observed decisions may be compatible with several different sets of preferences (Manski, 2004). In light of this, I collect and study several beliefs about students' major choice. I use these beliefs to identify important features of students' major choice decisions that would not be possible using observational data alone. Specifically, by collecting subjective data about different majors, I can better characterize the leaky pipelines out of as well as into STEM fields and link these phenomena to beliefs about ability.

Thirdly, this paper contributes to the literature on performance feedback in education. Papers in this literature study the effect of learning about your performance on an academic assessment (eg. grade) *relative to others* on subsequent academic outcomes (Azmat and Iriberri, 2015; Azmat et al., 2019; Azmat and Iriberri, 2010; Bandiera et al., 2015; Murphy and Weinhardt, 2020; Goulas and Megalokonomou, 2018; Brade et al., 2018; Gonzalez, 2017). These studies find that providing feedback to students changes students' perceptions of their ability or self-confidence (Murphy and Weinhardt, 2020). The information I provide students is a unique form of performance feedback that allows students the rare opportunity to compare themselves to other students within a field of study while in college. This information is highly salient to students, as the measures of ability I provide in my intervention are derived from statistics most students spend a great deal of time considering when applying to college; namely high school (HS) GPA, SAT and ACT scores. This paper is the first to assess how receiving performance feedback about academic performance derived completely before entering college influences college major choice. As such, my results speak directly to objectives of university administrators and policy makers hoping to bolster the academic success of those students about to enter college. It is also the first paper to provide feedback to college students across a set of majors.

My results are also important for the study of labor supply in STEM occupations in the U.S. Along with a leaky pipeline found in STEM fields in higher education, there has also been a slowdown in the domestic supply of STEM-capable workers in the U.S. labor force (Carnevale et al., 2011). This slowdown has led policymakers to call for a drastic increase in the number of STEM-capable workers (Olson and Riordan, 2012). This paper studies a plausible explanation for this slowdown; that STEM majors leave STEM (and non-STEM students fail to switch *into* STEM) because of misperceptions of their ability to succeed in those majors. As I describe later, I find evidence that by providing students with information that they are above average in their top field of study increases STEM major choice, highlighting the potential for larger policy interventions aimed at addressing this slowdown in STEM labor supply.

Lastly, I contribute to the literature studying the use of nudges in education settings. While nudges are often deployed in these settings, existing evidence is mixed on their efficacy in changing behavior (Oreopoulos et al., 2020; Oreopoulos and Ptronijevic, 2019; Damgaard and Nielsen, 2018). I show that light touch interventions can indeed induce meaningful behavioral change in educational decision making. Later on in the discussion, I consider what attributes of my intervention may be influential in changing behavior.

The rest of the paper is structured as follows; section 2 describes the experimental design and setting, including a discussion of the information intervention and how it was constructed; section 3 describes the data, presents the descriptive results and discusses the leaky pipeline out of and into STEM; section 4 presents the experimental results; section 5 provides a discussion of my findings and concludes.

2 Experimental Details

The experiment was conducted during the fall 2018 and winter 2019 academic quarters at University California at Davis (UC Davis). UC Davis is a selective public research university in Northern California with an undergraduate enrollment of over 30,000 students. The 75th percentile of HS GPA for the 2019 freshman class was 3.86, while the 25th percentile was 4.18. To study STEM major choice, the sampling frame was chosen to consist of large, introductory STEM courses. Course instructors and department administrators were contacted for participation during the preceding academic terms, with over a dozen instructors agreeing to advertise the survey.

Several pieces of the experiment were arranged prior to students taking the survey. Firstly, to create my information treatment, the university's registrar provided me with average scores of recent graduates within the a set of 16 major groups. These averages were calculated for five different measures of ability; HS GPA, SAT combined score, SAT math score, SAT reading and writing score and ACT score. These average scores were derived using scores from the five most recent cohorts of UC Davis graduates and were calculated *within each major group*. This implies that I was given 16 x 5 different measures of ability that were calculated using the universe of recent UC Davis graduates. These averages were incorporated into the survey and used as part of the survey's internal display logic. Secondly, for all students included in the experiment's sampling frame, scores from all five measures were also uploaded to be used within the survey[2]. Students from participating classes were incentivized to take the survey by being entered into a raffle to win one of several amazon gift cards.

Upon taking the survey, participants were asked several questions about their educational preferences and beliefs. First, students were asked to identify their top and second choices of majors. Students were given 16 options; economics, biological sciences, physics, chemistry, communications, psychology, engineering (any type), mathematics, statistics, foreign language, computer science, English, history, philosophy, political science and sociology. As most of the literature on major choice has focused on the pecuniary returns to majors, students were then asked about their expected earnings both five and 20 years after graduating in both their top and second choices of major.

To capture students' subjective expectations about graduating with different majors, student were also asked "what is the probability you will believe you graduate in your top choice of major, second choice of major, or some other major?", with the sum of the probabilities constrained by the survey to sum to one. To study their beliefs about their relative ability in different fields, students were then asked a series of questions concerning their top choices of major. This series of

[2]This was necessary due to a research design constraint from my campus partners that restricted me to only give information to students whose own score was above the average score. I discuss this further later on in the paper.

questions was designed to avoid any direct elicitation of beliefs about ability, as these responses may have been more prone to experimenter bias or motivated reasoning. In my elicitation procedure, students were first asked to select which academic measure best represents ability in their top and second choices of major. Students were given the same options for those I was provided average scores of recent graduates; HS GPA, SAT, SAT math, SAT reading and writing and ACT score. After students selected these measures for both their top and second choice of major, they were then asked "What do you believe is the average score of recent UC Davis graduates is in your top choice of major?", where "score" was replaced with the academic measure they selected and "top choice of major" with their selection for most preferred major.

After students provided their beliefs of the average score of recent graduates in their top choices of major, the survey determined who is eligible to be randomized into either treatment or control groups. To do this, the survey compared the student's *own score* in the measure they selected for their top choice of major with the *average score* of recent graduates in that measure and major. If this criterion was satisfied, students were then randomized into either treatment or control groups. For students randomized into the treatment group, a message appeared that read "The average score of recent graduates in your top choice of major is (*actual average major-measure specific score*)", where again "score" is the measure students selected as most representative of ability and "top choice of major" is students selection for top choice of major. This message was then followed by a small nudge that stated "Our records show that your score is above the average score of graduates in your top choice of major. We hope that this information helps you in your college major decision." The survey then followed the same procedure for the student's second choice of major, after which the survey concludes. All survey items as well as the information I provided to participants can be found in the appendix.

Due to design constraints imposed by my institutional collaborators, I was not permitted to provide information to students whose own score was below the average score of recent graduates. I discuss this restriction towards the end of the paper when I consider the policy implications of my findings. Lastly, students were also asked to sign a Family Educational Rights and Privacy Act (FERPA) release so that I could access their academic records, including their major choice history

history, as well as their demographic and background characteristics.

3 Data and Descriptive Results

3.1 Data

The data for this project consist of 728 completed baseline surveys, as well as demographic and academic background information, and major choice history up to three years after the experiment for all students who signed a FERPA release. Due to the research design constraint described above, 483 of these students were eligible for treatment in their top choice of survey, as they had scores in majors/measures they selected that were in fact above the average score of recent graduates in that major/measure [3]. Slightly fewer, 456, were eligible to receive information in their second choice of major[4].

3.2 Experimental Balance

To ensure that my randomization procedure worked as designed, I conduct several tests. Through my collaboration with the university, I received a rich set of variables on student demographics and pre-collegiate academic performance from the university's registrar, including race/ethnicity, gender, low-income and first-generation status as well as HS GPA and standardized test scores. I also observe each student's major at time of admission to the university. Table 1 shows results from regressions that study the relationship between treatment status and survey responses and demographic variables for both top and second choice of major. We see that none of the coefficients from either model are statistically distinguishable from zero. I view this as strong evidence that students were in fact randomly assigned between treatment and control groups for treatment in

[3] One clear question here is why is the number of students who are "above average" more than half of the sample. There are two answers, one slightly less obvious than the first. Firstly, this may represent sample selection, with those who are above average more likely to take the survey than those who are not. Another explanation come from the fact that standardized test and HS GPA scores at UC Davis have increased over the years. This would mechanically push up the number of students who are above average when compared to average scores of previous cohorts.

[4] This was due to students not being above average in their measure/major for their second choice of major or not having a valid choice for second choice of major

both a student's top and second choice of major.

3.3 Sample Descriptives

Table 2 provides demographic information for students in my analysis sample[5]. The sample is almost exactly two thirds female, slightly higher than the proportion of undergrads that are female at UC Davis (61%). Almost half of the sample is Asian or Asian-American, a 30%, a sixth Hispanic and about 2% African American. While there are small differences, these numbers mirror the student population at UC Davis quite well[6]. Low-income and first-generation students, however, appear to be slightly under-represented in my sample when compared to the UC Davis population. They represent 21% and 32% of my sample respectively, while they constitute 37% and 42% of the student body. As my sampling frame consisted of large introductory STEM classes, 63% of students in my sample are freshman.

Table 3 presents results on top and second choice of major for the full set of survey respondents. For these results, I aggregate majors into four groups; social sciences (economics, sociology, political science, psychology); humanities (English, foreign language, history, philosophy); Biological Sciences; and STEM (physics, chemistry, mathematics, statistics, computer science and engineering (any type)). We see that biology is the most popular top choice of major (47.6% of students), followed by social sciences (24.6%), STEM (22.6%), and humanities (5.2%). The relative popularity of biology is striking, but somewhat consistent with major choices at UC Davis, with it's strong agricultural focus and popular biochemistry fields[7].

Table 2 also presents descriptive statistics broken down by whether students select a STEM field as their top choice of major[8]. Here we see that STEM students are almost 9 percentage points more likely to select the math portion of the SAT as most representative of ability in those

[5]This includes all students who were eligible for treatment in their top choice of major

[6]The Asian/Pacific Islander population at UC Davis represents about 32% of the student population. Another 17% of students are international, the vast majority of which are from Asian countries, predominantly China. The sum of these two terms is 49%, almost identical to the number of Asian students in my sample. Unfortunately, I do not have international status in my data.

[7]The sampling frame for this study was introductory STEM courses, which ended up including two large introductory biology courses. This fact may be skewing the distribution towards biology students

[8]As I discuss below, I separate biology from STEM in all of my descriptive analyses.

fields. These beliefs are consistent with stereotypes both of STEM students being math-focused and STEM curriculum being relatively math-heavy. We also see that STEM students expect to earn significantly more than non-STEM students, both five and 20 years after graduation. Looking at gender, I find that STEM students are 30 percentage points less likely to be female. Focusing on beliefs about ability, figure 2 plots the distribution of the difference between students belief of the average score of recent graduates in the top major/measure and their own score (own score - belief of average). Students who have a negative value for this variable believe the average score is above their own, effectively rating themselves as "below average" in this major. Figure 2 also plots this distribution for students whose own score is *actually* above the average score (which makes them eligible to receive information). Two facts emerge from inspecting these plots. First, about half of students who select STEM as their top field believe they are "below average". Second, we see here that about 27% of STEM students who are actually above average believe they are below average (these students represent my primary analysis sample). All of these results are robust to controlling for majors within these groupings.

3.4 The Leaky Pipelines Out of and Into STEM

To explore the dynamics of major persistence and major switching over time, I perform several analyses. When doing so, I exclude both those who where ineligible for treatment (those who had scores below the average in their selected major/measure) as well as students who received information in their top choice of major from these analyses. I first compare the distribution of top choice of major to the distribution of major choices I see three years later[9]. These results on persistence can be found in Table 4. Due to the large number of students intending to study biology, I have separated it from other STEM fields and presented the three major groups along with biology.

Looking at table 4, we see relative increases in the number of students majoring in biology, social sciences and humanities three years after the experiment compared to the number of students who

[9] For students who are no longer enrolled at this point, I use their most recent major. As the control group were all students who were above average students in their top field of study, all departures from the university are through graduation and not dropping out.

selected those fields as their top choice of major at the time of the survey. While biology and the humanities stay about the same over this period (increases of 4.5% and 0% respectively), social sciences saw a 13.5% increase in the number of students over this time. In sharp contrast, however, STEM fields saw a decrease of 33.3% during this time.

Perhaps a more direct way to assess whether students of different majors are more or less likely to persist in those fields is to see which of these groups of majors has the highest persistence rate, conditional on selecting it a major in that group as your top choice . To do this, I create a variable that equals one if the student is majoring in their top choice of major two years after the experiment. We see in table 5 that 92% of biology students and 88% of social science students are majoring in their top choice of major two years later. Looking at STEM students, however, only 61% are still majoring in their top field [10].

Given that STEM fields are highly mathematical and are known for "weeding out" students with insufficient aptitude in mathematics, these transitions out of STEM may reflect differential mathematical preparation. Instead of observing a leaky pipeline that reflects incorrect beliefs about ability, we may simply be observing the least mathematically prepared students switching to other majors. To study this, I compare the SAT math scores of those STEM students who switched out of their top field to those who persisted as measured three years after the intervention. Table 9 presents descriptive comparisons between these "leakers" and "persisters", namely those students who top choice of major was a STEM field, were randomized into control, and who ultimately did not (leakers) or did (persisters) major in a STEM field. While these samples are small (n = 31, n = 21 respectively), they provide a unique glimpse into the demographic makeup of students who switch out of STEM. Here we see that these students have an average SAT math score that is 14 points (800 point scale) higher than those students who continue on in their top field. While this result is not statistically significant, it raises doubts about the role of mathematical aptitude in explaining exit out of STEM in this setting.

Table 9 also shows that STEM students who switch majors are more likely to be female (significant at 10% level), first-generation students and Hispanic, although there is no statistically

[10] Only 57% of students who chose a field in the humanities are still majoring in that field two years later, although there are only 14 of these students so it is hard to draw sharp conclusions about these fields.

detectable difference for these last two characteristics. Focusing again on beliefs about ability, students who switch out of STEM are more likely to rate themselves as being relatively less academically capable in those STEM fields (own score - belief of average) and are also appear more likely to overestimate the actual average score of recent graduates in STEM fields (actual average - belief of average). These differences, however, are not quite statistically significant.

These dynamics out of STEM may not truly reflect a leaky pipeline if student expectations are in line with the distribution of major choices three years after the experiment. For example, students who begin with a STEM field as their top major may expect to switch out of that field more so than students whose top choice of major is another field. This might be true if students place a higher option value on starting college in a STEM field. As we saw earlier, students whose top choice of major was a STEM field expected to earn significantly more in those fields conditional on graduating in those majors. This would imply that students experiment with STEM, but place a lower probability on the likelihood that they ultimately persist in that field. If students were indeed as earnest in their top choice of major in STEM as in other fields, the differences in likelihoods of graduating in your top majors would not be very different between STEM and non-STEM fields.

As part of the survey, students were also asked to provide the likelihood they believed they would graduate in their top choice, second choice or some other major. Table 6 in the appendix shows that vast majority (90.2 percent) of probability is placed on either the top or second choice of major, demonstrating that students are mostly considering majoring in either their top or second choice of major, rather than a larger set of majors. I incorporate these subjective probabilities into my analysis of the leaky pipeline to assess the following hypothesis; do students who intend to major in STEM place less probability on doing so than students of non-STEM fields? To do so, I condition on top choice of major group and compare the average subjective probability students report that they will graduate in that field to the average empirical probability they in fact do. Again here I restrict the sample to the control group for top choice of major. Table 6 presents the results. Here we again see strong evidence of a leaky pipeline out of STEM fields. STEM students appear to report subjective probabilities of graduating in their top field that are only slightly different than students of other fields. Importantly, however, STEM students are much less likely to persist in that field two years after the survey than students of other fields.

All of these results provide clear evidence of a leaky pipeline *out of* STEM fields when excluding biology, but strikingly not for biology itself. If anything, students appear to underestimate the rate they will ultimately study biology. For this reason and those previously mentioned, I focus on STEM fields excluding biology when studying my experimental results.

Next, I leverage novel data I collect on students' second choices of major to study whether there is evidence of a leaky pipeline *into* STEM fields. To study this, I perform similar analyses as before, comparing the distribution of second choice of major as measured in the survey to the distribution of majors three years after the intervention. For this second distribution, I restrict the sample to students who are not majoring in their top choice of major three years later. This comparison tells us whether students' second choice of major matches up with the distribution of majors, *for those who are not majoring in their top choice three years later*. If there is no leaky pipeline into STEM, under certain assumptions, these distributions should be similar[11]. Table 7 shows that while biology, social sciences and humanities all have higher representation in the distribution of students who switch out of their top field compared to the distribution of second choice of major, STEM sees a sharp decline. Using student's subjective probabilities that they believe they will major in their second choice of major instead of the actual distribution of second choice of major yields a similar result. Students appear to over-estimate the rate they will switch into STEM, a result similar to those found in Stinebrickner and Stinebrickner (2013). Similar to the evidence of students switching out of STEM discussed earlier, I see this as evidence of a leaky pipeline *into* STEM. I now turn to whether receiving information about your ability in your top choice of major had any impact on tightening either of these leaky pipelines.

[11]The primary assumption is that for any level of major switching, the individual transition probabilities from top choice of second choice of major do not favor any major over the other. Conditional on not majoring in your top choice of major and being in the control group, the distribution of majors is much more uniform than top choice; social sciences and STEM are very similar with 27.9% and 25.6% respectively, while Biology and Humanities are smaller at 20.9% and 11.6%. The low representation of biology in the switcher distribution is likely driven by the fact that biology is by far the most popular top choice of major and only 1.6% of students who select biology as their top choice of major select a biology field as their second choice.

4 Experimental Results

To study whether the information provided to students in my intervention influenced STEM major choice, I estimate the following statistical model:

$$STEM_i = \alpha + \beta TREAT_i + \boldsymbol{X}_i\boldsymbol{\phi} + \boldsymbol{S}_i\boldsymbol{\gamma} + \psi_m + \epsilon_i$$

where $STEM_i$ is an indicator for whether the student is majoring in a STEM field three years after the intervention, $TREAT_i$ is an indicator if they receiving information in their top choice of major, $\boldsymbol{X}_i$ is vector of background characteristics such as race/gender and standardized test scores, $\boldsymbol{S}_i$ contains baseline survey responses and ϵ_i is random error term. I also include an indicator for receiving information in your second choice of major, although I focus my interpretation on treatment in a student's top choice of major[12]. Random assignment of students into treatment status assures me that $E[\epsilon_i|TREAT_i] = 0$, allowing me to estimate the causal impacts of information on major choice decisions.

To conduct inference, I estimate standard errors and calculate statistical significance under standard asymptotic assumptions. I also follow Athey and Imbens (2017) and perform randomization inference. In this procedure, treatment assignment is permuted across the analysis sample and and treatment effects are calculated for each permutation[13]. Empirical p-values are then calculated by ranking these treatment effects and assessing where the true model lies within this distribution. This approach has many advantages for hypothesis testing. I present both standard errors and empirical p-values in my results.

For each sample, I present two sets of results; one from a model that includes treatment indicators for both top and second choice of majors and; one which adds top major fixed effects and controls for demographic characteristics and survey responses.

[12] As the sample of students who were eligible for treatment in their top choice of major does not perfectly overlap with those eligible in their second choice, I create an indicator that equals one if you are in the latter but not the former. I then replace missing values for treatment in second choice of major with zeros and then include this indicator in the regression as well. Results are qualitatively very similar when excluding these variables in the analysis.

[13] I perform 500 permutations for each outcome.

4.1 Main Effects on STEM Persistence

Table 10 in the appendix presents results for students whose top choice of major was a STEM field[14]. Focusing on these students captures the how well the treatment tightens the leaky pipeline of switching *out of* STEM fields. We see in columns one and two that treatment effects are large, representing an increase in persistence of about seven percent, although none of the estimates are significantly different from zero. This may be due to the fact that students who aspire to major in STEM fields are not considering non-STEM fields as alternatives. In this case, the treatment is unlikely to increase persistence, as this subset of students rarely choose non-STEM fields, even if they might switch majors within STEM.

As we saw earlier, students place very little probability on graduating in a field that is neither their top nor second choice of major. I therefore use data on students' second choice of major to characterize students who select a STEM field as their top choice of major, but also select a non-STEM field as their second choice of major as "marginal *out* STEM" students. These are the the students whose beliefs about their own ability in STEM fields are likely to play a larger role than those who are *only* considering STEM majors. Columns three and four of table 10 show results for these students. Here we find large and marginally significant effects of information on persistence, although when including the full set of controls the estimate becomes less precise. Putting this result into context, this tells us that learning you are above average in your top choice of (STEM) major increases persistence by 40 percent for this group.

4.2 Main Effects on Switching into STEM

As discussed earlier, I find evidence of a leaky pipeline *into* as well as out of STEM fields. To assess whether treatment increased switching into STEM fields, I estimate models studying students whose top choice of major is a non-STEM field. We see in columns five and six of table 10 that I cannot detect any significant patterns switching into STEM for this group. Similar to the effects on persistence discussed above, however, this may be explained by students who are not considering

[14]While the sample size for these models may seem small (n = 109), it is similar Stinebrickner and Stinebrickner (2013), who studied similar questions as I do here using a sample sizes of n = 139 and n = 93 when focusing on students considering science fields.

STEM *at all* not responding to treatment. These are students who select a STEM field for neither their top nor second choices of major. In this case, beliefs about ability may play little role in switching into STEM as STEM is not in their consideration set. To address this, I focus on "marginal *into* STEM" students, meaning those who select a non-STEM field as their top choice but select a STEM field as their second choice of major. Table 10 shows that learning you are above average in your top choice of major increases switching into STEM by 7 percentage points for this group. Given that the control mean for STEM major choice in this group is 1.6 percentage points, this represents an incredibly large treatment effect for this group.

I next study whether receiving information that you are above average in your second choice of major induces switching when your second choice of major is a STEM field. Somewhat surprisingly, I fail to detect any significant effects when studying treatment in a student's second choice of major when that choice of major is a STEM field. These results in columns five through eight in table 10. While the effect of learning you are above average in your second choice of major for marginal *in* STEM students is large, these estimates are imprecise. What I can say in light of these results is that switching into STEM may only take place through learning one's ability in one's top choice of major, even when that major is not a STEM field. These results show that shocking beliefs in majors that are not a student's most preferred major have a relatively weaker impact on the decision to switch into STEM.

Lastly, table 10 also shows estimates from models that examine the effect of being treated in a student's top choice of major on STEM major choice across the entire sample. These estimates provide the combined effect of both persistence within and switching into STEM fields. Here we see an increase in STEM major choice across the entire sample of 5 percentage points, representing an increase in STEM major choice of about a third compared to the control mean (although here only the model with the full set of controls is significant at the 10 percent level). Provided that learning you are above average in your top choice of major can influence STEM major choice in two distinct ways, these results provide a valuable reference point for how a policy designed to influence beliefs about ability may change STEM major choice across a sample of students with different preferences for majors.

4.3 Heterogeneous Treatment Effects

I study potential heterogeneous treatment effects of my internvetion across three dimensions; gender, first generation college student status, and whether a student is eligible for the Pell Grant (low-income status). To do so, I estimate the following interaction model:

$$STEM_i = \alpha + \beta_1 TREAT_i + \beta_2 C_i + \beta_3 TREAT_i * C_i + \boldsymbol{X}_i \boldsymbol{\phi} + \boldsymbol{S}_i \boldsymbol{\gamma} + \psi_m + \epsilon_i$$

where C_i is one of the student characteristics mentioned above. Here, β_3 is the parameter of interests. These models estimate treatment effect heterogeneity for STEM major choice overall. Table 11 presents results for all three groups.

Earlier I showed that students who selected a STEM field as their top choice of major were significantly less likely to be female. Somewhat surprisingly, we see the treatment did not differentially influence female students to major in STEM fields[15]. Treatment effects for both low-income and first-generation students, however, are large and, in the case of first-generation students, precisely estimated. Previous work as shown that first-generation college students typically have lower self-efficacy, a trait linked with persistence in difficult tasks Thompson (2021). As shown earlier, "leakers", those who select a STEM field as their top choice of major but fail to persist in STEM, are seven percentage points more likely to be first-generation students (although this difference is not statistically significant). Using a large representative sample collected across several colleges, Thompson (2021) documents that high performing first-generation students are more likely to leave STEM compared to continuing-generation students. Here, the author shows this is likely due to first-generation students receiving negative shocks to their ability through lower grades in introductory STEM courses. In light on this, my results show that learning about how they compare to their peers using alternative measures of ability is important for first-generation students when deciding on what to major to choose in college, particularly when considering STEM fields. I discuss the relationship between the information I provide students and the information about ability contained in grades later in the paper when I compare my findings to the previous literature.

[15] In a sub-analysis, focusing on marginal *into* STEM students, I do observe large positive differential treatment effects on STEM persistence by gender. These results are not significantly different than zero, but are promising considering efforts to increase female persistence in STEM fields. Results available upon request from the author.

4.4 Mechanisms

I next explore whether the information I provide students has a differential impact for students based on their initial beliefs about their relative ability. To do so, I estimate an interaction model, in which I add to the model used to study my main experimental results both a variable that incorporates students' beliefs about the average score of recent graduates are and an interaction between treatment status and this variable. This variable is constructed by comparing the true value of the average score of recent graduates in a given major/measure pair with a student's belief of that score. I create an indicator variable that captures if a student's belief of the average was below the actual average:

$$BD_i = \mathbb{1}\{Actual\ Average_{(major,measure)} > Belief\ of\ Average_{(major/measure)}\}$$

Students who have $BD_i = 1$ can be thought of as having underestimated the academic ability of their peers, relative to their own. Table 12 in the appendix presents results on STEM major choice for all students, marginal *out* and marginal *into* STEM students. For brevity, I present results from models that include a full set of controls. Here we see no differential effect on STEM major choice overall, nor for marginal *out* STEM students. I do find, however, a significant differential effect for marginal *into* STEM students. These students appear more likely to switch into STEM upon receiving treatment if they had originally underestimated the ability of their non-STEM peers.

One way the information I provide may influence STEM major choice is by shifting students' mean beliefs of peers' ability towards the true value contained in the intervention. An alternative mechanism is through reducing the variance of students' beliefs. Put another way, this would translate to reducing students' uncertainty about their ability. Given that I find an increase in STEM persistence as a result of my intervention, the null results here for marginal *out* STEM students support the latter mechanism as ex-ante mean beliefs do not seem to influence persistence in light of new information about ability.

I next study whether the information I provide students has a greater effect depending on how close a student's own score is to the revealed true score. To do so, I construct a continuous "actual difference" variable that captures how far a student's own scores is from the revealed score:

$$AD_i = \frac{Own\ Score_{(major/measure)} - Actual\ Average_{(major,measure)}}{Actual\ Average_{(major,measure)}}$$

Unfortunately, I cannot discretize this variable as only students who had scores that were above the average were eligible for treatment. Therefore, all students would have a value of one for a variable that indicated if a student's own score was above the revealed score. The continuous variable defined above, however, allows me to see how students responded to treatment differentially depending on how much higher their own score was from the revealed score. Table 12 shows us the estimates of this interaction term. In this case, a negative value would imply that the treatment effect is weaker for students with scores that are further away from the revealed true score. This also implies that students whose scores are closer to the true score experience a stronger treatment effect. This is in fact what I find. Coefficients for all three outcomes are negative. The differential effect for marginal *out* STEM students is economically large, but imprecise. Looking at marginal *into* STEM students, the differential impact of having a score much higher than the revealed score is again quite large and here is much more precisely estimated, as is the effect for the entire sample .

5 Conclusion and Discussion

In this paper, I conduct an information intervention aimed at increasing the number of students majoring in STEM fields by changing their beliefs about their ability in their top fields of study. Using various measures, I find strong evidence of a leaky pipeline out of STEM that is consistent with a story where students leave STEM partly because they believe they are not academically suited for those fields. I also find evidence of a leaky pipeline *into* STEM, as students fail to switch into those majors at the same rates as other fields. In my experimental results, I find that providing STEM students with information that they are above average in that field increases STEM persistence among marginal *out* STEM students by 40% as well as increases switching into STEM among marginal *into* STEM students. Combining these two effects, the information

I provide increases STEM major choice by about 30% of the control mean. I also find that the effects are strongest for first-generation students.

Few papers have directly assessed how beliefs about ability might factor into a student's major choice decision. Stinebrickner and Stinebrickner (2013) use a novel panel data set containing information similar to what what I collect in the present study to assess how students update their perceptions of how likely they are to graduate with a degree in science. To do so, they model the belief updating process as a function of noisy signals students receive about their ability via grades they receive in science and non-science classes. They conclude that if students had entered college with the beliefs about graduating with a science degree they have later on, they would have been less likely to pursue science at the outset. Achieving this would effectively fix the leaky pipeline not by patching the leak but by turning down the water pressure. My results point to an slightly different interpretation. My findings are consistent with an updating process where students' beliefs about their ability are a function not just of grades received in STEM classes, but of results from highly salient pre-collegiate academic performance measures, namely HS GPA and standardized test scores. Uncertainty about completing a STEM degree can be reduced by resolving uncertainty in either of these two domains. Even in my setting, it may be that low grades in STEM courses do take a toll on students perceptions of their ability, but those who received information that they are above average in that field have beliefs that may be more resilient to these negative shocks. Therefore, the effect of lower grades on beliefs about ability may be smaller.

Previous work studying major choice and ability can also help to put the magnitudes of the effects I find here into context. I find that my treatment increased STEM major choice across the entire sample by about one third of the control mean. While this effect may seem large or implausible given the nature of the intervention, my results are in line with findings from other light-touch interventions on major choice outcomes. Studying how female students in an introductory economics course respond to information about their relative performance, Li (2018) finds that a combination of this information and a nudge to continue pursuing economics increases economics major choice by about 50 percent. Also studying persistence among female economics students, Porter and Serra (2019) find a 100 percent increase in economics majoring as a result of their light-touch role model intervention. Despite the large increase in both STEM persistence and switching I find as a result of my treatment, they do not seem implausible in light of the results from these previous studies.

The analyses I perform to study STEM major choice in this paper rely on unique measures of students' consideration set of majors, as well as beliefs about how likely they are to major in those fields. Given that switching one's major is a relatively frictionless choice at most U.S. universities and colleges, understanding both the extent and nature of the STEM leaky pipelines requires collecting these types of unique data, as students are not constrained to persist in their initial field of study. For example, as I find in my results, nudges aimed at increasing persistence in STEM fields are likely to be more effective if targeted towards students who are seriously considering majoring in non-STEM fields, (ie. marginal *out* or *into* STEM students). Being able to identify these students will help administrators, educators and policy-makers design more effective interventions. Lastly, as mentioned earlier in the paper, it would be extremely difficult to fully understand the nature of the leaky pipeline into STEM fields without the information collected as part of this project. Eliciting this broad set of student information helps provide a clearer picture of how students are thinking about their college major decisions as well as how to influence them.

The supply and demand of STEM-capable workers in the U.S. has received much attention from academics and policy-makers alike over the past decade (Olson and Riordan, 2012; Carnevale et al., 2011). Empirical work studying the supply of STEM-workers has focused on educational pipelines from the classroom to the labor force and has shown that STEM students are more likely to switch out of STEM more so than students of other fields (Chen and Soldner, 2014). This comes at a time when the growth in demand for STEM workers appears to be growing faster than other occupations.[16] The results from this paper highlight both potential reasons why the supply of STEM-capable workers is failing to keep up with demand and ways to address it. I find evidence that students' beliefs about their ability to complete a STEM degree play a crucial role in STEM persistence in college. Moreover, these beliefs appear to be sensitive to nudges that provide information to students about their relative ability in their top fields of study. Information nudges

[16] Bureau of Labor Statistics: https://www.bls.gov/emp/tables/stem-employment.htm

such as the one used in this paper may be powerful policy tools used in closing the gap between the supply and demand of STEM graduates.

One limitation of my research design is that I do not elicit students' preferences for different pieces of information directly. Using students' actual academic measure selections, however, I can study whether students believed this information to be useful[17]. I first study whether students were indifferent between selecting any of the five academic measures as being most representative of ability. There are two possibilities that I would view as consistent with this hypothesis; the majority of students selecting the first option that was displayed (HS GPA), or; students being equally likely to select any of the five measures[18]. About half of students select HS GPA as most representative of ability in either their top or second choices of major (55% for top choice, 50% for second). While this is by far the most common selection, it does not comprise the overwhelming majority. Also, even among the remaining measures, I do not observe equal likelihoods of being selected. The remaining percentages range from SAT combined (19%) to SAT Reading and Writing (2.8%). Put together, I do not see this as evidence that students were indifferent about which measure they selected.

An additional question is whether students simply selected the measure for which they were best at. To study this, I rank all students for whom I collect FERPA signatures across all five academic measures and then create percentage rankings for students for each measure. I then create a variable that captures in which academic measure students have the highest percentage rank. I find that only about a third of students select the measure for which they have the highest percentage rank as the measure that best represents ability in their top choice of major. This number is much closer to what we would expect if students were to select their top performing measure by chance (20%) than if they were systematically selecting measures in which they performed best.

Lastly, if students did not consider the information I offered as part of my intervention useful, we would not expect students to select different measures for different majors. This would be true both across and within student selections. As mentioned earlier, students who selected a STEM field as

[17] I here use all survey respondents and do not restrict my analysis to students who were eligible for treatment in their top choice of major. This leaves me with 860 students when studying measures in students' top choice of major and 847 when looking at their second choice.

[18] Unfortunately, I did not randomize the ordering of these measures in the survey.

their top choice of major were more likely to select the SAT math portion as most representative of ability in those fields. Students are even more likely to select SAT math when listing STEM as a second choice. I find similar patterns for the humanities and the SAT Reading and Writing portion. This measure is the second most chosen (after HS GPA) for humanities fields. When studying selections within students, I find that 35% of students select different measures when considering their top two choices of major. These results are generally consistent with student behavior in which these measures are carefully considered, rather than selected thoughtlessly. This careful consideration of measures may be what explains why students were likely to incorporate this information into their behavior. Finally, my findings also show that HS GPA is likely playing a large role in students perceptions of their ability, compared to the results of standardized tests.

A further limitation of this project is that I do not collect measures of beliefs about ability after I provide information to students. I therefore do not observe the extent and manner in which students update their beliefs upon learning they are above average in their top choice of major. This is an important question as a central characteristic of virtually all educational institutions is the provision of performance feedback to students on a regular basis. As such, my results should be interpreted as reduced form effects of my treatment on STEM major choice. I leave to further research the task of providing a more complete picture of how students update their beliefs about ability when deciding on what major to choose.

One additional, important limitation of my research design is that I cannot test how students who are below average would respond to information. This is an important limitation as prior research has demonstrated that these students may respond negatively to such information (Franco, 2020; Azmat et al., 2019). Understanding how these students might respond to learning they are below average would help policy-makers balance the trade offs when considering making average scores of recent graduates in different majors public. Below average students may increase their study effort in response to learning they are in fact below average. Other work in the performance feedback literature shows that this may be the case (Azmat et al., 2019). Also, there may be savings from informing students they are below average and inducing them to change majors, as courses that do not contribute to a degree or skills can be costly for both the student and the institution.

Lastly, there continues to be a dramatic under representation of female students in STEM fields. Disappointingly, I do not find that my treatment had a differential impact on STEM major choice for female students. In contrast, my results for first-generation students demonstrate that this subgroup is likely poised to use information about performance of other college students that is not publicly available. These findings highlight a possible way to address a particurly accute leaky pipeline out of STEM for this group (Thompson, 2021).

Taken together, my results demonstrate the importance of learning about one's own ability relative to other students when decided whether to continue or switch into STEM fields. Information about the academic measures I discuss here are virtually cost less to institutions of higher education. For those concerned with the increasing the rate of STEM major choice and completion at U.S. colleges, these findings may provide a road map for how they may be used to support students in that endeavor.

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6 Figures and Tables

Table 1: Selection Regressions

	(1) Treat (Top Choice) b/se	(2) Treat (2nd Choice) b/se
Biology Top Choice	0.054	0.080
	(0.109)	(0.119)
STEM Top Choice	0.060	-0.098
	(0.114)	(0.124)
Soc Sci Top Choice	0.067	0.088
	(0.113)	(0.123)
Pr(Graduate Top Choice)	0.094	-0.135
	(0.094)	(0.098)
E[Salary Top Choice] 5y	0.000	0.001
	(0.001)	(0.001)
Believe Good (Top Choice)	0.012	-0.089
	(0.054)	(0.057)
Female	0.066	-0.085
	(0.051)	(0.055)
Black	-0.243	-0.330
	(0.200)	(0.220)
White	-0.161	-0.158
	(0.121)	(0.130)
Asian/Asian American	-0.085	-0.134
	(0.117)	(0.126)
Hispanic	-0.066	-0.104
	(0.129)	(0.142)
Low-Income	0.051	-0.009
	(0.067)	(0.070)
First Generation	-0.074	0.002
	(0.059)	(0.062)
SAT/ACT score	0.000	0.000
	(0.000)	(0.000)
Freshman	-0.054	0.011
	(0.050)	(0.053)
Missing Demographic Vars	0.070	-0.012
	(0.082)	(0.094)
Observations	485	429

Notes: Each column represents a regression of all row variables onto treatment assignment. For column one, this sample consists of the analytic sample studied throughout the paper. As discussed in the experimental section, the number of observations in column two does not match up perfectly with the number of observations in column one. This is because the overalp between treatment in top choice and second choices of major was not perfect, as some students were above average, and therefore eligible for treatment, in their top choice but not their second choice of majo. I zero out missing treatment status values for second choice of major and add an indicator that equals one if a student is missing a value for that variable when studying treatment effects in top choice of major. Standard errors are in parentheses.

Table 2: Sample Descriptive Statistics

	(1) All students	(2) Top non- STEM	(3) Top STEM	(4) Difference
Earnings 5y post grad (thousands)	$78.52	$76.04	$86.98	$10.94
				(3.27)
Earnings 20y post grad (thousands)	$113.13	$110.70	$121.42	$10.72
				(3.31)
Prob grad Top Major	72.01	72.02	71.98	-0.04
				(0.01)
Believe good Top Major	69.15	69.51	67.89	-1.62
				(0.32)
HS GPA top measure	68.53	69.52	65.13	-4.5
				(0.87)
SAT math top measure	8.70	6.68	15.60	8.91
				(2.94)
Female	66.87	73.80	43.12	-30.68
				(6.21)
First-Gen	31.68	32.89	27.52	-5.36
				(1.06)
Low-Income	21.11	20.32	23.85	3.53
				(0.79)
Black	2.07	2.41	0.92	-1.49
				(0.96)
Asian	48.65	47.06	54.13	7.07
				(1.30)
Hispanic	15.73	15.78	15.60	0.18
				(0.45)
White	29.19	30.49	24.77	-5.71
				(1.15)
Observations	483	374	109	

Notes: The sample here consists of students who were eligible for treatment in their top choice of major and signed the FERPA release (so that I can observe their major choice decisions). Numbers represent either means for each variable. Column 2 restricts students who selected a non-STEM field as their top choice of major, while column 3 does the same for students who selected a STEM field. Column 4 reports both the difference between columns 2 and 3 as well as tests for statistical differences between the samples. t-statistics are in parentheses.

Table 3: Majors and Academic Measures

	(1) Top Choice	(2) Second Choice
Majors		
Biology	47.62%	11.33%
STEM (No bio)	22.57%	41.13%
Social Sciences	24.64%	30.30%
Humanities	5.18%	17.24%
Academic Measures		
HS GPA	68.53%	54.09%
SAT Combined	10.56%	16.36%
SAT Math	8.70%	15.30%
SAT Reading/Writing	0.62%	6.86%
ACT	11.59%	7.39%
Observations	483	406

Notes: The sample here consists of students who were eligible for treatment in their top choice of major, signed the FERPA release (so that I can observe their major choice decisions) and who have valid selections for second choice of major. The bottom right panel (academic measure for second choice of major) only has 379 observations. The lack of perfect overlap in number of observations comes from the fact that not all students answered the second choice of major questions.

Table 4: Leaky Pipeline *out of* STEM #1

	(1) Top choice Prob.	(2) Empirical Prob.	(3) Δ	(4) Percentage Δ
Biology	46.86%	48.95%	+2.09	+4.46%
	(50.0)	(49.8)		
STEM (No bio)	22.59%	15.06%	-7.53	-33.33%
	(41.9)	(37.7)		
Social Sciences	24.69%	28.03%	+3.34	+13.52%
	(43.21)	(45.01)		
Humanities	5.86%	5.86%	+0.0	+ 0%
	(23.53)	(23.53)		
Observations	239	239		

Notes: The sample here consists of students who were assigned to control in their top choice of major and signed the FERPA release (so that I can observe their major choice decisions). Column one provides the distribution of top choice of major by the four major groupings. Column two presents the distribution of actual major selections three years later. Column three takes the difference between columns one and two, while column four divides this difference by the value found in column one.

Table 5: Leaky Pipeline *out of* STEM #2

	(1) Pr(Persist 2ys Later)	(2) PP Drop
Biology (n = 112)	91.96%	-8.04%
	(27.03)	
STEM (No bio) (n = 54)	61.11%	-38.89%
	(49.21)	
Social Sciences (n = 59)	88.14%	-11.86%
	(32.61)	
Humanities (n = 14)	57.14%	-42.86%
	(51.36)	

Notes: The sample here consists of students who were assigned to control in their top choice of major and signed the FERPA release (so that I can observe their major choice decisions). Each row restricts the sample to those students who selected a major in the indicator major group as their top choice of major. Column one presents the average probability students placed on graduating in their top choice of major. Column one shows the percentage of students who are majoring in their top choice of major three years later for reach of these major groups. Column two presents this number minus 100.

Table 6: Leaky Pipeline *out of* STEM #3

	(1) Subjective Prob.	(2) Empirical Prob.	(3) Δ	(4) Percentage Δ
Biology (n = 112)	73.27%	91.96%	+18.69	+25.50%
	(23.57)	(27.31)		
STEM (No bio) (n = 54)	70.48%	51.85%	-18.63	-26.43%
	(25.39)	(50.43)		
Social Sciences (n = 59)	68.31%	83.05%	+14.74	+21.57%
	(26.09)	(37.84)		
Humanities (n = 14)	57.71%	50.0%	-7.71	-13.35%
	(20.81)	(51.89)		

Notes: The sample here consists of students who were assigned to control in their top choice of major and signed the FERPA release (so that I can observe their major choice decisions). Each row restricts the sample to those students who selected a major in the indicator major group as their top choice of major. Column one presents the average probability students placed on graduating in their top choice of major. Column two shows the actual distribution of major choices three years later. Column three takes the difference between columns one and two, while column four divides that difference by the value found in column one.

Table 7: Leaky Pipeline *into* STEM #1

	(1) Sec choice Prob.	(2) Empirical Prob.	(3) Δ
Biology	20.93	32.56	11.63
	(41.16)	(47.41)	
STEM (No bio)	25.58	6.98	-18.60
	(44.15)	(25.78)	
Social Sciences	27.91	34.88	6.97
	(45.39)	(48.22)	
Humanities	11.63	13.95	2.32
	(32.44)	(35.06)	
Observations	43	43	

Notes: The sample here consists of students who were assigned to control in their top choice of major, signed the FERPA release (so that I can observe their major choice decisions) and who have valid selections for second choice of major. I also restrict the sample here to students who did not major in their top choice of major. Column one shows the distribution of second choice of major for this group, while column three shows the distribution of actual major choices three years later. Column three takes the difference between columns one and two.

Table 8: Leaky Pipeline *into* STEM #2

	(1) Subjective Prob.	(2) Empirical Prob.	(3) Δ	(4) % Δ
2nd Biology (n = 20)	17.40%	40.00%	+22.60	+129.88%
	(13.61)	(50.26)		
2nd STEM (No bio) (n = 87)	19.87%	6.90%	-12.97	-65.27%
	(16.77)	(25.49)		
2nd Social Sciences (n = 70)	22.66%	20.00%	+2.66	+11.73%
	(20.27)	(40.29)		
2nd Humanities (n = 30)	12.63%	3.33%	-9.33	-73.63%
	(14.23)	(18.26)		

Notes: The sample here consists of students who were assigned to control in their top choice of major, signed the FERPA release (so that I can observe their major choice decisions) and who have valid selections for second choice of major. Each row consists of the set of students whose second choice of major is in the indicated major group. The first row represents the average probability those students placed on majoring in their second choice of major. The second row shows the percentage of students who actually selected a major in their second major group. Column three takes the differences between columns one and two, while column four divides that differences by the value in column one.

Table 9: Comparison of STEM Leakers and Persisters

	(1) Persister	(2) Leaker	(3) Difference
SAT Math score	691	705	14
			(0.50)
Female	27.27	57.14	29.87
			(2.26)
First-Generation	21.21	38.10	16.88
			(1.35)
Low-Income	15.15	23.81	8.66
			(0.78)
Asian	54.55	38.10	-16.44
			(1.17)
Hispanic	15.15	28.57	13.42
			(1.19)
White	27.27	23.81	-3.46
			(0.24)
Believe Good	63.63	61.90	1.73
			(0.13)
(Own Score - Belief)/Belief	7.17	3.78	-3.34
			(1.13)
(Actual - Belief)/Actual	-0.44	-3.37	-2.94
			(1.21)
Observations	33	21	

Notes: The sample here consists of students who were assigned to the control group for treatment in their top choice of major, who selected a STEM field as their top choice of major but ultimately chose to switch out of STEM.t statistics in parentheses.

Table 10: The effect of treatment on STEM Major Choice

	(1) Top=STEM	(2) Top=STEM	(3) Marginal out	(4) Marginal out	(5) Sec=STEM	(6) Sec=STEM	(7) Marginal In	(8) Marginal In	(9) Entire Sample	(10) Entire Sample
Treat (Top Choice)	0.069	0.046	0.235	0.203	0.068	0.027	0.070	0.075	0.057	0.055
	(0.092)	(0.093)	(0.125)	(0.145)	(0.068)	(0.053)	(0.042)	(0.044)	(0.035)	(0.026)
	[0.478]	[0.638]	[0.080]	[0.200]	[0.336]	[0.590]	[0.080]	[0.084]	[0.116]	[0.062]
Treat (Second Choice)					-0.027	0.039	0.038	0.025		
					(0.078)	(0.059)	(0.048)	(0.049)		
					[0.702]	[0.520]	[0.378]	[0.584]		
Control Mean	0.611	0.611	0.517	0.517	0.288	0.288	0.016	0.016	0.151	0.151
Observations	109	109	58	58	167	166	116	115	483	481
FE+Controls	N	Y	N	Y	N	Y	N	Y	N	Y

NoteThis table presents results from equation (1) in the text. The outcome of interest is whether a student is majoring in a STEM field three years after the intervention. Models without fixed effects and controls include indicators for treatment in top and second choice of major, as well as an indicator for whether a student is missing a valid value for treatment in their second choice of major. Odd numbered columns include indicators for whether a students top choice of major was a Biology, STEM or Social Science field, as well as the full suite of demographic and survey response controls. These include indicators for gender, race/ethnicity, SAT/ACT scores, first generation and low income status. Survey responses include expected pecuniary returns in one's top choice of major, the probability they believe they will graduate in their top choice of major and whether they believe they are above average in their top choice of major:

Table 11: Heterogeneous effects by gender, low-income and first generation status on STEM Major Choice

	(1) Recent = STEM	(2) Recent = STEM
Female x Treat	-0.018	-0.032
	(0.070)	(0.056)
	[0.826]	[0.636]
Low Income x Treat	0.130	0.078
	(0.085)	(0.065)
	[0.120]	[0.256]
First Gen x Treat	0.130	0.111
	(0.074)	(0.056)
	[0.056]	[0.066]
Observations	483	483
FE+Controls	N	Y

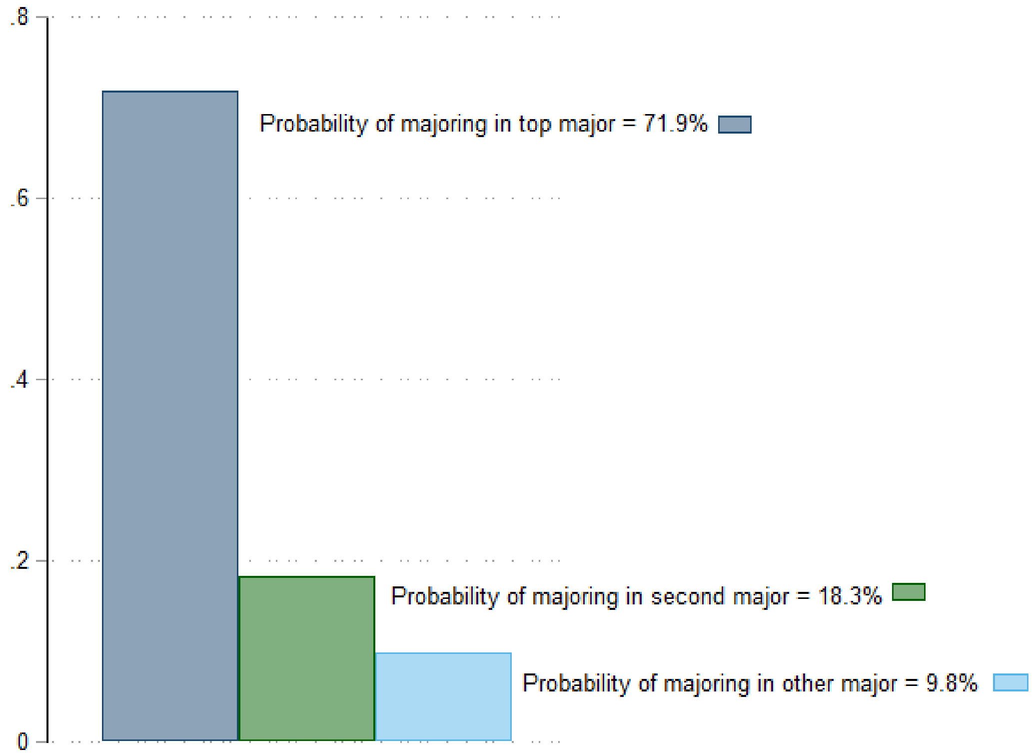
Notes: Both columns study the differential effect of treatment on the student characteristic of interest on STEM major choice for the entire analytical sample. Each row shows the coefficient of the interaction term including treatment in top choice of major with the characteristic of study. Models also include indicators for treatment status in top choice of major as well as an indicator for the student characteristic. Standard errors are in parentheses, empirical p-values are in brackets.

Table 12: Studying Mechanisms and STEM Major Choice

	(1) Marginal Out	(2) Marginal In	(3) Entire Sample
BD x Treat	0.040	0.021	0.204
	(.053)	(.329)	(.084)
	[.482]	[.948]	[.030]
AD x Treat	-0.421	-1.023	-0.763
	(2.348)	(0.692)	(.436)
	[.862]	[0.12]	[.012]
Observations	483	58	116
FE+Controls	Y	Y	Y

Notes: All columns study the differential effect of treatment based on students' beliefs and their own average score. Columns represent models looking at whether a student's most recent major is a STEM field based on three different samples; marginal out students; marginal in students; and the entire analytical sample. Each row shows the coefficient of the interaction term including treatment in top choice of major with the characteristic of study. Models also include indicators for treatment status in top choice of major as well as an indicator for the student characteristic. Standard errors are in parentheses, empirical p-values are in brackets.

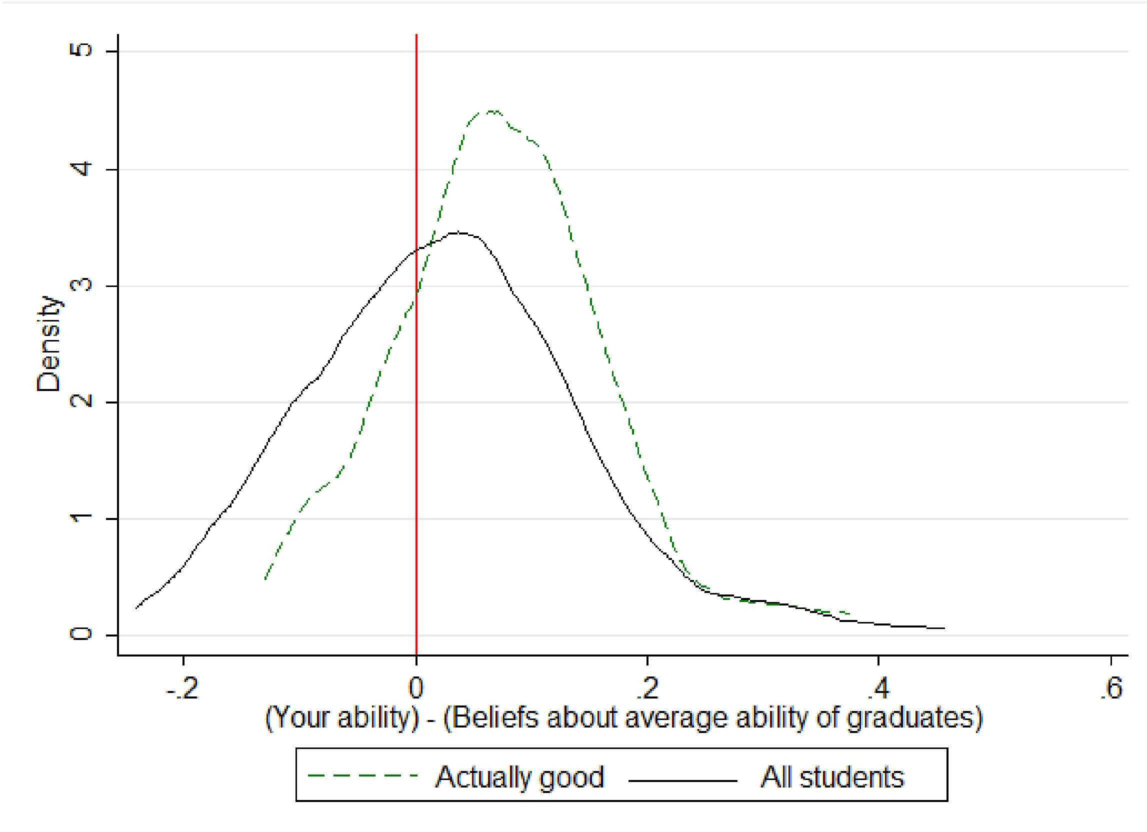
Figure 1: Probability of Graduating in Top or Second choice or some other major



Note: The sample here consists of students in the analytic sample. This implies that the sample size for this analysis is n = 438.

Note: The sample here consists of all students answering the following survey question: "What is the probability you believe you will graduate in your top choice of major, your second choice of major, or some other major (remember that the sum of the probabilities must add up to 1)"

Figure 2: Beliefs about Ability (STEM Top Choice)



Note: The sample here consists of all students who selected a STEM field as their top choice of major. The distributions are of the difference between one's own score of their selected measure for their top choice of major and the actual average score of recent graduates in that major. The second plot does the same but for the students whose own score is actually above the average score.