Major Malfunction

A Field Experiment Correcting Undergraduates' Beliefs about Salaries

John J. Conlon

ABSTRACT

In a field experiment at a flagship state university in the United States, I test whether providing college students salary information can affect their choices of major and classes. I find that undergraduates are substantially misinformed about mean salaries by major. On average, students in my sample underestimate mean salaries, but there is also large heterogeneity in beliefs across individuals. I also find that providing information to correct these errors has a large impact on students' choices; students in the treatment group were nine percentage points (16 percent) more likely to major in a field about which they received information.

I. Introduction

When an undergraduate student is deciding between college majors, one important factor is the salary they expect to earn depending on their choice.[1] These expectations will depend on many considerations, including beliefs about one's own ability relative to students who graduate with these majors and about the salary

1. See Arcidiacono, Hotz, and Kang (2012); Montemarquette, Cannings, and Mahseredjian (2002); and Wiswall and Zafar (2015a). Though salary expectations are important, nonpecuniary outcomes also play a key role in determining major choice. See Beffy, Fougère, and Maurel (2012) and Zafar (2013).

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distribution of such people postgraduation.[2] Given the importance of a student's undergraduate major in determining their economic future,[3] we might expect college students to expend considerable effort in making sure these beliefs are correct. Furthermore, fairly detailed information about salary distributions conditional on major is readily and freely available online.[4] Taken together, we might expect students' beliefs to be fairly accurate. However, a growing literature has found that college students are substantially misinformed about salaries conditional on major.[5] Such findings raise the possibility that policy interventions providing information to correct such errors could beneficially affect students' choice of major or classes.[6]

This work details the results of an experiment testing whether correcting undergraduate students' beliefs about salaries can affect the choices they make regarding their college education. An online survey of freshmen at the Ohio State University (OSU) elicited students' beliefs about the average salary of workers who graduated with degrees in various fields. A randomly selected half were then shown the correct answers to these questions. Using respondents' transcript data for the entirety of their freshman through senior years, I investigate the impact of the information on the majors and classes that they went on to choose.

I find, first, that there is considerable heterogeneity in students' salary beliefs—that is, many students make large errors. Mean absolute errors range between \$16,200 and \$49,000, and between 22 and 42 percent of the true values, depending on field and level of education. Furthermore, on average, students in my sample underestimate the salaries of almost every field. For the majority of fields, students underestimate the average salary by \$15,000 (19 percent of the average true value) or more. In addition, I find that students are substantially misinformed about the differences in average salary between fields. Across all pairs of fields, the mean error in the difference in average salary is more than \$19,500 (84 percent of the average true difference). Prior to providing their beliefs, respondents ranked the fields by their perceived likelihood that they would graduate with a major in each. Almost one-third of respondents incorrectly guess which of the two fields they are most considering has a larger average salary, and two-thirds incorrectly rank their top three fields.

Next, I find that those in the treatment group were 9.0 percentage points (16.2 percent) more likely to major in one of the fields about which they received information than respondents in the control group. They also took more classes in these fields, with significant effects appearing as early as the semester immediately following the experiment. The effect of the information is largely concentrated in the field respondents

2. See Wiswall and Zafar (2015b) for evidence that correcting students' beliefs about population salaries changes their beliefs about their own salary expectations conditional on major.
3. See, for example, Hastings, Neilson, Zimmerman (2013); Kinsler and Pavan (2015); Kirkeboen, Leuven, and Mogstad (2016); and Robst (2007).
4. For example, Georgetown's Center on Education and the Workforce puts out *The Economic Value of College Majors* (https://cew.georgetown.edu/cew-reports/valueofcollegemajors/), which provides salary statistics by state and major. This report is easily found online.
5. See Betts (1996), Hastings et al. (2016), and Wiswall and Zafar (2015b).
6. For studies looking at the impact of information provision on educational choices outside the college major context, see, for example, Bettinger et al. (2012), Dinkelman and Martínez (2014), Hastings and Weinstein (2008), and Jensen (2010).

initially said they were most likely to major in, with those in the treatment group 7.1 percentage points more likely to eventually major in this field. However, I do not find strong evidence that the information primarily affected students' choices by changing the mean of their salary beliefs. This leaves open the possibility that it worked mainly by reducing uncertainty, though I lack data on the precision of students' priors to test this hypothesis.

This study represents the first evidence, to my knowledge, that providing salary information to U.S. undergraduates affects their actual choices of classes or major. Hastings, Neilson, and Zimmerman (2015), however, find that government-provided salary information causes low-income Chilean college applicants to enroll in higher paying majors and colleges. Though that work shows how information interventions could be scaled up to national levels, there is no behavioral evidence as yet of the impact of information on undergraduate students' choice of major in the U.S. context.[7]

Testing whether providing information affects undergraduates' choices is a natural extension to a small literature investigating the impact of salary information on students' beliefs and stated intentions regarding their college major. Ex ante, whether such information should have an effect is not obvious. If students do not find aggregate statistics (like average salaries of groups of majors) informative about their own eventual earnings (or if they already know such statistics), then information interventions should have little effect. However, Wiswall and Zafar (2015b) find that correcting students' beliefs about average salaries causes them to revise their expectations about what they themselves would earn if they chose various majors. These revisions in turn caused a full 12 percent of respondents to switch which major they reported being most likely to pursue. In addition, Arcidiacono, Hotz, and Kang (2012) use a model of major choice and estimate that correcting beliefs about average salaries would cause 7.8 percent of students to change their major. My finding that major-specific information has a large effect on undergraduates' actual choice of major lends credence to these conclusions.

Next, this study adds to a somewhat sparse literature on undergraduates' beliefs about the salaries of workers conditional on undergraduate major. Most studies agree that students' beliefs are quite heterogeneous, and thus often erroneous. But findings are mixed on whether beliefs are also biased. Although previous studies have found that beliefs are either unbiased (Arcidiacono, Hotz, and Kang 2012; Betts 1996) or on average too high (Hastings et al. 2016; Wiswall and Zafar 2015a), students in my study substantially *underestimate* salaries on average. These differences suggest that more work is needed to understand the underpinnings of these beliefs.

In addition to looking at students' beliefs about the absolute levels of salaries, I also study the veracity of undergraduates' beliefs about the differences in average salary between fields of major. A student's choice of major presumably depends in large part

7. There are also significant institutional differences between Chile and the United States. Most saliently, American students, as opposed to their Chilean counterparts, generally apply to colleges independently of major and then choose, and can switch, their major once they have enrolled. Another issue is that information on earnings conditional on major for American workers seems to be much more readily available than the corresponding data for Chilean workers. Thus, American students who care to learn such information may find it easier to do so than Chilean students, and we might thus expect smaller effects of providing that information to undergraduates in the United States.

not just on the salary they expect to earn with a given major, but on how much more or less they expect to earn with that major than with other majors. Thus, we might wonder whether students have accurate beliefs about the differences in salaries between fields. Previous studies have tended to report students' beliefs only about the salaries of individual fields, though Betts (1996) does find that most students correctly rank the average salaries of fields with highly disparate earnings. My findings only partially corroborate this result. Almost all respondents, for example, correctly guess that engineers outearn education majors, but large proportions of students incorrectly rank other pairs or trios of fields, such as biology/chemistry and pharmacy, or engineering and math/computers. What's more, the magnitudes of both individual and average errors are often quite large.

The remainder of the paper is organized as follows. Section II describes the survey and experiment embedded within. Section III.A describes the data, while Sections III.B through III.D present the main results. Section IV concludes.

II. Experimental Design

A total of 728 first-semester freshmen at the Ohio State University completed an online survey administered through Qualtrics during November of 2014.[8] The median respondent took seven minutes to complete the survey, and the overwhelming majority completed it within 12 minutes. To incentivize participation, I raffled off 40 $50 Amazon gift cards to those who took the survey. The entire freshman class, 7,020 students, was invited via email, making the response rate 10.4 percent.

The survey was designed to elicit beliefs and provide information about salaries by major. However, there are too many majors for students to provide their beliefs about each of them individually, so I was forced to group them into "fields." I defined ten fields chosen based on two criteria: similarity of subject matter and similarity of average salary postgraduation. So, for example, economics was grouped together with accounting, business economics, and marketing to comprise the "Economics and Business" field instead of being included in "Social Science" because economics graduates significantly outearn other social science graduates on average. See Online Appendix D for the full list of fields and the majors they include.

After providing some demographic information,[9] respondents were shown the ten fields of major and were asked to rank them in the order of their perceived likelihood of graduating with a major in each. Next, the survey asked their beliefs about the average salaries associated with each of their top five most likely fields. Specifically, the questions asked about the average salaries of workers in Ohio between the ages of 30

8. The survey period was intended to be before students scheduled their classes for the spring 2015 semester. However, after the fifth day of the survey window, the website through which students gave consent and accessed the survey crashed and was not back online for another week. At that point, a question was added to the survey asking whether respondents had already scheduled their classes for the following semester. Only 38 students (of the 105 who saw the question) answered "Yes," so, despite the outage, the vast majority of respondents had not yet scheduled for the following semester's classes. Thus, it is still reasonable to expect a treatment effect for spring 2015.

9. These included parental education, expected student debt, and risk and time preferences. These last two questions are ignored in this paper, but their inclusion as controls does not change any of the main results.

and 50, provided they had a full-time job.[10] Each question was divided into two parts, one about workers with only a bachelor's (four-year) degree and one about workers who held any type of postgraduate degree. Respondents answered these questions either by dragging a slider to a number between \$0 and \$200,000 (well above the largest actual average salary) or by typing a number into a blank field to the right of the slider.

A randomly selected half of respondents took part in the third section of the survey, which was the information treatment. These respondents were shown the correct answers to the beliefs questions they had answered in the previous section. These statistics were calculated using data from the American Community Survey (ACS).[11] In order to ensure that students read the information, they were asked to enter the correct average salaries into a text box before they could proceed. Along with the correct information, they were shown what their own guess had been along with text telling them whether they had overestimated or underestimated the true average salary for each field. If a respondent's guess was within \$1,500 of the correct value, they were told that their guess was "very close to the actual number." These beliefs questions were necessarily unincentivized, else students might have just looked up the answers (they took the survey online from home).[12]

As part of the consent form preceding the survey, respondents were asked to provide permission to access their education records. Agreeing to this question was required in order to take the survey, so I have transcript data for all respondents from fall semester 2014 to spring semester 2018. These data include respondents' classes, cumulative GPA, major, honors status, and demographic information.

III. Results

A. Description of Data

Overall, my survey sample is fairly representative of the university as a whole, though there are some differences. Table 1 presents demographic information about the survey respondents and about the (main campus) OSU student body. The survey respondents

10. The survey asked about workers aged 30–50 for two reasons. First, it allowed the bachelor's and postgraduate degree questions to ask about the same age range. Second, it allowed for sufficiently many observations in the ACS data (see the following paragraph) to estimate mean salaries precisely for the information treatment. However, mean salaries for workers aged 30–50 are highly correlated with mean salaries for workers aged 23–27 (the correlation coefficient for the ten major fields is 0.94), so salary information for older workers is highly informative about early-career salaries. We might worry that some students who care more about earlier salaries may not know about this correlation and thus would not update their beliefs or choices in response to the information, but, given the large effect of the information on choices (see Section III.C), this appears not to have been the case.

11. Data from the years 2009–2012, the last year available at the time, were used. Average salaries by field of major were computed, adjusting for inflation, for workers aged 30–50 in Ohio working at least 40 hours a week.

12. Respondents were asked before the beliefs elicitation section and after the information section the percent chance that they would graduate "with the major you are currently pursuing" and with more than one major. I ignore these variables in this paper primarily because the main focus here is on behavioral outcomes, but also because changes in these answers do not appear significantly correlated with changes in later major choices.

Table 1
Summary Statistics

Variable	Survey Sample	Whole Student Body
Percent male	43.8	50.9
Percent Asian	7.7	5.7
Percent black	4.4	5.3
Percent Hispanic	3.6	3.5
Percent other race/ethnicity	6.5	2.8
Percent noncitizen	6.9	10.6
Percent whose parents have degree	78.7	Not reported
Percent expecting to graduate with student debt	70.2	Not reported
Mean (SD)		
Expected student debt conditional on expecting any	\$36,880 (\$25,275)	Not reported
GPA (1st semester)	3.25 (0.69)	Not reported

Notes: These are official data from the Ohio State University: https://www.osu.edu/osutoday/StatisticalSummary2014.pdf (accessed December 3, 2020).

are somewhat more likely to be female, more likely to be U.S. citizens, and more likely to be Asian-American and of "other"[13] ethnicities.

For several of the analyses below, it is necessary to decide into which field a major falls. The survey listed only a few majors per field, and the names of these majors were drawn from the ACS (see Online Appendix D). Many of the majors OSU offers, although not identical to any of these listed majors, clearly fall into one of the ten fields. I was thus required to match OSU majors to each of the ten fields, plus an "Uncategorized" field and an "Undecided" field. See Online Appendix E for a list of which majors were assigned to each field. Online Appendix Figure A1 shows that the survey respondents and the rest of the freshman class are similarly distributed across the ten fields, plus "Uncategorized" and "Undecided" (chi-square p-value = 0.39).[14]

B. Salary Beliefs

In this section, I investigate the veracity of students' salary beliefs. In the main text I focus on beliefs about those with only a bachelor's degree and leave discussion of beliefs about those with a postgraduate degree to footnotes and the Online Appendix. Figure 1

13. This category includes Alaskan Natives/American Indians, Native Hawaiians/Pacific Islanders, and people of more than one race.
14. Data on the majors of the rest of the freshman class come from anonymized transcript data for the 6,233 OSU students in the respondents' cohort who did not take the survey. These data include only the classes and major of each student.

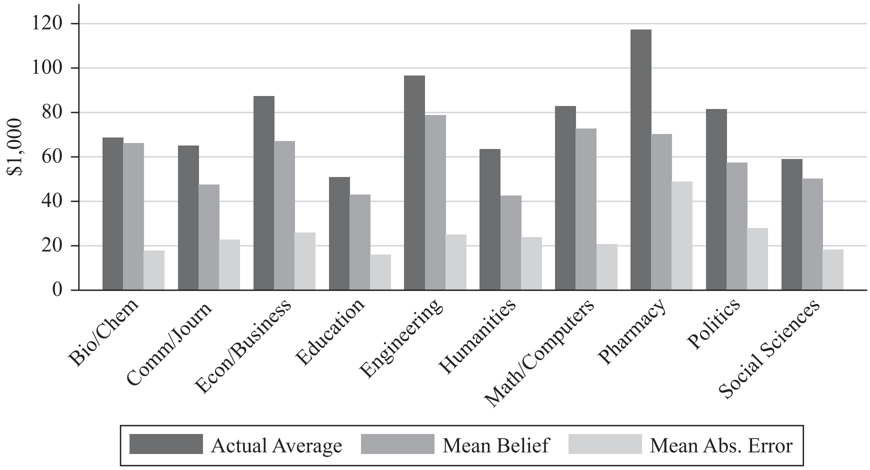

Figure 1
Beliefs about Average Salaries of Workers with Only a Bachelor's Degree

shows that respondents are systematically misinformed about salaries.[15] Mean absolute errors range between $16,200 and $49,000, or between 27 percent and 42 percent of the true values. Sixty-two percent of respondents have an absolute error for their top-ranked field that is more than 20 percent of the true average salary. In addition to having large absolute errors, respondents' beliefs also appear to be biased downward; that is, on average, respondents significantly underestimate salaries for every field ($p < 0.05$ for each). For seven of the ten fields, the average belief is more than $10,000 below the true average salary.[16,17]

Many factors could explain why students in my sample appear to significantly underestimate salaries on average, in apparent contrast to findings in previous studies.[18]

15. See Online Appendix Table A1 for the exact numbers.
16. Similarly, average beliefs about those with any postgraduate degree are also significantly below the true average salary for seven of the ten fields (see Online Appendix Figure A2 and Table A2). Here again the majority of salaries are underestimated by more than $10,000.
17. Respondents indicated their beliefs about average salaries by dragging a slider to a number between 0 and 200,000. One potential concern is that the upper limit of the slider would induce an anchoring effect, with respondents answering closer to $200,000 simply in virtue of its saliency in the question. $200,000 is well above the average salary for any field (the highest average salary is $131,495, for Biology/Chemistry majors with a postgraduate degree), so I would expect an anchoring effect to cause respondents to increase their guesses of salaries. Thus, if any such anchoring effect occurred, it makes the result that respondents underestimate the salaries for so many fields even more extreme.
18. For example, perhaps (on average) students know the median of the wage distribution but underestimate its skewness, and thus underestimate the mean. However, Wiswall and Zafar (2015b) also ask about mean, not median, salaries, and they actually find that students *overestimate* salaries. Another potential explanation is that students (again, on average) know about starting salaries but underestimate the slope of the wage profile, and thus underestimate mid-career salaries (my survey asked about those aged 30–50). Betts (1996) finds some evidence to this effect. A further explanation could be that students know on average what people with different

However, my study agrees with the literature that there is substantial heterogeneity in beliefs across individuals. Column 2 of Online Appendix Table A1 shows the standard deviation of beliefs, which range from 22 to 39 percent of actual average salaries. The finding that students underestimate salaries on average masks this heterogeneity; many students underestimate salaries by even more than the average, others overestimate, and a small minority have roughly correct beliefs (for no field do more than 21 percent of students have beliefs within 10 percent of the true average salary).[19]

In addition to making large errors about the salaries of individual fields, respondents also make large errors about the differences in average salaries between fields. Because each respondent answered questions about five different fields, my data include each respondent's beliefs about the differences between ten of the 45 pairs of fields. The average absolute error in the difference between salaries is $19,500. The median respondent's absolute error between their two top-ranked fields is $13,900, a full 18 percent of the actual average salary of their top-ranked field.

Another, less stringent way of measuring whether such beliefs are accurate is to ask whether respondents' guesses of salary correctly rank fields from highest to lowest paying. Thirty percent of respondents incorrectly rank their top two fields, but even this likely overstates how informed students are. If we imagine, somewhat unrealistically, that students are either "knowers," who with certainty correctly rank fields, or "guessers," who randomly choose how to rank them, then only 40 percent of students are knowers regarding their top two fields (40 percent plus half the 60 percent who are guessers would make the correct guess). Respondents randomly ranking their top three fields should correctly rank them 17 percent of the time. Actually, 35 percent correctly rank them, implying that only 22 percent are knowers and 78 percent guessers regarding their top three fields.

Some fields have somewhat similar average salaries, so perhaps a fairer question is: What proportion of respondents correctly rank fields with substantially disparate average salaries? Reassuringly, 99 percent of respondents correctly believe that Engineering majors outearn Education and Humanities majors.[20] But only 71 percent believe that Engineering majors have a higher average salary than Math/Computers majors, and only 58 percent say that Pharmacy majors outearn Biology/Chemistry majors. Moving to trios of fields, 39 percent correctly rank Engineering, Math/Computers, and Biology/Chemistry (in that order), and 22 percent correctly rank Politics, Humanities, and Social Science. Thus, I conclude that no matter how one measures it, students are substantially misinformed, not only about the absolute salaries of each field, but also about their relative salaries.[21]

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majors can afford, but they underestimate the cost of living. Of course, this list is not meant to be complete, and further possible explanations could be supplied.

19. There is also considerable heterogeneity both within and across individuals regarding the perceived premium associated with a postgraduate degree. For example, the median respondent's range across their top five major groups in the percent increase in mean salary when moving from beliefs about those with only a bachelor's degree to those with any postgraduate degree is 42 percentage points; the median range in dollar terms is almost $23,000. Across individuals, the interquartile range in premiums is more than 28 percentage points for each of the ten major groups.

20. This near unanimity suggests that respondents were answering these salary questions seriously and therefore that the incorrect answers they give are in fact evidence of mistaken beliefs.

21. The corresponding numbers for beliefs about those with a postgraduate degree are, in general, no better.

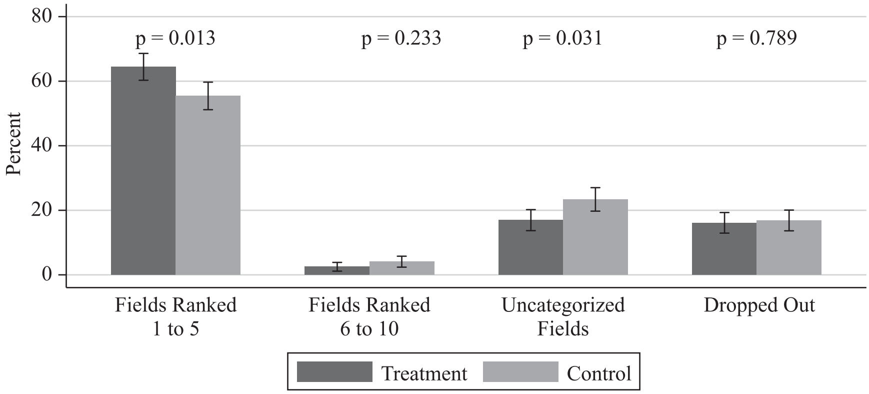

Figure 2

Percent of Respondents in Each Field of Major, by Treatment Group

Notes: Bands indicate 90 percent confidence intervals.

Online Appendix B looks at the correlates of students' errors and beliefs. I find that observable characteristics do little to explain the heterogeneity in beliefs.

C. Experimental Results

As mentioned above, a randomly selected half of respondents received the correct answers to the questions about the average salary of people who graduated with each of their five top-ranked fields. Figure 2 shows that respondents in the information group were 9.0 percentage points (16.2 percent) more likely than those in the control group ($p = 0.013$) to be majoring in one of these fields as of spring semester of their senior year, over three years after the information intervention.[22] Most of this effect comes from students' top-ranked field of major, with those in the treatment group 7.1 percentage points more likely to be majoring in that field than those in the control group ($p = 0.056$).

Which fields of major are respondents in the information group forgoing in favor of their top-ranked fields? They are 6.4 percentage points less likely ($p = 0.031$) to major in an "Uncategorized" field, which they neither ranked nor provided beliefs about (see Online Appendix E for a list of these majors). They are also 1.6 percentage points less likely to major in a field they ranked sixth through tenth and 0.7 percentage points less likely to drop out, though neither of these differences is statistically significant.

Table 2 shows how the treatment effect evolved over time. We see that the estimated effect increases gradually, starting from close to zero (and even negative) in spring 2015, one semester after the intervention, to positive though insignificant during students' junior year (fall 2016–spring 2017), to positive and significant their senior year (fall

22. Note that in most of the analyses to follow (all except Columns 1–7 of Table 3), I include students who drop out of OSU. They are counted as not having a major in any field and, in Column 8 of Table 3, as taking no classes in any field each semester after they drop out. Removing them from the analyses entirely does not qualitatively change the results.

Table 2
Effect of Information on Declared Major, over Time

	Spring 2015 (1)	Fall 2015 (2)	Spring 2016 (3)	Fall 2016 (4)	Spring 2017 (5)	Fall 2017 (6)	Spring 2018 (7)
Panel A: Fields Ranked 1–5							
Info	−2.44	1.10	0.01	4.11	4.96	5.71*	8.12**
	(1.52)	(2.51)	(2.86)	(2.99)	(3.08)	(3.14)	(3.26)
Began in Rank 1–5 field	0.89***	0.60***	0.47***	0.40***	0.39***	0.38***	0.34***
	(0.02)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	728	728	728	728	728	728	728
Panel B: Top-Ranked Field							
Info	0.92	1.82	1.31	4.26	5.12	4.81	7.48
	(1.73)	(2.67)	(3.01)	(3.15)	(3.19)	(3.22)	(3.27)
# Rank 1 classes in fall 2014	0.89***	0.63***	0.51***	0.44***	0.42***	0.42***	0.37***
	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	728	728	728	728	728	728	728

Notes: Table shows linear probability model estimates. Dependent variable is whether respondents' major in the semester listed in the column headings is in one of their (pre-experiment) top-five-ranked fields (Panel A) or top-ranked field (Panel B). Robust standard errors in parentheses. Significance: *$p<0.10$, **$p<0.05$, ***$p<0.01$. Controls include gender, race, fall 2012 GPA, expected student debt, whether either of the respondents' parents has a college degree, and dummy variables indicating which of the ten fields the student ranked first.

2017–spring 2018). This could indicate either that students did gradually change their minds due to the information or that declared major is a lagging indicator of actual choices.[23] Table 3 tries to distinguish between these two explanations by showing the effect of receiving information on the number of classes respondents take in their top-ranked field(s) each semester. Here we see significant results starting as early as spring 2015, the semester directly after the survey, suggesting that the information intervention did have some immediate effects.

One interesting feature of the estimated effects presented in Table 3 is how modest they are. Table 2 shows that respondents are 7.5 percentage points more likely to major

23. Anecdotally, there is often little incentive for undergraduate students at OSU to promptly fill out the paperwork necessary to officially change their majors, even if they have decided to pursue a different subject. Incentives become stronger in later years as some upper-level classes are restricted to those with certain declared majors, and then obviously all students must declare the correct major prior to graduating for it to appear on their diplomas.

Table 3
Effect of Information on Classes, over Time

	Spring 2015 (1)	Fall 2015 (2)	Spring 2016 (3)	Fall 2016 (4)	Spring 2017 (5)	Fall 2017 (6)	Spring 2018 (7)	Total (8)
Panel A: Fields Ranked 1–5								
Info	0.14*	0.07	0.07	0.27**	0.13	0.28*	0.27*	1.23**
	(0.08)	(0.10)	(0.12)	(0.13)	(0.14)	(0.15)	(0.15)	(0.62)
# Rank 1–5 classes in fall 2014	0.38***	0.37***	0.37***	0.35***	0.44***	0.34***	0.31***	2.30***
	(0.04)	(0.05)	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)	(0.31)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	728	717	696	686	672	655	608	728
Panel B: Top-Ranked Field								
Info	0.06	0.09	0.02	0.21*	0.10	0.17	0.15	0.87
	(0.06)	(0.09)	(0.11)	(0.12)	(0.13)	(0.14)	(0.15)	(0.57)
# Rank 1 classes in fall 2014	0.31***	0.37***	0.46***	0.57***	0.58***	0.47***	0.44***	2.93***
	(0.04)	(0.06)	(0.07)	(0.08)	(0.09)	(0.09)	(0.10)	(0.57)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	728	717	696	686	672	655	608	728

Notes: Table shows ordinary least squares (OLS) estimates. Dependent variable is the number of classes in one of their (pre-experiment) top-five-ranked fields (Panel A) or top-ranked field (Panel B) the student took in the semester listed in the column headings (or all semesters combined, for Column 8). Robust standard errors in parentheses. Significance: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Controls include gender, race, fall 2012 GPA, expected student debt, whether either of the respondents' parents has a college degree, and dummy variables indicating which of the ten fields the student ranked first.

in their top-ranked field, while Table 3 estimates that they took only 0.87 more classes in that field ($p = 0.128$). If this difference comes entirely from the 7.5 percent who are induced into majoring in this field, such students would need to take 0.870/0.075 = 11.6 extra classes to produce this estimated effect. For comparison, among the control group, students majoring in their top field take on average 14.2 more classes in that field than students who do not. If the information caused some students to take a few classes or take up a minor in their top field (in addition to those majoring in it), then we might have expected a larger effect on class-taking than on major choice. Of course, standard errors are nontrivial here, but my data provide no evidence of such behavior.

Note that, although the information made students more likely to major in their top-ranked fields, these fields differed across respondents. It thus does not follow that the information substantially changed the proportion of students majoring in any particular field or type of field.[24] Columns 1 and 2 of Table 4 show that students in the information group are no more likely to major in a high-paying field, defined as one of the five fields with the highest average salary for those with just a bachelor's degree and those with a postgraduate degree (Columns 1 and 2, respectively).[25] This is perhaps not surprising, as the ex ante prediction is ambiguous. For example, if a student learns that one field outearns another, they might switch to the higher-paying field. On the other hand, if they learn a lower-paying field earns more than they thought, they may actually switch to it despite other fields paying more (presumably because it dominates along some nonpecuniary dimension). As shown above, many students underestimate salaries in my data, and the importance of nonpecuniary factors in major choice is well known. The confluence of these two effects may therefore explain the lack of a significant net effect of the information on the lucrativeness of students' chosen fields. Columns 3 and 4 show that the information also had no net effect on the likelihood that students majored in STEM or "difficult" fields (defined as those with the lowest GPAs in the control group), respectively.

We might worry that if information pushes students into some particular fields, then a scaled-up version of this intervention would have smaller effects, due to space constraints and increasing competition. However, as we have seen, the information treatment had no net effect on the likelihood of majoring in any particular field or type of field. I thus find no evidence that the impact of information would be smaller in general equilibrium due to such crowding-out effects.

D. Mechanisms

The information affected students' choices presumably by changing their beliefs about the salary distribution they would face if they majored in various fields.[26] This could happen in at least two ways. First, it may have changed students' beliefs about the mean

24. A chi-square test fails to reject the hypothesis that the distribution of fields does not differ by treatment status ($p = 0.485$).
25. These results are robust to using a continuous measure of lucrativeness.
26. I implicitly assume throughout this discussion that students only updated their beliefs about salary in response to the information, but this need not be true. For example, a student might come to believe that because graduates in a certain field earn more than they thought that they also work longer hours or that the associated classwork is more difficult.

Table 4
Effect of Information on Type of Field of Major

	Lucrative (BA) (1)	Lucrative (PGD) (2)	STEM (3)	Difficult (4)
Info	0.85	2.57	2.57	1.52
	(2.69)	(2.99)	(2.53)	(2.44)
Began in lucrative (BA) field	0.31***			
	(0.05)			
Began in lucrative (PGD) field		0.39***		
		(0.04)		
Began in STEM field			0.40***	
			(0.04)	
Began in difficult field				0.29***
				(0.05)
Controls	Yes	Yes	Yes	Yes
N	728	728	728	728

Notes: Table shows linear probability model estimates. Dependent variable is whether respondents' field of major in spring 2018 was in the category listed in the column headings. The lucrative (BA) fields are the five fields with the highest average salary for those with only a bachelor's degree. They are Economics/Business, Engineering, Mathematics/Computers, Pharmacy, and Politics. Lucrative (PGD) fields are the five fields with the highest average salary for those with any kind of postgraduate degree. They are Biology/Chemistry, Economics/Business, Engineering, Pharmacy, and Politics. The STEM fields include Biology/Chemistry, Engineering, Mathematics/Computers, and Pharmacy. The "Difficult" fields are those with the five lowest average cumulative GPA as of spring 2018 among the control group. They are Biology/Chemistry, Communications/Journalism, Engineering, Mathematics/Computers, and Pharmacy. Robust standard errors in parentheses. Significance: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$. Controls include gender, race, fall 2012 GPA, expected student debt, whether either of the respondents' parents has a college degree, and dummy variables indicating which of the ten fields the student ranked first.

of the salary distribution: students who underestimate a field's average salary might come to believe that they would earn more on average in that field. Second, information could change the variance of their beliefs. For example, if a student correctly guessed the average salary of engineers but was uncertain about that guess, the information may still make engineering more attractive because it now appears less risky. In this section, I investigate whether the effect of the information can be attributed primarily to its effect on the mean of students' beliefs. I then return to a discussion of the variance.

If students changed their behavior because the information changed the mean of their beliefs, we should expect students to move toward the fields whose salaries they particularly underestimated. There are two caveats to mention before investigating whether this prediction holds in the data. First, prior beliefs are not randomly assigned, and if they are correlated with factors that affect responsiveness to salary information, this will bias any estimates. For example, students who underestimate their top field ranked it highly despite its perceived low salary. We might expect such people to care less about earnings and thus respond less to the information than those who overestimate.[27] The second caveat is that because respondents in my survey gave beliefs and received information about only a subset of majors, it is difficult to know from their reported priors how they ought to respond to information. For example, more than one-half of students underestimated all five of their top fields, but if they extrapolated from this and revised their beliefs about other fields as well, then we may not actually expect them to move towards any of their top fields.

I define two types of error in students' beliefs. The first, which I call "outright error," is simply the difference between respondents' belief about the average salary of their top-ranked field and the true average salary of that field.[28] The second, "relative error," is a student's belief about the difference in average salary between their two top-ranked fields minus their actual difference in average salary. Note that these two definitions can go in opposite directions: a student might think their top field outearns their second field by more than it actually does (positive relative error) while underestimating both of their average salaries (negative outright error). Whether correcting a student's outright or relative error will affect their choices more will depend on what they perceive to be their most likely alternatives to their top-ranked field. If they are primarily deciding between their top field and a field about which they do not receive any information, then outright error is likely the most relevant definition. But if they are deciding between their first- and second-ranked fields, then relative error may be more important.

Table 5 shows how treatment status interacts with each of these types of error. Column 1 shows that the information had a large positive effect on whether those who underestimate their top field (that is, have a negative outright error) eventually major in it, as expected. However, we also see a positive (though smaller and insignificant) effect for those who overestimate. Columns 2 and 3 interact treatment status with error in dollar and log terms, respectively. We see that in both cases outright error positively predicts whether those in the control group will major in their top field, meaning that those who particularly overestimate their top field are more likely to major in it. We see estimates close to zero for the treatment group, suggesting that these students may have corrected their beliefs and acted accordingly. However, the difference between the coefficients for treatment and control are not statistically different from zero in either case, so this is at best suggestive. Columns 4–6 of Table 5 repeat this analysis using relative error instead of outright error. Here the estimates are the opposite of what we would expect. There is a larger estimated treatment effect for those who overestimate their top-ranked field compared to their second-ranked field than for those who underestimate. We also see that relative error predicts eventual major choice for students in both the treatment and control groups.

Taken together, these results provide little evidence that the information affected students' choices primarily by changing the mean of their beliefs. Though speculative, a remaining possibility is that the information affected students' choices mainly by reducing uncertainty. If a student is uncertain about the mean of the salary distribution, then learning the true average will reduce the variance of their beliefs. Assuming utility

27. The omitted variable bias could also go the other way. Suppose people who overestimate their top field do so because they are more prone to various forms of motivated reasoning. They might then be less receptive to information than people who underestimate.
28. Results are broadly similar if we instead use beliefs about those with a postgraduate degree.

Table 5
Heterogeneity of Treatment Effect, by Error in Prior Beliefs

	Outright Error			Relative Error		
		Dollars	Logs		Dollars	Logs
	(1)	(2)	(3)	(4)	(5)	(6)
Overestimate × info	6.07			8.69**		
	(6.35)			(4.30)		
Underestimate × info	7.86**			5.40		
	(3.79)			(4.91)		
Overestimate	3.04			1.30		
	(5.30)			(5.01)		
Error × info		0.04	0.25		0.29***	19.14***
		(0.10)	(7.41)		(0.11)	(4.99)
Error × control		0.18**	8.76		0.29***	14.45**
		(0.09)	(6.28)		(0.09)	(6.39)
Info		5.81	5.44		7.58**	6.97**
		(3.56)	(3.81)		(3.25)	(3.27)
Began in Rank 1 field	0.37***	0.38***	0.38***	0.37***	0.37***	0.37***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Controls *N*	Yes	Yes	Yes	Yes	Yes	Yes
N	728	728	728	728	727	727

Notes: Table shows linear probability model estimates. Dependent variable is whether the respondent's spring 2018 major is in their (pre-experiment) top-ranked field. Robust standard errors in parentheses. Significance: $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$. "Outright error" is the difference between a respondent's beliefs about the average salary of their top-ranked field and the actual average. "Relative error" is the difference between a respondent's beliefs about the average salaries of their two top-ranked fields minus the difference in their actual average salaries. "Error" refers to outright error in Columns 1–3 and to relative error in Columns 4–6. "Overestimate" ("Underestimate") is a dummy variable indicating whether the error is positive (negative). Error is measured in dollars in Columns 2 and 5 and log points in Columns 3 and 6. Controls include gender, race, fall 2012 GPA, expected student debt, whether either of the respondents' parents has a college degree, and dummy variables indicating which of the ten fields the student ranked first. Columns 4–6 also include dummy variables indicating which of the ten fields the student ranked second.

is concave in income, information should make a field more attractive unless the student substantially overestimated its average salary. Such a dynamic might explain why students in the treatment group were more likely to major in the fields about which they received information, but not in any particular field or type of field. My survey did not elicit students' uncertainty about salaries conditional on major, so I cannot test this hypothesis directly. However, the large errors and heterogeneity in beliefs across individuals in my sample are consistent with substantial uncertainty.[29]

29. Wiswall and Zafar (2015b) do collect data on the distribution of their survey respondents' beliefs about salary conditional on major (see their Table 4). Though they find large amounts of uncertainty, they do not

IV. Discussion and Conclusion

This paper describes a field experiment testing the impact of providing salary information to college students on their choices regarding their undergraduate education. I find large effects on students' choice of major, with those in the treatment group being 9.0 percentage points more likely to major in a field they received information about. I do not find strong evidence that the information affected students' choices primarily by changing the mean of their salary beliefs. This leaves open the possibility that it worked mainly by reducing uncertainty.

These large effects may be surprising given the paucity of data with which students were presented. The information intervention provided only the average salaries of people living near them who graduated with majors in five broadly defined (and non-exhaustive) fields. We might have thought, if students care only about particular majors within fields or if they do not find these averages very informative about what they themselves might earn, then they would ignore this information. Though I nonetheless find large responses, an intervention providing more detailed salary information about individual majors or schools could have larger and more beneficial effects.

This work contributes to a growing body of evidence that undergraduates are misinformed about the distribution of salaries conditional on major. But how do students form such beliefs, and what is the primary source of these errors? Is it misperceptions about the salaries of particular jobs, or about the distribution of jobs by major, or something else? Policies providing information must aggregate data somehow in order to present it to students in an understandable way. But we might worry that students will update their beliefs incorrectly in response to such aggregated information. For example, after learning they had underestimated the average salary of biology majors, a student might wrongly come to believe that more biology majors become doctors than they had thought, rather than realizing they had underestimated the salary of doctors. Learning the structure of students' beliefs, and locating the errors within that structure, would help to determine what sort of information would help students the most.

A related question is why students, who respond to information and thus seem to value it, do not seek it out on their own. Betts (1996) is the only study I know of attempting to answer this question in this context, and the advent of the internet would seem to have drastically expanded students' access to cheap information in the intervening 20 years. Indeed, detailed salary information by major is readily available for free online (see Footnote 4). Why do students nonetheless fail to correct their beliefs about salaries? Do they believe themselves to be well informed and thus decide against expending the (small) effort required to correct their beliefs? Or do they not know such information is so readily available? Further research could perhaps answer these questions by eliciting students' certainty about their salary beliefs, their knowledge and use of information sources, and their willingness to pay for information. Understanding when and why students seek out information would aid in formulating effective policies.

This study dealt exclusively with beliefs and information about the average salaries of those currently in the labor market with various majors. But many other factors contribute to students' decisions, and students' nonsalary beliefs may also be mistaken.

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investigate how much of this is due to uncertainty about the population distribution of salaries or about individuals' abilities and future choices.

One could imagine similar experiments, and policies, eliciting beliefs or providing information about unemployment rates, occupations, work hours, or other factors. Nonpecuniary aspects of work may be especially important, given recent findings about workers' preferences over job characteristics (Wiswall and Zafar 2018). The College Scorecard, put out by the U.S. Department of Education, provides information about costs, graduation rates, and salaries for individual U.S. colleges. A similar tool could be designed to help students choose majors once they reach college, and determining exactly what information students most need and value remains an important question for future research.

Students' choice of college major has a large effect on their economic future. If those choices are based on faulty information, it not only harms the individual students, who would have preferred a different major, but also society at large by inefficiently sorting workers to occupations or industries. Further research is needed to see if the results presented here generalize to other schools and types of schools (for example, community or for-profit colleges), but my results contribute to the case for larger-scale policy interventions designed to help students make informed choices.

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