Job Security and the Informed Major Choice of U.S. University Students*

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Abstract

We partner with a large public university system in the United States to survey students about job security expectations in different college majors. Based on an educational choice model of costly search, we ask students to estimate job security in their counterfactual majors and preferred majors; we also assess differences in expectations by SES. We find students' expectations in counterfactual majors are not consistent with the labor market outcomes of past graduates. To assess the impact of information disclosure, we randomize the provision of labor market information about job security and find that students respond to the intervention in a manner consistent with belief updating. We find no evidence that the information intervention affects student preferences over major. The findings are consistent with scholarship that shows information interventions affect labor market expectations but have a small influence on major choice given students strong pre-existing preferences over fields of study.

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When students choose a college major, they face a complex decision with significant implications for their future careers. In their decision-making process, students weigh, for example, work-life balance, job security, earnings, and obtaining the type of job that fits their interests and that they enjoy (Zukin and Szeltner 2012). Students, as well as parents and policymakers, also consider increasing levels of student debt and how poor labor market outcomes increase the probability of loan default (Federal Reserve 2017; Looney and Yannelis 2015). Perhaps because the decision is complex, up to 48% of college graduates wish they had been more careful about choosing a major or had chosen a different major (Godofsky et al. 2011; Stone et al. 2012).

An increasingly common, low-cost policy response to this problem is information disclosure (e.g., PayScale 2017; USDOE 2017; UTS 2017). While taking a variety of forms, disclosure policies generally offer individuals some information about the costs and benefits of different educational choices. The assumption behind these policies is that individuals lack information on the actual labor market outcomes of past college graduates. Information disclosure through tools such as online scorecards provides individuals with the outcomes data of past graduates; individuals use this data to choose colleges or majors that are more likely to lead to better economic outcomes.

Hastings et al. (2017) note that the effectiveness of disclosure policies depends on the accuracy of prospective students' knowledge of labor market outcomes and whether students value these outcomes when making a choice. Our paper asks how labor market information influences student expectations about job security in different college majors, and how this information relates to student expectations about completing a degree in these different majors. Job security is cited as one of the most important attributes of a future job, being mentioned more frequently than compensation, flexible hours, or advancement opportunities (Zukin and Szeltner 2012). Furthermore, recent empirical research shows that perceptions of job security are related to college and major choice (Baker et al. 2017; Hastings et al. 2015;

Wiswall and Zafar 2016).

We partner with a large, public university system with four socioeconomically diverse campuses to conduct a survey with an embedded information experiment. Previous studies with information interventions typically focus on a smaller sample of students at a single college, while our survey includes nearly 3000 students with diverse economic and social backgrounds and who study in different institutional settings in the United States.

We first examine the impact of disclosure of job security information on student expectations of their own future job security. As motivating theoretical framework, we use the informal model proposed in Hastings et al. (2015). The model uses the concept of search costs to predict the impact of disclosure policies. In the model, students invest in time and effort to learn about outcomes of different education choices. For some groups of students, these search costs are likely to be higher. Hastings et al. (2015) and Huntington-Klein (2016b) find support for the model's predictions.

First, students have less incentive to acquire information about college majors other than their preferred major choices. In other words, the costs of acquiring the information outweigh the benefits. The risk is that students may have different preferences if they were fully informed about the returns to different majors. Without the incentive to research counterfacutal fields, students are more likely to hold incorrect beliefs about the labor market outcomes of past graduates.

Second, students from lower socioeconomic (SES) backgrounds are likely to face higher search costs than their higher-SES peers. Among explanations for why these discrepancies exist, scholars in both human and cultural capital theory traditions argue that lower-SES students lack the same degree of access to accurate information about the costs and benefits of a higher education degree as their higher-SES peers (Betts 1996; Coleman 1988; Perna 2000; Perna and Titus 2005). Hastings et al. (2015) and Huntington-Klein (2016b) find support for the model's predictions

In this paper, we first examine whether job security expectations systematically differ between students' preferred major and counterfactual majors, and second, between low-SES students and higher-SES peers. We find students have significantly lower job security expectations about counterfactual majors. Moreover, these students' ordering of majors by job security does not correspond to labor market data on past graduates. For example, students significantly underestimate job security in the healthcare and education fields. We find no significant differences in job security expectations between low-SES respondents and their higher-SES peers.

To examine the impact of information disclosure on job security expectations and expected major of completion, we randomly assign respondents into one of two conditions. One group sees a bundle of information related to post-graduate job security and earnings: the unemployment rate, past graduates' perceived job security, earnings dispersion, and median earnings for six major fields. The treatment for the comparison group omits job security and earnings dispersion information, which offers students an estimate of the earnings risk associated with each major (Caner and Okten 2010; Saks and Shore 2005). The data we present is from the U.S population of college graduates from four-year universities. After seeing the information treatment, we ask respondents to report their own expected future job security, expected earnings, and the probability of completing a degree in each major field.[1]

We find that labor market information about job security impacts student expectations about their own future job security. However, we find an impact only for the majors in which there is a large discrepancy between the respondents' job security estimates and the population data. For counterfactual majors, a low percentage of respondents expect secure careers in healthcare and education despite the data indicating these are the most secure fields.

[1]In our question wording, we define job security as the probability of becoming unemployed or losing full-time employment status. This issue is discussed in Section 3.

Those who see the information treatment have significantly higher estimates of job security in these fields. A high percentage of respondents who intend to major in science/technology (STEM) fields believe these careers are the most secure despite having the third lowest perceived job security among recent college graduates. Those who see the information treatment have significantly lower estimates of job security in this field. Our estimated impact is consistent with belief updating when prior beliefs about past graduates' outcomes are significantly different than the actual data. These results follow Hastings et al. (2017), who find that the information treatment has the largest effect on respondents whose beliefs differ most from the population data.

Next, we estimate the impact of the information disclosure on expected major choice. Our aim is to assess how a bundle of career-related information valued by college students impacts their choice compared to seeing only expected returns. Among college students, 90% rate job security and 88% rate good compensation as an "essential" or "very important" job attribute. Our treatment thus measures the value of disclosure policies aimed at providing students with a bundle of useful information, compared to the more common approach of only providing the expected return of past graduates.

We find no evidence that the information intervention affects students' expected probability of degree completion in different fields. Thus, the information treatment effects job security expectations but not expected choice. Our finding is similar to Kerr et al. (2014), who find an information treatment has a large effect on earnings expectations but no effect on actual choice. We suggest one explanation for the null finding is that students in the sample expect to major in their preferred major with near certain probability and often express near zero probability of choosing a counterfactual major. As Hastings et al. (2017) note, information disclosure is unlikely to shift preferences across fields of study.

The information treatment also has no heterogeneous effect on low-SES respondents. Hastings et al. (2017), in contrast, find that labor market information has a large effect on this group, as predicted by a model of degree choice with limited information. Our findings with respect to SES are not consistent with information disclosure causing belief updating about earnings due to lower-SES students having low information at the pre-treatment baseline.

Our findings with regard to expected choice are consistent with students placing more weight on factors other than earnings when making their major choices (Wiswall and Zafar 2015). For example, Hastings et al. (2017) find that the effect of earnings on choice is mitigated by students' preferences over field of study and geographic proximity. Baker et al. (2017) find that students place the most weight on course enjoyment when choosing a major.

Our work contributes to research investigating the impact of labor market expectations on educational choice (Baker et al. 2017; Hastings et al. 2015; Huntington-Klein 2016a,b; Hurwitz and Smith 2016; Jensen 2010; Kelly 2015). We add to this literature by examining the impact of a randomized information intervention on a large, diverse student sample from a public university system in the United States. In addition, our partnership with the university system gives us access to administrative data that includes a large number of academic and demographic control variables.

Our work also builds on scholarship examining the relationship of socioeconomic discrepancies in the knowledge of college labor market outcomes and educational choice (Beattie 2002; Betts 1996; McDonough and Calderone 2006; Walpole 2003). Similar to Bleemer and Zafar (2015); Hastings et al. (2015) and Rouse (2004), we find lower-SES respondents have generally similar post-graduate labor market expectations as their higher-SES peers.

More broadly, our approach of providing information builds on work that investigates the impact of information interventions on educational choices (Bettinger et al. 2012; Fryer 2013; Hoxby and Turner 2013; Nguyen 2013), as well as work examining how information provision is used by college students to navigate the complex choices in higher education (Grubb 2006; Karp 2013; Scott-Clayton 2015). Even though our treatment is a relatively complex bundle of information, our treatment estimates suggest that respondents update their beliefs about the outcomes of past graduates. As we discuss in Section 5.4, we find evidence to suggest respondents were able to interpret the data and were not overwhelmed with an "information dump," which can cause respondents to revert to status-quo beliefs.

The paper is organized in the following manner. In Section 1 we review the relevant literature on labor market outcomes and education choice. Sections 2 through 4 discuss the research questions, the survey and administrative data, and the experimental design. Section 5 presents the results, and Section 6 concludes.

1 Background

Studies of the labor market determinants of educational choice form a large body of work. Early work focuses on how expected earnings influence the demand for post-secondary education (Berger 1988; Dominitz and Manski 1996; Manski 1993; Manski and Wise 1983; Willis and Rosen 1979). More recent studies examine how students' subjective expectations about future earnings influence major choice or college enrollment (Arcidiacono et al. 2012; Attanasio and Kaufmann 2012; Delany et al. 2011; Jensen 2010; Wiswall and Zafar 2015). This work suggests that student expectations of post-graduation earnings influence their educational choices, although the impact of preferences or taste is greater than expected earnings.

Expectations of future job security is increasingly recognized as an important determinant of major choice. Wiswall and Zafar (2016) examine the role of preferences for job stability, measured as the likelihood of being fired from a job. They find that job stability is a strong predictor of major choice. With a sample of Chilean students, Hastings et al. (2015) find that the probability of future employment is associated with both college and major choice. Baker et al. (2017) use a sample of community college students in the United States and show that the probability of employment is significantly associated with program choice. They also use an experimental information intervention and find employment probability has a positive and statistically significant effect on the probability of choosing certain major fields but not others.

1.1. Information and Search Costs

An idealized human capital framework assumes that students possess perfect information about the costs, benefits, and risk of educational choices, and use that information to rationally choose the most efficient educational option. Scholars have investigated the validity of these assumptions by asking what students actually know about post-graduate earnings outcomes, how expectations are measured, and how students' expectations are formed in the first place (Avery and Kane 2004; Beattie 2002; Betts 1996; Botelho and Pinto 2004; Manski 1993; Paulsen 2001).

Hastings et al. (2015) propose an informal model of degree choice that makes several predictions related to the cost of acquiring information about an educational choice. In their model, students face uncertainty over the earnings and costs of different degree programs. Students reduce uncertainty by acquiring degree-specific information through a costly search process.

Respondents may have more knowledge about the labor market outcomes for their own preferred major since they have a greater incentive to seek out information for the types of careers they are interested in pursuing than for those in which they lack interest (Arcidiacono et al. 2012). Costly search reduces students' incentives to learn about majors outside of their interest area (Hastings et al. 2015).

Certain groups, such as low-SES students, face higher search costs than higher-SES students as the process of acquiring this information is more difficult. The model predicts that low-SES students have less accurate expectations about post-graduate earnings. They find support for this prediction when analyzing a large sample of students in Chile, while Huntington-Klein (2016b) finds partial support for the model's prediction using a sample of

U.S. students.

The assumption that lower-SES college students have less access to college information is related to a large literature on SES and educational choice. Scholars have documented SES discrepancies in college enrollment and persistence (e.g., Beattie 2002; Engle and Tinto 2008) and major choice (e.g., Lundy-Wagner et al. 2014; Ma 2009). Some scholars find that individuals from lower-income families make less accurate estimates about the estimated benefits of a college degree (e.g., Betts 1996), and know less about financial aid (Hoxby and Turner 2013; Olson and Rosenfeld 1984). However, Paulsen (2001) concludes that students are "reasonably careful and accurate in their acquisition of information about earnings differentials . . . [they] acquire information that is adequate to make more or less economically rational college-going decisions" (Paulsen 2001, p. 63). Similarly, Rouse (2004) finds that high- and low-income students have similar expectations of the economic returns to college attendance. Hastings et al. (2015) and Bleemer and Zafar (2015) find that low-income students hold less accurate beliefs about past graduates' earnings, though students' own beliefs are similar across income groups.

Family background impacts career expectations through various mechanisms. The advantages held by higher-SES students often begin before students enroll at college and persist throughout college and into the labor force (Astin 1993; Hu and Wolniak 2010, 2013; Lareau 1993; Walpole 2003). Lower-SES students form different career expectations than their higher-SES peers (Ali et al. 2005; Metheny and McWhirter 2013; Trusty et al. 2000). Social and career-related barriers, such as lack of role models, financial support, and internal and external barriers to career progress, influence career outcome expectations (Lent et al. 2000). Similarly, Ma (2009) discusses the role of parental involvement in the educational decision-making process and the domain-specific expertise about careers that parents provide their children.

Betts (1996) offers several explanations for why family income is related to information about the costs and benefits of college: higher income allows families to acquire more information; working parents offer prospective college students an example of what employment is like in specific careers; and information about the returns to college may not be extensively disseminated in low-income neighborhoods.

1.1.1 Measurement

Student socioeconomic status is a broad construct that includes a student's financial, social, cultural, and human capital resources (NCES 2012). Because SES includes so many different factors of a student's family and personal background, no consensus exists on how to measure it. In general, SES measurement involves an index of the "big three" items: parental education, parental occupational status, and household or family income (NCES 2012).

Our focus in this project is on two components of the broader concept of student SES: family educational status and family income.[2] While only representing a partial component of SES, low-income students who are the first in their family to attend college share many of the same barriers to higher education as do most lower-SES students. In particular, first-generation college students are likely to lack information sources about college and different academic majors that are available to students with a college graduate in the family (Horn and Nuñez 2000; Ishitani 2006). Low-income students are likely to lack institutional resources—such as quality school counselors and teachers—that help disseminate information about college and careers (Avery 2009; Hoxby and Turner 2013).[3]

2 Research Questions

Search costs for labor market information are higher for students assessing counterfactual choices and low-SES students. These students are more likely to make large belief errors in

[2] Our survey includes no information about family occupational status.

[3] At points in this manuscript, the terms "SES" and "family background" are used interchangeably for stylistic reasons.

their estimates of the population job security data; we expect the labor market information to have a greater impact on these groups of students.

1. Does providing students with labor market information about job security of past graduates change their own job security expectations, relative to students who see only median earnings of past graduates?

2. Does providing students with labor market information about job security and earnings uncertainty of past graduates change their own expectations about the field of study in which they intend to complete a degree, relative to students who see only median earnings of past graduates?

The first research question concerns the impact of information disclosure on respondents' own expectations of future job security. The mechanism through which our information treatment impacts respondents' own expectations is that respondents' revise their own beliefs about the job security outcomes of past college graduates, which leads to revisions in students' own future job security expectations.

The second research question concerns the effect of a specific type of information disclosure on respondents' expectations on completing a degree in several major fields. Our intent is to better understand the impact of disclosing information other than the average earnings of past graduates. Policymakers, counselors, and colleges themselves have the option to provide students with extensive amounts of information related to college choice and majors. This process can lead to an "information dump" in which students are inundated with college information Grubb (2006); Scott-Clayton (2015). The volume and complexity of information limits student capacity to rationally use the information to make a better choice.

A basic information disclosure policy is median earnings. However, showing median earnings alone omits information that students highly value in major and career choice job security and future earnings (Zukin and Szeltner 2012). The information bundle we provide adds only more information about these two elements. It includes the unemployment rate and the perceived job security of past graduates. In addition, we provide a more complete assessment of the past earnings of graduates by providing the range of earnings made by past graduates. The range of earnings provides students with an estimate of the risk associated with future earnings.

Uncertainty over future earnings can also influence major choice. Several papers examine how the risk or uncertainty in post-graduate earnings influences major and career choice (Attanasio and Kaufmann 2012; De Paola and Gioia 2012; Fouarge et al. 2014; Nielsen and Vissing-Jorgensen 2006; Wiswall and Zafar 2015). This work finds large differences in earnings risk across majors, and that college students are generally risk-averse when choosing majors. Bonin et al. (2007) measure individual risk preferences and show that individuals with low risk tolerance sort into occupations with low earnings risk. Saks and Shore (2005) and Caner and Okten (2010) find that individuals with higher levels of family wealth, which tends to make one less risk-averse, select riskier careers.

3 Data and Survey Design

Our data source is an original survey administered to the students at four separate campuses of a large, public university system.[4] To administer the survey, we partnered with the university system's office of institutional research (OIR), which has extensive experience fielding large surveys with the student body. Before OIR launched the survey, we designed a university system-wide marketing strategy to raise awareness about the forthcoming survey. Research assistants distributed fliers in high-traffic areas of campus, engaged with student clubs and residential halls, and used social media accounts to post advertisements. We also

[4]For the major choice analysis, we exclude respondents from one specialty campus that has its own admissions process and all students must major in the field of healthcare. For these students, there is no option to change majors as that would imply leaving college. The results are not substantively different with this group of 109 students included.

partnered with university staff in student affairs and other special offices whose primary mission involves service to lower-SES students. Through these partnerships, we spoke to several different student groups about the survey, or provided advertisement material to administrative staff who then distributed it to the students via an email campaign and in-person discussion. These outreach efforts began in September 2015 and continued until we closed the survey.

OIR emailed the survey to all undergraduates at the four campuses on 11/3/2015. The office sent follow-up emails on 11/9/2015, 11/16/2015, and 11/23/2015. The survey closed on 11/30/2015.[5] The email text explained the survey and the incentive structure. Students who completed the survey were entered into a lottery for one of six $500 Visa gift cards or one of ten $100 gift cards.[6] The email included a link to an online survey hosted by Qualtrics, where students agreed to take the survey by signing an online consent form.

The email invitation reached 48,139 undergraduate students. The response rate was 12.9 percent, with 6,243 students responding and 4,908 students completing the survey.[7] We remove foreign students and 98 respondents for which the administrative data is missing first-generation status.[8]

The full survey includes three randomized treatment conditions: a No Information condition where respondents view no information of any kind, a Median Earnings condition, and a Security/Dispersion condition. We remove all respondents in the No Information condition, as the no information baseline is not relevant to this current study.[9] In addition, the No

[5]Together with OIR, we decided to field the survey late in the fall academic semester as OIR had another survey in the field earlier in the semester and was concerned about survey fatigue. The office generally prefers to have only one survey in the field.

[6]Each week, we randomly selected up to three winners from the list of completed respondents. With the winners' permission, we included their names and photos in the follow-up emails in order to encourage more participation.

[7]We find non-completers had slightly lower SAT scores than completers.

[8]The findings for the overall treatment effect are unchanged when including these cases. Though missing first-generation status, these cases have data on Pell status. We analyze the results using a Pell grant indicator only for SES status and find similar results.

[9]Since the treatment groups are formed through randomization, excluding one group results in no sys-

Information condition is not an appropriate comparison group for the Security/Dispersion condition. That comparison involves a bundle of information—median earnings and job security—compared to no information. Our comparison group holds median earnings constant, while the treatment group only adds elements of job security and earnings dispersion. The remaining sample size is 2976 students.

The average time to complete the survey was 10 minutes and 53 seconds. Descriptive statistics that compare the respondent sample to the overall university system and U.S. undergraduate student population are presented in Table 1.

	Sample	University System	National
First-year	21%	20%	25%
Sophomore	20%	20%	19%
Junior	26%	26%	21%
Senior	33%	32%	28%
Male	34%	48%	44%
Caucasian	43%	40%	71%
African American	10%	10%	16%
Asian	25%	23%	6.8%
Hispanic	16%	15%	12%
Other	6%	5.5%	
SAT Math	608	603	522
SAT Verbal	579	559	518
First Gen.	19%	20%	31%
Pell Grant	29%	28%	39%
Business	17.3%	19%	20%
Education	0.00%	0.06%	6.9%
Health	7.8%	8.2%	12.2%
Humanities	6.7%	5.9%	14%
Other	6.6%	5.9 %	9.3%
Social Science	13.1%	11.4%	18.6%
STEM	17%	17%	17%
Undeclared	31%	32%	1.9%

Table 1: Descriptive statistics of the sample and university data from the university office of institutional research. U.S. data from the National Center of Education Statistics, 2008/2012 Baccalaureate and Beyond (B&B). Large percentage of "undeclared" students in survey and university data due to many students not officially declaring major until the second semester of their second year.

The descriptive statistics in Table 1 show that the sample is similar to the overall university population on a number of observable demographic and academic characteristics. The one exception is gender, with the sample including a lower percentage of men than the overall

tematic biases in the sample. The supplementary materials contain analysis showing that the randomization procedure successfully balanced observable characteristics across treatment groups.

university population (34 percent in the sample versus 48 percent in the university system). This gender discrepancy has been documented in the institutional research literature (see Underwood et al. 2000).

The percentage of respondents enrolled in education is zero because Table 1 uses the university coding system, which allows us to compare our sample to the university population. In the university coding system, students are coded as majoring in education only when they are enrolled in the Department of Education. In our analyses, we use self-reported academic major, which allows us to code education majors enrolled in departments that offer education-related degrees even though they are not in the Department of Education (for example, other departments in the College of Arts and Sciences).[10]

We also compare the university system to the United States population of undergraduate students in 2014. While similar on many dimensions, the university system has a different racial profile with a higher percentage of Asian students than the national student population. The university system also has slightly higher SAT scores than the national average, and a lower percentage of first-generation college students and Pell grant recipients. As such, we use caution when extrapolating the results presented below to the general four-year college student population; however, the experimental design presented in the following section allows us to measure, with a high degree of internal validity, the treatment effect on a large, diverse convenience sample of college students.

3.1. Survey and Experimental Design

Upon agreeing to take the survey, respondents answer several questions about their educational background. We then ask questions related to their expectations of post-graduation job security and expected major choice. Students evaluate six major fields: Business, Education,

[10]Our results are substantively similar if we use the university official codes for declared major. The disadvantage of the university codes are the low number of students enrolled in the Department of Education and the high number of officially undeclared major students. The university system typically does not require students to declare their major until the second semester of their second year.

Healthcare (Health), Humanities, Social Science, and STEM.[11] For each major grouping, we ask students to consider the type of careers associated with each major, and then to estimate their job security if they were working full time in the fifth year after graduation.[12]

> **Job security question:** Thinking about the types of careers available to you if you were to graduate with a degree in each field of study, what type of job security do you believe you would have with a degree in each field?
>
> That is, how likely is it you would have a job with secure employment where you have a low chance of losing your job or of being forced to accept part-time employment?

> **Major Choice:** What is your likelihood of completing a degree in each field of study? That is, what do you believe is the percent chance (or chances out of a 100) that you would graduate with a major in each of the following categories?

The job security question includes two components of job security: unemployment and stability, where stability refers to the loss of full-time job status. Wiswall and Zafar (2016) and Caner and Okten (2010) focus on unemployment probability. We expand the definition to include the probability of involuntary part-time work, which has received increased attention after the 2008 recession and recovery (Valletta and Van Der List 2015).

The first question asks respondents to estimate perceived job security in each field. Respondents use a slider to pick a discrete value from 1 (low security) to 9 (high security). One alternative measurement would be to ask respondents to report their own perceived probability of unemployment. We use the ordinal scale because we want to capture a more

[11]There are many specific majors in the university system. To reduce the number of options given to students, we group majors into these categories, which are similar to those used in Caner and Okten (2010). We define STEM as a combination of engineering, biological and physical sciences, and computer science.

[12]We ask students to consider five years for two primary reasons: 1) asking students to consider a period right after graduation would perhaps not allow for sufficient time to find a job in the major; and 2) we allow students who plan to attend graduate school time to complete their advanced degrees and enter employment.

general perception of future job security that is not defined by any single metric and includes the probability of unemployment and part-time employment in a simple measure easily interpetable to respondents. Pretesting, which is discussed below, aided us in this choice.

We then ask respondents to report their expected likelihood of completing a degree in each of the major groups.[13] Respondents type a percentage directly into six cells that together must sum to 100.[14]

Our survey also asks respondents to report their earnings expectations.[15] This study focuses on job security expectations; a detailed analysis of earnings expectations is in a companion paper in which the information treatment is designed to impact earnings expectations alone. However, in this paper we also report earnings expectations since the information treatment may effect job security expectations and earnings expectations. As shown in Section 5.3, we find that the Security/Dispersion treatment has a small, positive effect on earnings expectations for all majors. This result is similar to Ruder and Van Noy (2017), who find that the disclosure of earnings dispersion information leads to higher earnings expectations than the disclosure of median earnings alone.

3.2. Treatment Description

The following two experimental treatments allow us to answer whether information provision changes students' estimates of job security and expected major of degree completion, relative to a baseline where students see median earnings alone:[16]

[13]The wording for both these questions is similar to Wiswall and Zafar (2015).

[14]As in Baker et al. (2017) and Wiswall and Zafar (2015), the percentages are constrained to sum to 100 in order to approximate a real-world choice situation. For some particular research questions, this constraint also allows the researcher to use a generalized ordinal logit model to estimate the choice probabilities.

[15]The question wording is, "If you were to receive a Bachelor's degree in each of the following fields of study areas and you were working full time 5 years after graduation, what do you believe is the most likely amount that you would earn per year?" Respondents use a slider scale to enter a dollar amount.

[16]Data source for labor market information is the U.S. Department of Education, National Center for Education Statistics, 2008/12 Baccalaureate and Beyond Longitudinal Study (B&B), accessed through NCES PowerStats. We use data from the year 2012 so that data reflects respondent status four years after graduation. Data is unavailable for the period of five years after graduation. To correspond with our question wording, respondents were told that the data was from five years after graduation rather than four. Respondents were not told the data are from 2012. We limit B&B data to graduates who are working full-time.

Median Earnings: Respondents receive the median earnings of graduates in each major field.

Security/Dispersion: In addition to median earnings, respondents receive the earnings dispersion, unemployment rate, and percent of graduates satisfied with job security in each major field.

The treatment Security/Dispersion in Table 2 shows several aspects of post-graduate labor market outcomes related to job security: the unemployment rate of graduates, and the percent of graduates who report being satisfied with the job security in their current job.[17] Our survey question on job security specifically asks respondents to consider the probability of keeping a full time job; the question does not refer to uncertainty over future earnings of a full-time position.

Field of Study	Unemployed %	Satisfied with Job Security %
Healthcare	3.0	77.4
Education	6.3	66.7
Computer/Engineering /Physical/Bio Sciences	6.6	66.8
Business	9.3	70.5
Humanities	12.1	60.2
Social Sciences	12.9	62.2

Table 2: Job security data used in the Security/Dispersion condition of the information treatment, arranged by unemployment rate. Data from the National Center of Education Statistics, Baccalaureate and Beyond 2008/2012. Percent satisfied includes respondents who answer "Satisfied" or "Very Satisfied" when asked about job security at primary job, in 2012.

Majors vary considerably in terms of job security. Based on the metrics of the unemployment rate and the percent of graduates satisfied with job security, Healthcare is the most

See supplementary materials for the survey instrument and the tabular and graphical data displays we show respondents.

[17] B&B survey question wording: "Indicate your level of satisfaction, from very dissatisfied to very satisfied, with each of the following areas of this job: Job security." We calculate percentage of respondents either "satisfied" or "very satisfied."

secure field. Only 3% of graduates working in Healthcare are unemployed and 77.4% of graduates are satisfied with their job security. Graduates in Education have the second lowest unemployment rate at 6.3%, and a job security satisfaction at 66.7%, which is approximately equal to STEM. The STEM field has the third lowest unemployment rate at 6.6%, and the third highest job security satisfaction at 66.8%. Social Sciences and Humanities graduates have the highest unemployment rates and the lowest job security satisfaction.

Field of Study	25th %	Median	75th %
Computer/Engineering /Physical/Bio Sciences	43000	60000	75000
Healthcare	42500	54288	67000
Business	38400	50000	70000
Social Sciences	31200	39998	54000
Education	32000	38000	46141
Humanities	28600	37500	48090

Table 3: Earnings data used for the Risk/Dispersion condition of the information treatment, sorted by median earnings. Data from the National Center of Education Statistics, Baccalaureate and Beyond 2008/2012. Dataset includes only those working full-time five years after graduation with a Bachelor degree.

Tables 3 shows the earnings dispersion information presented to respondents in the Security/Dispersion treatment condition. Those in the Median Only treatment group only see the middle column in Table 3.[18]

3.3. Pretesting

We pretested the survey instrument and experimental design for several months before the November launch. In total, we had 70 test responses spread over 9 different test surveys. We worked with several administrative offices in the university system in order to ensure the pretesting subjects represented the economic diversity of the students in the university system. These surveys tested different branching schemes, question types, and digital layouts. The first tests took place in August and September 2015. After survey completion,

[18]To ease interpretation, we also present this information on earnings in graphical form.

we debriefed subjects and then revised question wording, graphics, and layouts. The tests continued into October 2015, and the survey was finalized for distribution the first week of November 2015.

3.4. Administrative Data

Through our partnership with the university system's office of institutional research, we use unique student identifiers to match survey responses to an administrative database of student and family characteristics. These data include demographics and academic information as well as our key variables of student first-generation status and whether or not the student receives a Pell grant, which is our measure of family income.[19]

4 Empirical Strategy

We observe several outcome variables in our survey. The first outcome is an ordinal rating of perceived job security; the second outcome variable is the annual dollar amount a respondent expects to earn post-graduation for each major field; and the third outcome is the expected probability of completing a degree in each major field. Each outcome measure requires a different estimation strategy.[20]

4.1. Estimation of Perceived Security

The ordinal nature of the response for the question about perceived job security requires a different statistical model than ordinary least squares.[21] For simplicity of the presentation of results, and since some major-by-security rating cells have near zero observations, we recode

[19]The university office of institutional research specifically identifies each student as first generation or not. The data on family income dollar amount are missing in too many instances to be of use; we therefore use Pell grant status as the alternative.

[20]We top-code earnings responses at $150,000 to reduce the influence of any outlier responses. We also calculate the probabilities from the percentages, which we then recode from 0 to 0.001 and from 1 to 0.999. This allows us to take the log of the probability, and, similar to Wiswall and Zafar (2015) and Baker et al. (2017), allows for the use of a log-odds model of choice, which we use in a related paper.

[21]In pretesting, we determined it was best to use an ordinal scale over alternative measures as students had less difficulty interpreting the ordinal response.

the security ratings from a 1 to 9 scale to a 1 to 5 scale. The final distribution of responses is in Table 4. All results are substantively similar using the 1 to 9 scale.

Original Security Rating	1 and 2	3 and 4	5	6 and 7	8 and 9
Revised Security Rating	1	2	3	4	5
Percent of Responses	7%	22%	17%	30%	23%

Table 4: Distribution of all job security ratings by original and revised coding. The response category 5 is the modal category in the original 1 to 9 coding, and we keep it a separate category.

Standard statistical models used with ordinal response data include ordinal logit and ordinal probit. We estimate an ordinal logit model of the following form:

$$\Pr(S_k \leq j) = \frac{\exp(t_{jk} - \boldsymbol{\beta_k X})}{1 - \exp(t_{jk} - \boldsymbol{\beta_k X})}, \tag{1}$$

where a respondent's job-security perception S in major k is modeled as a latent variable $\Pr(S_k \leq j)$, t_{jk} is the cutpoint for security rating j, and $\boldsymbol{\beta_k}$ represents a vector of covariates: an indicator for the Security/Dispersion treatment, an indicator for low-income or first-generation status, an indicator for low-income and first-generation status, as well as controls for gender, age, race, indicators for self-reported probability of attending graduate school, campus, and class level in school (first-year through senior).

4.2. Estimation of Major Completion

Our second outcome measure is the log probability of choosing and completing a degree in major group k. We use ordinary least squares to estimate the following equation:

$$\ln \pi_{ik} = \beta_{0k} + \beta_{1k} * \mathrm{T}_{i1} + \beta_{2k} * \mathrm{FB}_{ia} + \beta_{3k} * \mathrm{FB}_{ib} + \boldsymbol{\beta_{4k} X_i} + \epsilon_{i,k}, \tag{2}$$

where $\ln \pi_{ik}$ is the log expected probability of completing a degree in group k. The covariates are the same as in Equation 1. Our specification to estimate major completion probability is similar to Baker et al. (2017).

For the choice analysis, we limit our analysis to first-year, sophomore, and junior students only since they are likely to face fewer academic and financial barriers to switching majors than senior students. Examples of barriers to switching majors include the investment in prerequisite coursework for the current major. Switching majors may require additional coursework and effort, delaying graduation and increasing the overall costs of college attendance. Results obtained using the full sample of students are substantively similar.

In the choice analysis, 226 respondents answer by assigning the same maximum probability of completing a major to more than one major (for example, 50% for Social Science and 50% for Humanities). Of these 226 respondents, 184 select two majors to be their most likely major. These respondents are likely dual majors, while respondents choosing more than two major fields are likely undecided. Results reported below are substantively similar if we include a dummy variable for these respondents or omit them from the analysis.

5 Results

We now present the estimation results for Equations 1 and 2. We first show the results of the impact of the information treatment on job security expectations for both groups. Second, we show the impact of the information treatment on earnings expectations. Third, we present estimates of the impact of the information treatment on expected major completion probability. To evaluate the statistical significance of all main regression estimates, we mark coefficients with stars representing significance at the 0.05 level, the 0.01 level, and a more stringent 0.0042 level. The 0.0042 level is a conservative significance level obtained using the Bonferroni method to account for the multiple hypothesis testing.[22]

[22] We adjust for the α to account for 12 hypothesis tests: 6 majors with 2 tests per major (treatment indicator and treatment indicator interacted with either family background status or counterfactual major).

5.1. Security

5.1.1 In-Major versus Counterfactual Majors

Table 5 shows the percent of respondents choosing each security rating, by major field and major status. These summary statistics are calculated using the comparison subsample of respondents who only see median earnings. Across all majors, those who plan to earn a degree in the major expect higher job security in the field. Several large differences are apparent. In Health, 65% of respondents who plan to earn a degree in Health expect high job security, compared to only 34% of respondents who do not plan to earn a degree in Health. Respondents in both groups expect high job security in the STEM field: 63% of respondents in-major and 52% of respondents for counterfactual majors choose category 5.

		Security Rating				
Major	Status	1	2	3	4	5
Business***	Counterfactual	6	15	19	42	18
	In-major	1	6	13	44	36
Education*	Counterfactual	7	25	24	31	13
	In-major	2	22	26	33	16
Health***	Counterfactual	4	9	12	40	34
	In-major	1	2	5	28	65
Humanities***	Counterfactual	19	46	20	13	2
	In-major	10	38	24	21	7
Social Science***	Counterfactual	15	44	23	16	2
	In-major	5	26	31	27	10
STEM***	Counterfactual	4	5	7	32	52
	In-major	1	3	5	28	63

Table 5: Security rating by major and major status (in-major and counterfactual major). Sample limited to respondents in the comparison Median Earnings condition. Each cell shows the percentage of respondents selecting the given security rating. A rating of 1 signifies "low security," and a rating of 5 signifies "high security." Stars indicate statistically significant difference between major status groups, calculated using Wilxox rank-sum test: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 6 provides a relative ranking of the security of different majors. For each respondent, we sort the six majors by security rating in decreasing order and then assign a ranking to the six majors, from first to sixth. We allow ties in the ranking.[23] In Table 6, for example, 36% of respondents who intend to earn a degree in Business rated Business as the most secure major.

Table 6 reveals similar patterns to those in Table 5. In Health, 75% of respondents who expect to earn a degree in Health rank Health as the most secure major, relative to other fields. Only 39% of respondents in the counterfactual condition rate Health with the highest job security rating. This low rating is a stark contrast with the labor market data in Table 2, which shows Health to have the highest job security of any field. A high percentage of in-major and counterfactual major respondents rate STEM as the most secure major. Respondents expect social Science and Humanities to be less secure relative to other major fields. Even respondents planning to major in Humanities and Social Science do not rate the fields as more secure than others. Only 16% of in-major respondents rate Social Science higher than other majors, while only 12% of in-major respondents rate Humanities higher than other majors.

[23] We allow ties because we cannot separately rank major fields with the same security rating. A student can assign a "5" to STEM and Health, and a 4 to all other major fields. In this example, STEM and Health would be tied for first, and all other fields would be tied for second.

		Security Rank					
Major	Status	1st	2nd	3rd	4th	5th	6th
Business	Counterfactual	18	39	29	12	2	0
	In-major	36	43	16	5	1	0
Education	Counterfactual	15	25	36	19	5	0
	In-major	22	35	25	12	5	0
Health	Counterfactual	39	35	20	5	1	0
	In-major	75	17	6	1	1	0
Humanities	Counterfactual	4	11	28	37	17	3
	In-major	12	17	35	26	9	2
Social Science	Counterfactual	4	15	32	37	12	2
	In-major	16	26	30	20	7	1
STEM	Counterfactual	60	27	10	3	1	0
	In-major	75	20	4	1	0	0

Table 6: Ordered ranking of security rating and major status (in-major and counterfactual major). Sample limited to respondents in the comparison Median Earnings condition. To calculate ranking, we order the majors by highest security rating for each respondent. Each cell shows percentage of respondents that rank the given major first, second, third, fourth, fifth, and sixth out of six. Ties in major rankings are allowed.

We now present the ordinal logistic regression estimates. Table 7 shows results only for in-major respondents, where respondents are reporting perceived security for the major field for which they intend to earn a degree. We find substantively large estimates only in Education and STEM. The coefficient on STEM is -0.31, suggesting respondents who see the Security/Dispersion treatment have lower perceived future job security in STEM than those who see median earnings alone. The estimate is statistically significant at the 0.05 level. The Education field has large, positive coefficient estimate of 0.28. Respondents who view the Security/Dispersion treatment are more likely to expect high job security in Education. The estimate, however, is statistically imprecise. All other estimates are substantively small and statistically imprecise.

To aid substantive interpretation of the ordinal logit coefficients, we calculate the predicted probability of choosing each security rating by treatment condition. Using these predictions, we calculate the estimated difference in the predicted probability of choosing

Security/Dispersion	Business	Education	Health	Humanities	Social Science	STEM
Security	-0.14	0.28	-0.08	0.03	0.10	-0.31^{*}
	(0.14)	(0.24)	(0.18)	(0.20)	(0.16)	(0.13)
Low-Income or First-Generation	-0.34^{*}	0.09	$-0.34^{\cdot}$	-0.39	-0.18	-0.24
	(0.17)	(0.28)	(0.20)	(0.24)	(0.18)	(0.15)
Low-Income and First-Generation	-0.38	-0.31	-0.07	-0.23	-0.10	-0.07
	(0.26)	(0.39)	(0.30)	(0.33)	(0.28)	(0.25)
Gender	-0.55^{***}	0.06	-0.30	-0.18	-0.21	0.04
	(0.15)	(0.27)	(0.22)	(0.23)	(0.19)	(0.13)
Age	$-0.03^{\cdot}$	0.04	$-0.04^{\cdot}$	0.03	0.04^{*}	0.02
	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)
N	719	240	548	346	513	1054

$^{***}p < 0.0042$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Table 7: Ordinal logistic regression estimates of estimated security on treatment indicators, family background indicators indicators, and demographic and academic controls. In-major respondents only. Estimates for all covariates presented in supplementary materials. Three stars indicate statistical significance at the level determined by the Bonferroni correction.

each security rating, by treatment condition. Formally, the estimated difference is defined as $\Delta = E[\gamma|\text{Security/Dispersion}, X] - E[\gamma|\text{Median Earnings}, X]$, where Δ is the difference across treatment conditions, γ is the probability of completing degree k, and X is a vector of covariates. Table 8 shows these results. We highlight columns for Education and STEM to focus on the major fields with substantively large estimates in Table 7.[24]

	Predicted Difference (Δ) in Security Rating					
Security Rating	Business	Education	Health	Humanities	Social Science	STEM
1 (No Security)	0.00	-0.01	0.00	-0.01	-0.00	0.00$^{\bullet}$
2	0.01	-0.03	0.00	-0.00	-0.01	0.02*
3	0.01	0.00	0.00	0.00	0.00	0.01
4	0.00	0.02	0.00	0.00	0.01	0.01
5 (High Security)	-0.02	0.03	-0.01	0.00	0.01	-0.03*

Table 8: Predicted differences in security rating by treatment status for in-major respondents. Cell values are differences in predicted probability of choosing each security rating between those who see the Security/Dispersion treatment and those who see the Median Earnings treatment. Star indicates that the 95% confidence interval of the estimate does not overlap zero.

[24]Estimates and confidence intervals obtained via simulation using the R package Zelig and the ordinal logistic regression model (Imai et al. 2008; Venables and Ripley 2011).

The predicted probabilities illustrate how the treatment affects security ratings. Respondents in the Security/Dispersion treatment are three percentage points less likely to rate STEM as category 5 and two percentage points more likely to rate STEM as category 2. In Education, we estimate that respondents in the Security/Dispersion treatment are three percentage points more likely to rate Education as category 5, two percentage points more likely to rate Education as category 4, and three percentage points less likely to rate Education as category 2. Estimates for other majors are close to zero and statistically imprecise.

The estimates for STEM and Education are consistent with respondents updating their population security estimates after seeing the population data. Recall that 75% of in-major respondents rated STEM more secure than all other majors. However, the population data in Table 2 show that STEM has only the third lowest unemployment rate and the third lowest perceived job security. Respondents who see this data expect less job security in STEM than those who see median earnings alone.

The pattern is similar with the Education field. The population data in Table 2 shows that Education has the second lowest unemployment rate and approximately the same perceived job security as STEM. However, only 16% of in-major respondents rated Education as a high security field. The predicted probabilities suggest the data cause respondents to rate Education as a high security field relative to respondents who see median earnings alone.

	Business	Education	Health	Humanities	Social Science	STEM
Security/Dispersion	0.04	0.04	0.17^{*}	0.24^{***}	0.19^{*}	-0.09
	(0.08)	(0.07)	(0.08)	(0.07)	(0.07)	(0.09)
Low-Income or First-Generation	0.05	-0.12	-0.05	0.02	0.00	0.03
	(0.09)	(0.08)	(0.09)	(0.08)	(0.09)	(0.10)
Low-Income and First-Generation	0.09	0.13	0.03	0.14	0.19	0.19
	(0.14)	(0.13)	(0.14)	(0.13)	(0.13)	(0.15)
Gender	-0.43^{***}	0.24^{***}	-0.12	-0.06	-0.06	-0.23^{*}
	(0.08)	(0.07)	(0.08)	(0.08)	(0.08)	(0.10)
Age	-0.02	0.03^{***}	$0.02^{\cdot}$	$0.02^{\cdot}$	$0.02^{\cdot}$	$-0.02^{\cdot}$
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
AIC	6380.35	8210.33	6385.57	6994.59	6780.65	4507.46
N	2257	2736	2428	2630	2463	1922

$^{***}p < 0.0042$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Table 9: Ordinal logistic regression estimates of estimated security on treatment indicators, family background indicators, and demographic and academic controls. Counterfactual majors only. Estimates for all covariates presented in supplementary materials. Three stars indicate statistical significance at the level determined by the Bonferroni correction.

We now show the ordinal logistic regression results for respondents who are reporting security expectations of their counterfactual majors. The results are in Table 9. In row Security/Dispersion, the treatment indicator estimates are positive, substantively large, and statistically significant for Health, Humanities, and Social Science. The positive coefficient estimates suggest that the security information causes respondents to expect greater job security in Health, Humanities, and Social Science relative to respondents who see median earnings alone.

The positive coefficient estimates are consistent with the labor market data causing respondents to update their population security beliefs, particularly in the Health field. In Table 6, only 39% of respondents in the counterfactual major group rated Health as the most secure major, compared to 75% of in-major respondents. The labor market information provided in the Security/Dispersion treatment shows that Health has the lowest unemployment rate and the highest perceived job security. Thus, the positive and statistically significant coefficient estimate is consistent with the labor market information causing respondents to revise population beliefs that were biased downward.

Similarly, Table 5 shows that respondents in the counterfactual group expect very low job security in Humanities and Social Science. For Humanities, 19% of respondents select the lowest security rating, while 15% of respondents in Social Science select the lowest security rating. The labor market information in Table 2 shows that Humanities and Social Science have the highest unemployment rates and the lowest satisfaction with job security. The labor market information causes respondents to move from the lowest job security expectations to more moderate job security expectations.

	Predicted Difference in Security Rating					
Security Rating	Business	Education	Health	Humanities	Social Science	STEM
1	-0.00	-0.00	-0.00*	-0.04*	-0.03*	0.00
2	-0.00	-0.00	-0.01*	-0.01	-0.01	0.00
3	-0.00	0.00	-0.01*	0.02*	0.02*	0.00
4	0.01	0.00	-0.00	0.02	0.02*	0.00
5	0.00	0.00	0.03*	0.00*	0.00*	-0.02

Table 10: Predicted differences in security rating by treatment status for counterfactual major respondents. Cell values are differences in predicted probability of choosing each security rating between those who see the Security/Dispersion treatment and those who see the Median Earnings treatment. Star indicates that the 95% confidence interval of the estimate does not overlap zero.

These patterns are more easily seen in Table 10. We again calculate the predicted differences between those in the Security/Dispersion treatment and those in the Median Earnings treatment in selecting each level of security rating. In the Health column, the Security/Dispersion treatment results in a lower probability of selecting the lower security ratings and a three percentage point increase in probability of choosing the highest security rating of 5. Similarly, in Humanities, the Security/Dispersion treatment reduces the predicted probability of choosing the lowest security rating of 1 by four percentage points and increases the probability of choosing the moderate security rating of 3 by two percentage points. The

Social Science estimates show a three percentage point decreased probability of choosing the security rating 1 and a two percentage point increase of choosing categories 3 and 4.

Table 10 shows that the Security/Dispersion treatment had near zero substantive effect in Business, Education, and STEM. The null effect in Education suggests that the labor market information did not cause respondents to revise their security expectations. Respondents in the counterfactual major group in Table 5 had very low expectations for job security in the Education field. The Security/Dispersion treatment shows that Education has the second-lowest unemployment rate; nevertheless, respondents who see this information have similarly low security expectations as those who see median earnings alone.

5.2. Family Background Status

In contrast to the in-major versus counterfactual comparison, we find no significant difference in security expectations by family background status. Table 11 shows, by family background status, descriptive statistics of the percentage of respondents choosing each security rating. Not a single comparison reaches even the 0.1 level of statistical significance.

		Security Rating				
Major	Status	1	2	3	4	5
Business	Base	4	13	18	42	22
	Low-Income and First-Gen.	6	12	18	37	27
Education	Base	8	24	24	33	12
	Low-Income and First-Gen.	5	28	23	34	10
Health	Base	3	7	11	37	41
	Low-Income and First-Gen.	5	4	12	34	45
Humanities	Base	20	43	20	14	2
	Low-Income and First-Gen.	15	46	21	15	3
Social Science	Base	15	40	24	18	3
	Low-Income and First-Gen.	9	43	23	19	5
STEM	Base	2	4	7	31	55
	Low-Income and First-Gen.	3	6	4	27	61

Table 11: Security rating by family background status. Sample limited to respondents in the comparison Median Earnings condition. Status "Base" is respondents neither low-income nor first-generation. Each cell shows the percentage of respondents selecting the given security rating. A rating of 1 is signifies "low security," and a rating of 5 signifies "high security." Stars indicate statistically significant difference between family background groups, calculated using Wilxox rank-sum test: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

The ordinal logistic regression estimates are in Table 12. In these regressions, we control for respondents' preferred major with dummy variables indicating their chosen major.[25] The coefficient estimates on Low-Income or First-Gen and Low-Income and First-Gen represent SES-based differences in security estimates for those who see the Median Earnings treatment. Among this group, we find no evidence of SES-based differences in security estimates; none of the coefficient estimates are substantively large or statistically significant.

The estimated coefficients on the interaction terms are in row Security/Dispersion x Low-Income and First-Gen. These estimates represent differences in security estimates between those in the Median Earnings condition and those in the Security/Dispersion condition, conditional on being a low-income and first-generation student. None of the estimates is

[25] Results are substantively the same without these dummy variables. We include them since low-income, first-generation students may have different major preferences than higher-SES peers; in Section 5.3.1 we show that major preference is correlated with security expectations.

statistically significant at conventional levels. We also conduct likelihood ratio tests on the significance of the interaction effects against the null model with no interaction effects. Only in the Education field do the interaction terms significantly improve the model fit.

However, the results in the Education field offer no clear evidence in support of the hypothesis that lower-SES respondents are less informed than higher-SES peers about post-graduate job security. The estimated coefficient on the interaction term Low-Income or First-Gen. is negative and statistically significant at the 0.05 level, while the estimated coefficient on Low-Income and First-Gen is positive and not statistically significant.

	Business	Education	Health	Humanities	Social Science	STEM
Security	0.06	0.14	0.11	0.23^{**}	$0.16^{\cdot}$	-0.09
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Low-Income or First-Generation	0.06	0.07	-0.10	0.04	0.02	0.02
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
Low-Income and First-Generation	0.07	-0.00	0.04	0.05	0.06	0.26
	(0.17)	(0.16)	(0.17)	(0.17)	(0.17)	(0.18)
Gender	-0.41^{***}	0.21^{***}	-0.19^{**}	-0.06	-0.06	$-0.13^{\cdot}$
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)
Age	-0.02^{*}	0.04^{***}	0.01	$0.02^{\cdot}$	0.02^{**}	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Security	-0.14	-0.36^{*}	0.03	-0.13	-0.04	-0.16
x Low Income or First Gen.	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.16)
Security	-0.14	0.22	-0.01	0.08	0.11	-0.27
x Low Income and First Gen.	(0.23)	(0.22)	(0.24)	(0.23)	(0.23)	(0.25)
Log-likelihood test p-value	0.57	0.01	0.97	0.59	0.83	0.38
AIC	8107.36	8921.94	7461.89	8041.01	8319.24	6622.89
N	2976	2976	2976	2976	2976	2976

$^{***}p < 0.0042$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Table 12: Ordinal logistic regression estimates of estimated security per major on treatment indicator, family background indicators, interaction between treatment indicator and family background indicators, and demographic and academic controls. Specifications include indicator variables for respondents' preferred major. Estimates for all covariates presented in supplementary materials. Three stars indicate statistical significance at the level determined by the Bonferroni correction.

	Business	Education	Health	Humanities	Social Science	STEM
Security/Dispersion	0.04*	0.03	0.04*	0.05*	0.05*	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Pell Data.	−0.03	−0.01	−0.02	−0.01	−0.03	−0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
First-Generation	0.01	0.03	−0.01	0.01	−0.05	0.02
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)
Gender	0.08***	0.08***	0.05*	0.06**	0.05*	0.03·
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Age	0.00	0.01***	−0.00	0.00	0.00·	−0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Intercept	11.04***	10.47***	11.07***	10.54***	10.61***	11.17***
	(0.08)	(0.07)	(0.08)	(0.09)	(0.08)	(0.08)
R^2	0.04	0.03	0.04	0.02	0.04	0.02
N	2976	2976	2976	2976	2976	2976

$^{***}p < 0.0042$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Table 13: OLS estimates of expected earnings per major on treatment indicator, family background indicators, interactions between treatment and family background indicators, and demographic and academic controls. Robust standard errors in parentheses. Estimates for all covariates presented in supplementary materials. Three stars indicate statistical significance at the level determined by the Bonferroni method correction.

5.3. Earnings

Before presenting the major choice results, we show regression estimates for the expected earnings outcome. We use ordinal least squares to estimate the impact of the Security/Dispersion treatment on log earnings in each major. The covariates are the same as in Equations 1 and 2. Table 13 shows that the Security/Dispersion treatment has a small, positive affect on earnings expectations in all majors. This result is similar to Ruder and Van Noy (2017), who find that earnings dispersion information leads to higher earnings expectations when compared to median earnings information alone.

5.3.1 Choice

Before presenting the regression results, we examine the association between job security, earnings expectations, and expected major choice. These results are in Table 14. The probability of choosing a major is significantly associated with both perceived job security and

	Model 1	Model 2	Model 3
Security	0.41^{***}		0.34^{***}
	(0.02)		(0.02)
Earnings		0.71^{***}	0.51^{***}
		(0.04)	(0.04)
(Intercept)	-5.36^{***}	-11.78^{***}	-10.78^{***}
	(0.09)	(0.44)	(0.44)
R^2	0.06	0.06	0.07
N	17856	17856	17856

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 14: OLS results of regression of major completion probability on security estimate and earnings expectations. Regressions include dummy variables for each major field (unreported). Model 1 is results for the association of the security estimate; Model 2 is for the association of earnings expectations, and Model 3 is for both security and earnings estimates. Standard errors in parentheses.

earnings expectations in the major. This association is similar to the correlations reported in Baker et al. (2017) of unemployment expectations, earnings, and the probability of major choice.

Figure 1 shows the density of the distribution of log-probability of major choice for each major. The bi-modal distributions are similar to what Wiswall and Zafar (2015) find with their sample of New York University undergraduates. There is a large mass of respondents expressing near zero probability of completing a degree in each field, and a smaller mass of respondents expressing near certainty or certainty of majoring in a major field.

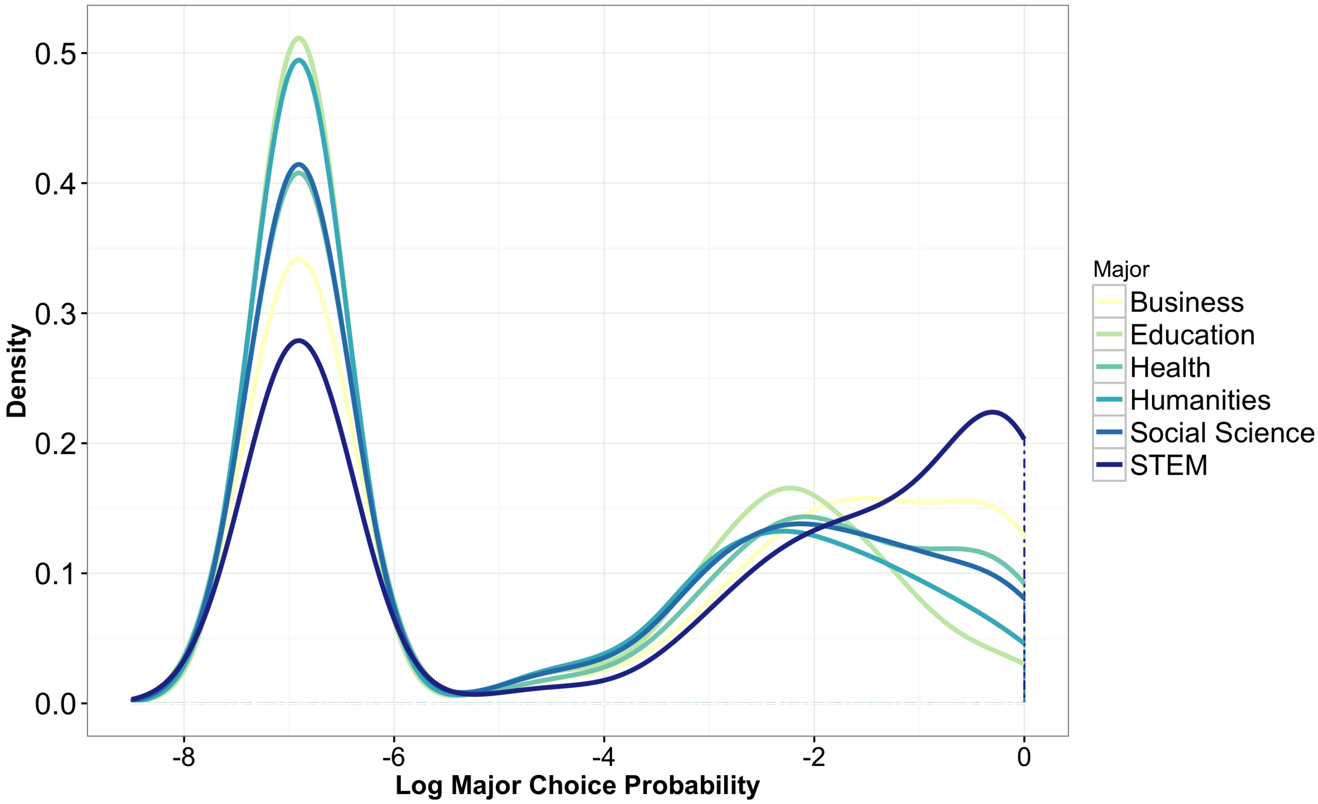

Figure 1: Log probability of expectation to complete a degree in each major field.

In this context of the relatively strong prior beliefs shown in Figure 1, we find no evidence that the Security/Dispersion treatment influences major choice. In Table 15, we present the OLS estimates of Equation 2. While the magnitude of the Business, Education, and Social Science coefficient estimates in row Security/Dispersion are substantively large, none of the estimates reaches conventional levels of statistical significance.[26] All estimates are imprecise with relatively large standard errors. Thus, we cannot reject the null hypothesis of zero effect.

We also assess whether the information treatment has a differential effect on low-SES respondents. The model of degree choice with higher search costs for low-SES students pre-

[26]The estimated Security/Dispersion coefficient of 0.10 is equivalent to a 10.5% change in probability of choosing Business.

dicts that the effect of the information intervention should be larger for low-SES respondents. In the supplementary materials, Table A11 shows regression results where we interact the Security/Dispersion treatment indicator with the indicators for family background status. We find no evidence of heterogeneous treatment effects. None of the interaction terms are statistically significant, nor are the F-test statistics of the null model compared to the model with the interaction terms. This result is in contrast to Hastings et al. (2017), who find that their specific information treatment has a larger effect on low-SES than higher-SES respondents.

	Business	Education	Health	Humanities	Social Science	STEM
Security/Dispersion	0.10	0.09	−0.04	0.05	0.09	−0.00
	(0.13)	(0.11)	(0.12)	(0.12)	(0.12)	(0.13)
Low-Income or First-Gen.	−0.11	0.02	0.10	0.06	0.22	−0.01
	(0.15)	(0.14)	(0.14)	(0.14)	(0.15)	(0.15)
Low-Income and First-Gen	−0.14	0.01	0.17	0.01	0.21	−0.06
	(0.23)	(0.21)	(0.23)	(0.21)	(0.23)	(0.23)
Gender	0.61***	−0.30*	−0.69***	−0.56***	−0.52***	0.82***
	(0.14)	(0.12)	(0.12)	(0.12)	(0.13)	(0.13)
Age	0.00	0.01	−0.05***	0.00	0.02	−0.04*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Intercept	−3.26***	−4.68***	−2.36***	−4.61***	−4.73***	−3.21***
	(0.55)	(0.47)	(0.46)	(0.45)	(0.51)	(0.53)
R^2	0.05	0.02	0.07	0.03	0.04	0.09
N	1911	1911	1911	1911	1911	1911

$^{***}p < 0.005$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Table 15: OLS estimates of expected probability of completion per major on treatment indicator. Sample excludes senior respondents. Regressions also include family background indicators, demographic and academic controls, and indicators for respondents' preferred major field. Robust standard errors in parentheses. Estimates for all covariates presented in supplementary materials. Three stars indicate statistical significance at the level determined by the Bonferroni correction.

5.4. Limitations

Given these findings, we note several limitations to this analysis. First, our sample of respondents is from a population already enrolled in college, such that our sample includes respondents who have already selected into college leaving out of the sample those who did not select into college. The selection problem affects the results when those who have selected into college are more informed about labor market outcomes than those who do not go to college, perhaps due to resources used during the college search or provided by the university itself.

Second, respondents who select into the survey may differ in observable and unobservable characteristics from the university population overall. We show in Table 1 that the sample is generally similar to the overall university population on all observables except gender.[27]

We cannot assess bias on unobservables. Those who respond, for example, may have greater motivation to take the survey because they are interested in the topic of career choice. This pattern would lead to bias when those who respond have already investigated careers and labor market information, while those who do not respond have not sought out this information.

Another concern is that respondents are unable to interpret the bundle of labor market information we provide. If the information is too complex, respondents may default to guessing or responding with status-quo beliefs. We have some evidence that respondents were able to interpret the job security and earnings information. One of our post-treatment survey questions reveals that the majority of students expressed that the labor market information presented in the survey was useful to them; sixty-two percent of respondents listed the information as "useful" or "very useful," while less than seven percent listed the information as "useless" or "very useless." In addition, one question in our survey asks, "What was most interesting or helpful to you about the data you just saw?" We conduct text analysis on the open-ended responses to this question. The two most frequently used words in the responses are "job" and "security."

Finally, our analysis of the treatment impact on low-income, first-generation status stu-

[27]Studies of response and non-response have noted that women are more likely than men to respond during online surveys taken by the student body (Underwood et al. 2000).

dents does not have a causal interpretation. Our experimental design only randomizes the information provided to respondents; we cannot randomize family background. All estimates of interaction effects that we present are associations, not causal effects.

6 Discussion

In this paper, we provide some evidence in support of a model of college major choice where individuals face varying search costs to acquire degree-specific labor market information. We focus on two types of varying search cost. First, we assess student expectations of labor market outcomes outside of their own preferred major. These students have less incentive to gather information for the majors outside of their most preferred options. Second, we analyze lower-SES students who lack the same ease of access to labor market information as their higher-SES peers.

Our analysis focuses on discrepancies in information about job security. We find significant differences in job security expectations between those assessing their preferred major and those assessing counterfactual majors. Respondents assessing counterfactual majors have significantly lower expectations than those respondents estimating security in their preferred major. Our information intervention causes respondents to have higher security ratings in their preferred major and counterfactual majors; however, we only find a significant effect in majors where respondents appear to make large errors in their baseline beliefs. Their own security rankings of majors is markedly different than the population data we present in the information treatment. That is, we find large discrepancies between the respondents' ranking of majors by job security and the ranking of majors according to actual unemployment rates and perceived job security of recent graduates.

The treatment effect is positive and statistically significant only where these discrepancies are large. As predicted by the model of search costs, these apparent errors are more likely to occur when estimating counterfactual majors. This is consistent with Hastings et al. (2017), who find the information treatment has the greatest effect where respondents' beliefs differ most from the real population data.

We then examine the effect of specific type of information disclosure on major choice. We design our information treatment in order to better understand the impact of disclosing information other than the average earnings of past graduates. We focus on what college students cite as two of the most important attributes of jobs: job security and future earnings (Zukin and Szeltner 2012). The information bundle includes the unemployment rate and the perceived job security of past graduates in each major. In addition, we offer a more complete summary of the past earnings of graduates by disclosing the range of earnings of past graduates in each major. The range of earnings provides students with an estimate of the risk associated with future earnings.

We find no evidence that the information intervention affects the probability of selecting a major in which to complete a degree. Our null finding is consistent with Kerr et al. (2014), who find evidence that information disclosure impacts earnings expectations but not actual choice. Furthermore, the finding is consistent with students placing less weight on earnings than on other attributes when choosing a major or college. Hastings et al. (2017) note that information disclosure alone is unlikely to shift student preferences across fields of study or other factors such as geographic location. We find that respondents in our sample have strong preference for their field of choice; we agree with Hastings et al. (2017) that it is hard for an information intervention to shift preferences away from a strongly preferred major field to another which, prior to disclosure, the student expresses little interest in pursuing.

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A Supplemental Tables Not for Publication

In order to reduce the length of the main manuscript, we have placed several items in the supplementary materials.

A.1. Drop Data Checks

In this section, we analyze differences between respondents who dropped out and those who completed the survey. We focus on differences in several key variables that are likely related to post-graduate labor market expectations: family background, gender, SAT scores, and academic class level. In short, we only find differences between those who complete and those who do not complete when analyzing SAT scores. Those who do not complete the survey are significantly more likely to have a lower SAT score on the math and verbal components, and more likely to have an SAT score missing from the dataset. This finding suggests that those who did take the survey have, on average, higher academic performance on the SAT

A.1.1 Family Background

Family Background	Complete Percent	Non Complete Percent
Base	79	21
Low Income or First Gen.	79	21
Low Income and First Gen.	76	24

Table A1: χ-squared = 2.5239, df = 2, p-value = 0.2831

A.1.2 Gender

Gener	Complete Percent	Non Complete Percent
Female	78	22
Male	80	20

Table A2: χ-squared = 1.7338, df = 1, p-value = 0.1879

A.1.3 SAT

	SAT Math mean	SAT Verbal mean
Complete	608	579
Non Complete	591	564

Table A3: ANOVA for Math SAT, F = 23, $p < 0.01$. ANOVA for Verbal SAT, F = 17, $p < 0.01$.

	0 Percent	1 Percent	0 Percent	1 Percent
Complete	79	21	79	21
Non Complete	74	26	74	26

Table A4: χ-squared = 11.525, df = 1, $p - value < 0.01$. Results the same for both math and verbal SAT missingness.

A.1.4 Class Level

	Complete Percent	Non Complete Percent
First Year	22	20
Junior	26	26
Senior	33	32
Sophomore	19	21

Table A5: χ-squared = 4.3586, df = 4, p-value = 0.36

A.1.5 Family Background

Family Background	Keep Percent	Drop Percent
Base	5	95
First-Gen or Low-Income	5	95
First-Gen and Low-Income	5	95

A.2. Randomization Checks

level.data	n	Median Earnings Percent	Security/Dispersion Percent
First Year	641	21	22
Sophomore	584	19	20
Junior	770	28	24
Senior	987	32	34
All	2982	100	100

		Age (mean years)
Median Earnings	1513	21
Security/Dispersion	1469	21

		GPA	SAT Math	SAT Verbal	First-Generation	Pell Receipt
Median Earnings	1183	3.20	608.34	580.89	0.17	0.30
Security/Dispersion	1176	3.17	607.12	577.74	0.20	0.29

A.3. Regression Tables

For space reasons, we present in the main body of the paper tables that contain only the key variables of interest. In this section, we present the full regression tables that include the estimates for all covariates.

Security/Dispersion	Business	Education	Health	Humanities	Social Science	STEM
Security	−0.14	0.28	−0.08	0.03	0.10	−0.31*
	(0.14)	(0.24)	(0.18)	(0.20)	(0.16)	(0.13)
Low-Income or First-Generation	−0.34*	0.09	−0.34·	−0.39	−0.18	−0.24
	(0.17)	(0.28)	(0.20)	(0.24)	(0.18)	(0.15)
Low-Income and First-Generation	−0.38	−0.31	−0.07	−0.23	−0.10	−0.07
	(0.26)	(0.39)	(0.30)	(0.33)	(0.28)	(0.25)
Gender	−0.55***	0.06	−0.30	−0.18	−0.21	0.04
	(0.15)	(0.27)	(0.22)	(0.23)	(0.19)	(0.13)
Age	−0.03·	0.04	−0.04·	0.03	0.04*	0.02
	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)
Asian	0.72*	0.88·	−0.32	−0.50	−0.38	−0.52·
	(0.29)	(0.53)	(0.33)	(0.43)	(0.34)	(0.28)
Latino	0.58·	0.68	−0.26	−0.25	−0.08	−0.64*
	(0.30)	(0.51)	(0.36)	(0.39)	(0.30)	(0.30)
Unknown	1.00·	−1.19	−0.23	−1.82*	−1.67**	−0.36
	(0.55)	(1.37)	(0.69)	(0.75)	(0.59)	(0.50)
Multiple Race	0.70	0.14	−0.99*	−0.22	0.10	−0.61
	(0.47)	(0.73)	(0.50)	(0.55)	(0.43)	(0.40)
Caucasian	0.29	0.28	−0.45	−0.58	−0.13	−0.31
	(0.28)	(0.47)	(0.31)	(0.36)	(0.27)	(0.28)
Sophomore	0.33	0.92*	−0.13	0.54	−0.11	0.29
	(0.24)	(0.39)	(0.28)	(0.35)	(0.30)	(0.19)
Junior	0.42·	−0.06	−0.21	0.18	−0.25	−0.22
	(0.22)	(0.36)	(0.27)	(0.33)	(0.28)	(0.19)
Senior	−0.01	0.19	0.28	0.13	−0.08	0.05
	(0.23)	(0.37)	(0.28)	(0.35)	(0.28)	(0.20)
Somewhat Likely	0.39*	0.26	−0.25	0.14	0.09	−0.04
	(0.20)	(0.42)	(0.36)	(0.34)	(0.27)	(0.20)
Somewhat Unlikely	0.38	0.01	−0.56	0.68·	−0.17	−0.31
	(0.28)	(0.63)	(0.52)	(0.41)	(0.39)	(0.26)
Very Likely	0.18	0.54	−0.11	0.21	0.32	0.25
	(0.20)	(0.39)	(0.32)	(0.32)	(0.25)	(0.19)
Very Unlikely	0.36	0.62	0.27	−0.23	−0.08	−0.27
	(0.35)	(0.63)	(0.66)	(0.48)	(0.44)	(0.28)
Campus 1	−0.30	−0.62·	−0.39	−0.17	−0.12	0.04
	(0.23)	(0.34)	(0.25)	(0.30)	(0.25)	(0.26)
Campus 2	0.45·	−0.31	−0.46	0.35	0.58·	0.16
	(0.27)	(0.45)	(0.34)	(0.41)	(0.31)	(0.33)
Campus 3	−1.32	−0.40	−0.26	−1.55	−1.41	0.44
	(1.29)	(1.24)	(0.31)	(1.29)	(1.72)	(0.52)
AIC	1687.26	717.41	1013.18	1037.45	1487.06	2065.48
N	719	240	548	346	513	1054

$^{***}p < 0.0042$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Table A6: Ordinal logistic regression estimates of estimated security on treatment indicators, family background indicators indicators, and demographic and academic controls. In-major respondents only. Three stars indicate statistical significance at the level determined by the Bonferroni correction.

	Business	Education	Health	Humanities	Social Science	STEM
Security/Dispersion	0.04	0.04	0.17^{*}	0.24^{***}	0.19^{*}	-0.09
	(0.08)	(0.07)	(0.08)	(0.07)	(0.07)	(0.09)
Low-Income or First-Generation	0.05	-0.12	-0.05	0.02	0.00	0.03
	(0.09)	(0.08)	(0.09)	(0.08)	(0.09)	(0.10)
Low-Income and First-Generation	0.09	0.13	0.03	0.14	0.19	0.19
	(0.14)	(0.13)	(0.14)	(0.13)	(0.13)	(0.15)
Gender	-0.43^{***}	0.24^{***}	-0.12	-0.06	-0.06	-0.23^{*}
	(0.08)	(0.07)	(0.08)	(0.08)	(0.08)	(0.10)
Age	-0.02	0.03^{***}	$0.02^{\cdot}$	$0.02^{\cdot}$	$0.02^{\cdot}$	$-0.02^{\cdot}$
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Asian	0.36^{*}	0.16	-0.13	$-0.25^{\cdot}$	-0.16	-0.03
	(0.15)	(0.13)	(0.16)	(0.14)	(0.15)	(0.17)
Latino	0.06	-0.14	-0.34^{*}	-0.17	0.00	-0.17
	(0.16)	(0.14)	(0.16)	(0.15)	(0.16)	(0.17)
Unknown	0.27	0.25	0.34	$-0.52^{\cdot}$	0.01	0.42
	(0.32)	(0.27)	(0.33)	(0.30)	(0.30)	(0.39)
Multiple Race	0.18	0.27	0.01	-0.08	-0.02	-0.42
	(0.22)	(0.21)	(0.23)	(0.22)	(0.23)	(0.26)
Caucasian	$0.25^{\cdot}$	0.04	$-0.27^{\cdot}$	-0.37^{**}	$-0.24^{\cdot}$	-0.21
	(0.14)	(0.13)	(0.15)	(0.13)	(0.14)	(0.16)
Sophomore	0.16	0.05	0.07	-0.11	-0.07	0.01
	(0.12)	(0.11)	(0.12)	(0.11)	(0.11)	(0.14)
Junior	0.12	0.09	0.18	-0.05	-0.11	$0.26^{\cdot}$
	(0.12)	(0.11)	(0.12)	(0.11)	(0.11)	(0.14)
Senior	0.31^{*}	0.05	0.32^{**}	-0.13	-0.31^{**}	$0.24^{\cdot}$
	(0.12)	(0.11)	(0.12)	(0.11)	(0.11)	(0.14)
Somewhat Likely	0.01	-0.05	$0.23^{\cdot}$	0.11	0.10	-0.09
	(0.13)	(0.11)	(0.12)	(0.12)	(0.12)	(0.14)
Somewhat Unlikely	0.14	0.11	0.07	-0.15	-0.13	0.06
	(0.18)	(0.15)	(0.16)	(0.16)	(0.16)	(0.19)
Very Likely	-0.08	-0.03	0.31^{**}	0.03	-0.02	-0.06
	(0.12)	(0.10)	(0.11)	(0.11)	(0.11)	(0.13)
Very Unlikely	-0.09	-0.12	-0.18	-0.00	$-0.36^{\cdot}$	0.01
	(0.20)	(0.18)	(0.18)	(0.19)	(0.18)	(0.24)
Campus 1	0.32^{**}	0.34^{***}	-0.01	-0.10	-0.06	0.36^{***}
	(0.12)	(0.11)	(0.12)	(0.11)	(0.11)	(0.12)
Campus 2	0.24	0.19	-0.03	$0.27^{\cdot}$	0.24	-0.03
	(0.16)	(0.14)	(0.16)	(0.15)	(0.15)	(0.16)
Campus 3	-0.33	0.21	0.91^{*}	-0.22	-0.11	0.04
	(0.21)	(0.20)	(0.46)	(0.21)	(0.21)	(0.23)
AIC	6380.35	8210.33	6385.57	6994.59	6780.65	4507.46
N	2257	2736	2428	2630	2463	1922

$^{***}p < 0.0042$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Table A7: Ordinal logistic regression estimates of estimated security on treatment indicators, family background indicators, and demographic and academic controls. Counterfactual majors only. Three stars indicate statistical significance at the level determined by the Bonferroni correction.

	Business	Education	Health	Humanities	Social Science	STEM
Security	0.06	0.14	0.11	0.23**	0.16·	−0.09
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Low-Income or First-Generation	0.06	0.07	−0.10	0.04	0.02	0.02
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
Low-Income and First-Generation	0.07	−0.00	0.04	0.05	0.06	0.26
	(0.17)	(0.16)	(0.17)	(0.17)	(0.17)	(0.18)
Gender	−0.41***	0.21***	−0.19**	−0.06	−0.06	−0.13·
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)
Age	−0.02*	0.04***	0.01	0.02·	0.02**	−0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Asian	0.42***	0.22·	−0.20	−0.27*	−0.22	−0.18
	(0.13)	(0.13)	(0.14)	(0.13)	(0.13)	(0.14)
Latino	0.17	−0.03	−0.40**	−0.16	−0.02	−0.27·
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.15)
Unknown	0.43	0.24	0.20	−0.71**	−0.34	0.17
	(0.27)	(0.26)	(0.30)	(0.28)	(0.27)	(0.30)
Multiple Race	0.17	0.23	−0.18	−0.10	0.02	−0.46*
	(0.20)	(0.21)	(0.21)	(0.21)	(0.21)	(0.22)
Caucasian	0.24·	0.07	−0.34**	−0.37***	−0.20	−0.23·
	(0.12)	(0.12)	(0.13)	(0.12)	(0.12)	(0.14)
Sophomore	0.15	0.07	0.02	−0.01	0.01	0.08
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.12)
Junior	0.16	−0.04	0.10	−0.01	−0.01	0.09
	(0.12)	(0.11)	(0.12)	(0.12)	(0.12)	(0.12)
Senior	0.22·	−0.08	0.29*	−0.08	−0.19	0.18
	(0.13)	(0.12)	(0.13)	(0.13)	(0.12)	(0.13)
Somewhat Likely	0.07	−0.03	0.21·	0.13	0.10	−0.07
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.12)
Somewhat Unlikely	0.17	0.08	0.00	0.01	−0.14	−0.07
	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)
Very Likely	−0.08	0.02	0.36***	0.06	0.04	0.05
	(0.10)	(0.10)	(0.11)	(0.10)	(0.10)	(0.11)
Very Unlikely	−0.00	−0.06	−0.13	−0.01	−0.34*	−0.07
	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.18)
Health	−1.15***	−0.20	1.18***	−0.20	0.12	0.16
	(0.19)	(0.19)	(0.22)	(0.20)	(0.19)	(0.21)
Humanities	−0.78***	−0.05	−0.23	0.17	0.22	−0.08
	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.16)
Other	−0.94***	−0.21	0.16	−0.11	0.19	−0.17
	(0.16)	(0.15)	(0.16)	(0.16)	(0.15)	(0.16)
Social	−0.75***	0.12	0.01	0.30*	0.86***	0.00
	(0.13)	(0.12)	(0.13)	(0.13)	(0.13)	(0.13)
STEM	−1.03***	0.05	0.07	−0.25*	−0.23·	0.18
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
Undeclared	−0.90***	−0.19·	0.07	0.00	0.23*	0.04
	(0.12)	(0.11)	(0.11)	(0.11)	(0.11)	(0.12)
Campus 1	0.19·	0.24*	−0.07	−0.13	−0.03	0.36***
	(0.11)	(0.11)	(0.12)	(0.11)	(0.11)	(0.12)
Campus 2	0.28·	0.10	−0.05	0.21	0.31*	0.10
	(0.14)	(0.14)	(0.15)	(0.14)	(0.14)	(0.15)
Campus 3	−0.26	0.21	−0.22	−0.15	−0.18	0.01
	(0.24)	(0.24)	(0.28)	(0.25)	(0.24)	(0.26)
Security	−0.14	−0.36*	0.03	−0.13	−0.04	−0.16
x Low Income or First Gen.	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.16)
Security	−0.14	0.22	−0.01	0.08	0.11	−0.27
x Low Income and First Gen.	(0.23)	(0.22)	(0.24)	(0.23)	(0.23)	(0.25)
Log-likelihood test p-value	0.57	0.01	0.97	0.59	0.83	0.38
AIC	8107.36	8921.94	7461.89	8041.01	8319.24	6622.89
N	2976	2976	2976	2976	2976	2976

$^{***}p < 0.0042$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Table A8: Ordinal logistic regression estimates of estimated security per major on treatment indicator, family background indicators, interaction between treatment indicator and family background indicators, and demographic and academic controls. Specifications include indicator variables for respondents' preferred major. Three stars indicate statistical significance at the level determined by the Bonferroni correction.

	Business	Education	Health	Humanities	Social Science	STEM
Security/Dispersion	0.10	0.09	-0.04	0.05	0.09	-0.00
	(0.13)	(0.11)	(0.12)	(0.12)	(0.12)	(0.13)
Low-Income or First-Gen.	-0.11	0.02	0.10	0.06	0.22	-0.01
	(0.15)	(0.14)	(0.14)	(0.14)	(0.15)	(0.15)
Low-Income and First-Gen	-0.14	0.01	0.17	0.01	0.21	-0.06
	(0.23)	(0.21)	(0.23)	(0.21)	(0.23)	(0.23)
Gender	0.61^{***}	-0.30^{*}	-0.69^{***}	-0.56^{***}	-0.52^{***}	0.82^{***}
	(0.14)	(0.12)	(0.12)	(0.12)	(0.13)	(0.13)
Age	0.00	0.01	-0.05^{***}	0.00	0.02	-0.04^{*}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Asian	$0.46^{\cdot}$	-0.14	0.16	-0.47^{*}	-0.86^{***}	1.03^{***}
	(0.24)	(0.21)	(0.23)	(0.21)	(0.23)	(0.24)
Latino	0.00	0.53^{*}	0.14	0.24	-0.12	0.66^{**}
	(0.25)	(0.22)	(0.24)	(0.23)	(0.24)	(0.25)
Unknown	0.12	$0.72^{\cdot}$	0.33	0.56	0.38	0.47
	(0.46)	(0.43)	(0.50)	(0.41)	(0.44)	(0.51)
Multiple Race	-0.45	0.08	-0.27	0.34	0.20	0.38
	(0.37)	(0.33)	(0.36)	(0.34)	(0.36)	(0.37)
Caucasian	-0.21	0.13	$-0.40^{\cdot}$	-0.23	$-0.37^{\cdot}$	-0.06
	(0.23)	(0.21)	(0.22)	(0.21)	(0.22)	(0.23)
Sophomore	-0.01	-0.06	-0.19	-0.13	0.05	-0.54^{***}
	(0.17)	(0.15)	(0.16)	(0.15)	(0.16)	(0.17)
Junior	-0.08	-0.08	-0.19	-0.03	0.33^{*}	-0.74^{***}
	(0.17)	(0.15)	(0.16)	(0.15)	(0.16)	(0.17)
Somewhat Likely	-0.07	0.05	0.14	0.15	0.23	-0.02
	(0.21)	(0.18)	(0.18)	(0.18)	(0.19)	(0.20)
Somewhat Unlikely	-0.05	0.00	0.11	0.41	0.06	0.38
	(0.29)	(0.25)	(0.25)	(0.26)	(0.26)	(0.28)
Very Likely	-0.96^{***}	-0.17	0.67^{***}	-0.14	-0.19	0.24
	(0.19)	(0.17)	(0.17)	(0.17)	(0.18)	(0.18)
Very Unlikely	-0.11	-0.59^{*}	-0.42	-0.02	$-0.63^{\cdot}$	0.27
	(0.36)	(0.30)	(0.31)	(0.33)	(0.34)	(0.37)
Campus 1	-0.27	-0.40^{*}	-1.04^{***}	0.18	$0.34^{\cdot}$	0.83^{***}
	(0.20)	(0.18)	(0.20)	(0.18)	(0.19)	(0.19)
Campus 2	0.39	0.07	-0.78^{***}	0.04	0.54^{*}	0.26
	(0.25)	(0.23)	(0.24)	(0.22)	(0.24)	(0.24)
Intercept	-3.26^{***}	-4.68^{***}	-2.36^{***}	-4.61^{***}	-4.73^{***}	-3.21^{***}
	(0.55)	(0.47)	(0.46)	(0.45)	(0.51)	(0.53)
R^2	0.05	0.02	0.07	0.03	0.04	0.09
N	1911	1911	1911	1911	1911	1911

$^{***}p < 0.005$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Table A10: OLS estimates of expected probability of completion per major on treatment indicator. Sample excludes senior respondents. Regressions also include family background indicators, demographic and academic controls, and indicators for respondents' preferred major field. Robust standard errors in parentheses. Three stars indicate statistical significance at the level determined by the Bonferroni correction.

	Business	Education	Health	Humanities	Social Science	STEM
Security/Dispersion	0.04*	0.03	0.04*	0.05*	0.05*	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Pell Data.	−0.03	−0.01	−0.02	−0.01	−0.03	−0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
First-Generation	0.01	0.03	−0.01	0.01	−0.05	0.02
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)
Gender	0.08***	0.08***	0.05*	0.06**	0.05*	$0.03^{\cdot}$
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Age	0.00	0.01***	−0.00	0.00	$0.00^{\cdot}$	−0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Asian	−0.00	−0.02	−0.08*	−0.09*	−0.11***	−0.04
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Latino	−0.04	−0.03	−0.10*	−0.06	−0.06	−0.01
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Unknown	0.01	0.01	−0.04	−0.07	−0.10	0.07
	(0.07)	(0.08)	(0.07)	(0.09)	(0.09)	(0.06)
Multiple Race	−0.06	−0.12*	−0.14*	−0.16**	−0.13*	−0.09
	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Caucasian	−0.00	−0.04	−0.09**	−0.10*	−0.12***	−0.01
	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)
Sophomore	−0.00	−0.02	0.03	−0.02	−0.01	0.03
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Junior	0.05	−0.01	0.05	0.01	0.02	0.03
	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
Senior	0.04	−0.03	0.04	0.01	−0.02	0.04
	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)
Somewhat Likely	0.02	0.02	0.05	0.04	0.04	0.04
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Somewhat Unlikely	0.01	−0.04	−0.05	−0.07	−0.09*	−0.03
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Very Likely	0.06*	0.04	0.13***	0.04	0.07*	0.06*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Very Unlikely	−0.03	−0.12*	0.01	−0.04	−0.00	−0.03
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Campus 1	0.09***	0.03	−0.01	0.01	−0.00	0.04
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Campus 2	0.17***	0.14***	0.04	0.14***	0.12**	0.06
	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)
Campus 3	0.07	0.06	0.12*	0.02	0.01	−0.01
	(0.06)	(0.06)	(0.05)	(0.07)	(0.07)	(0.06)
Health	−0.10*	0.03	0.16***	0.05	0.02	0.06
	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)	(0.04)
Humanities	−0.16***	0.01	−0.11*	0.03	−0.00	−0.10*
	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)
Other	−0.09*	0.02	0.02	0.02	0.07	−0.04
	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)
Social	−0.10***	−0.01	−0.04	0.01	0.12***	−0.05
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
STEM	−0.14***	−0.02	−0.01	−0.05	−0.07*	0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Undeclared	−0.12***	−0.03	0.03	−0.02	0.01	0.03
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Intercept	11.04***	10.47***	11.07***	10.54***	10.61***	11.17***
	(0.08)	(0.07)	(0.08)	(0.09)	(0.08)	(0.08)
R^2	0.04	0.03	0.04	0.02	0.04	0.02
N	2976	2976	2976	2976	2976	2976

$^{***}p < 0.0042$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Table A9: OLS estimates of expected earnings per major on treatment indicator, family background indicators, interactions between treatment and family background indicators, and demographic and academic controls. Robust standard errors in parentheses. Three stars indicate statistical significance at the level determined by the Bonferroni method correction.

	Business	Education	Health	Humanities	Social Science	STEM
Intercept	−3.24***	−4.65***	−2.38***	−4.60***	−4.71***	−3.24***
	(0.55)	(0.48)	(0.47)	(0.46)	(0.51)	(0.53)
Security/Dispersion	0.04	0.02	−0.02	0.04	0.02	0.07
	(0.16)	(0.14)	(0.15)	(0.14)	(0.15)	(0.16)
Low-Income or First-Gen.	−0.12	−0.04	0.16	0.03	0.22	0.07
	(0.20)	(0.19)	(0.19)	(0.19)	(0.20)	(0.20)
Low-Income and First-Gen	−0.39	−0.15	0.06	0.04	−0.14	0.07
	(0.32)	(0.29)	(0.31)	(0.29)	(0.30)	(0.32)
Gender	0.60***	−0.31*	−0.69***	−0.56***	−0.53***	0.82***
	(0.14)	(0.12)	(0.12)	(0.12)	(0.13)	(0.13)
Age	0.00	0.01	−0.05***	0.00	0.02	−0.04*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Asian	0.46·	−0.14	0.16	−0.47*	−0.85***	1.03***
	(0.24)	(0.21)	(0.23)	(0.21)	(0.23)	(0.24)
Latino	−0.00	0.53*	0.14	0.24	−0.12	0.66**
	(0.25)	(0.22)	(0.24)	(0.23)	(0.24)	(0.25)
Unknown	0.14	0.73·	0.35	0.55	0.41	0.47
	(0.46)	(0.43)	(0.50)	(0.41)	(0.44)	(0.51)
Multiple Race	−0.44	0.09	−0.27	0.34	0.22	0.37
	(0.37)	(0.33)	(0.36)	(0.34)	(0.36)	(0.37)
Caucasian	−0.21	0.13	−0.40·	−0.23	−0.36	−0.06
	(0.23)	(0.21)	(0.22)	(0.21)	(0.22)	(0.23)
Sophomore	−0.01	−0.06	−0.19	−0.13	0.05	−0.54***
	(0.17)	(0.15)	(0.16)	(0.15)	(0.16)	(0.17)
Junior	−0.08	−0.08	−0.19	−0.02	0.32*	−0.73***
	(0.17)	(0.15)	(0.16)	(0.15)	(0.16)	(0.17)
Somewhat Likely	−0.07	0.05	0.14	0.15	0.23	−0.02
	(0.21)	(0.18)	(0.18)	(0.18)	(0.19)	(0.20)
Somewhat Unlikely	−0.04	0.01	0.12	0.41	0.06	0.38
	(0.29)	(0.25)	(0.25)	(0.26)	(0.26)	(0.28)
Very Likely	−0.95***	−0.17	0.67***	−0.14	−0.18	0.24
	(0.19)	(0.17)	(0.17)	(0.17)	(0.18)	(0.18)
Very Unlikely	−0.12	−0.60*	−0.42	−0.02	−0.65·	0.28
	(0.36)	(0.30)	(0.31)	(0.33)	(0.34)	(0.37)
Campus 1	−0.28	−0.40*	−1.04***	0.18	0.32·	0.83***
	(0.20)	(0.18)	(0.20)	(0.18)	(0.19)	(0.19)
Campus 2	0.37	0.06	−0.79***	0.05	0.52*	0.26
	(0.25)	(0.23)	(0.24)	(0.22)	(0.24)	(0.24)
Median Earnings x Low Income or First Gen.	0.03	0.12	−0.13	0.07	0.01	−0.17
	(0.29)	(0.26)	(0.27)	(0.26)	(0.28)	(0.29)
Median Earnings x Low Income and First Gen.	0.53	0.35	0.23	−0.06	0.73·	−0.27
	(0.44)	(0.41)	(0.43)	(0.41)	(0.43)	(0.44)
R^2	0.06	0.02	0.07	0.03	0.04	0.09
N	1911	1911	1911	1911	1911	1911
Log-likelihood test p-value	0.49	0.65	0.72	0.94	0.22	0.74

Table A11: OLS estimates of expected probability of completion per major. We exclude senior students from analysis. Regressions also include demographic and academic controls. Models include interaction terms between Median Earnings treatment indicator and family background indicators. Robust standard errors in parentheses. Three stars indicate statistical significance at the level determined by the Bonferroni correction.