The Effect of Labor Market Information on Community College Students' Major Choice

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Abstract

An important goal of community colleges is to prepare students for the labor market. But are students aware of the labor market outcomes in different majors? And how much do students weigh labor market outcomes when choosing a major? In this study we find that community college students in California generally rank majors accurately in terms of labor market outcomes but their beliefs can significantly deviate from observed outcomes. Students believe that salaries are 13 percent higher than they actually are, on average, and students underestimate the probability of being employed by almost 25 percent. The main determinants of major choice are beliefs about course enjoyment and grades, but expected labor market outcomes also matter. Experimental estimates of the impact of expected labor market outcomes are much larger than OLS estimates and show that a 1% increase in salary is associated with a 1.4 to 1.8% increase in the probability of choosing a broad major.

Introduction

Community colleges serve a large, and rapidly increasing, share of college students in the United States. These students are more likely than their four-year peers to be underrepresented minorities and to come from disadvantaged backgrounds (Bailey, Jenkins & Leinbach, 2005). An explicit mission of community colleges is to improve the labor market outcomes of these disadvantaged student populations (American Association of Community Colleges; California Community Colleges). Much attention, at the federal, state, and institutional level, has recently been paid to the labor market outcomes of community college graduates from these career-oriented programs (see, for example, Jepsen, Troske & Coomes, 2014; Dadgar & Trimble, 2014; Xu & Trimble, 2015).

Labor market outcomes associated with various degrees and certificates vary dramatically. Many awards are associated with significant positive increases in earnings and probability of employment, while others have been shown to have insignificant effects on earnings (Stevens et al, 2015; Bahr, 2015). This means that, for community colleges to best fulfill their mission of improving the labor market outcomes of their students, students need to be aware of differences in outcomes across awards. The degree to which this is true is not clear.

The existing research on students' knowledge of labor market outcomes has focused on students attending selective four-year colleges. This work has shown that students have broadly accurate information about the relative rankings of labor market returns associated with various degrees but that many students make large errors in specific estimations (Arcidiacono, Hotz & Kang, 2010; Huntington-Klein, 2015). In particular, lower income and lower GPA students are less well informed (Attanasio and Kaufmann, 2012; Betts, 1996). Given that community college students are disproportionally disadvantaged and have weaker access to informed social networks, it is unclear to what extent previous findings apply to community college students.

Furthermore, information is not enough if it is not used as a basis for decision making. This premise, that expected labor market outcomes should be an important part of the major choice decision for students in community colleges, is foundational in a number of initiatives being undertaken by high-profile national players. The Aspen Institute, Jobs for the Future, the American Association of Community Colleges, various state community college systems, and most notably the U.S. Department of Education's College Scorecard have recently focused efforts on helping students, and schools, use labor market information in making decisions. But these efforts can only succeed if students take labor market outcomes into account when choosing a major.

In this paper, we provide empirical evidence on the potential efficacy of such initiatives. We examine to what extent community college students factor in labor market outcomes when choosing a degree. Studies of students in selective four-year colleges indicate that degrees are mostly chosen for non-pecuniary reasons, with expected salary playing a significant but minor role (Beffy et al, 2012; Wiswall and Zafar, 2015a; Stinebrickner & Stinebrickner, 2014). In this paper we ask if that is also the case for community college students. If community college students face stronger incentives to make ends meet, and if degrees in community colleges have more heterogeneous returns, one may expect labor market outcomes to play a larger role in determining major choice.

First, leveraging unique administrative data on the labor market outcomes of community college students, we examine the accuracy of students' beliefs about the labor market outcomes of different majors for alumni of their college. An important innovation of our study is that we examine beliefs about both wages and employment, while previous literature has focused mostly on wages. Furthermore, we ask students about labor market outcomes for graduates from their own college, as compared to the outcomes for a national sample of students, which should be the most directly relevant and perhaps the best known. We find that students have broadly accurate views of the average labor market outcomes of graduates in various fields. Students generally correctly rank fields in all outcomes. However, we also find that students overestimate salaries by 13% and underestimate the probability of finding employment by almost 25% in almost all fields. Finally, we find that low income students are more likely than their higher income peers to have large errors in estimating the probability of employment.

Second, we examine the determinants of major choice. An important innovation of our study is to compare the estimates from observational data with the estimates from an experiment. Indeed, with the exception of Hastings et al (2015) and Wiswall and Zafar (2015a,b) who focus respectively on Chilean students and NYU students, most of the previous literature is non-experimental. In our experiment, we provide students with hypothetical information about the labor market outcomes for various majors and elicit their probability of choosing a given major given this new information. In our observational data, expected course enjoyment is the most important predictor of major choice, followed by expected grades. Salary and employment probabilities have a positive relationship with major choice but the effect is not always statistically significant. On the other hand, in our experimental study, we find that salary and employment both have a significant effect on major choice, and this effect is quantitatively much larger than in the observational data. Based on our experimental estimates, a 1% increase in salary is associated with about a 1.4% (for business) to 1.8% (for humanities) increase in the probability of choosing a major, while a 1% increase in the probability of employment is associated with a 0.2 to 0.6% increase in the probability of choosing a major. Comparing the experimental and non-experimental estimates, we find evidence consistent with students' lack of information dampening the impact of labor market outcomes on major choice in observational data. Overall, these results show that estimates based on observational data are a poor predictor of the impact of labor market information on major choice.

Surprisingly, community college students are not very different from their peers in four-year schools: they also put the most weight on non-labor market outcomes, such as course enjoyment, when choosing a major. The preeminence of non-labor market outcomes in major choice is partly explained by students' lack of information about these labor market outcomes. Our results suggest that better information about labor market outcomes, as well as increasing the salience of information about labor market outcomes, could serve community colleges' goal of improving their students' labor market prospects.

Background and literature review

Traditional human capital theory posits that students will make educational decisions (how long to persist, what degree to pursue) based on a calculation of the perceived costs relative to the perceived discounted benefits (Becker, 1962). This simple model rests on a number of factors: how accurate students' information is, which kinds of benefits are weighted most heavily (labor market, consumption, etc.), and how students update their beliefs based on new information.

While there is a literature on major choice and labor market outcomes for four-year college students, this paper is the first to look at major choices for students in community colleges. We argue that it is important to examine this population for four main reasons. First, as compared to students in four-year schools, students in community colleges are more likely to be first generation college students, more likely to be from low-income backgrounds, and more likely to be underrepresented minorities (Bailey, Jenkins & Leinbach, 2005). In addition to consequences for equity and social mobility, this has important implications for the potential effects of information about labor market outcomes. Namely, we hypothesize that students in community colleges may be more sensitive to information gaps, as they have thinner social networks, less access to information, and are more likely to use in-school sources to get information about earnings (Scott-Clayton, 2011; Hastings et al 2015).

Second, on average, community colleges offer many more award options than four-year schools, and these awards are more heterogeneous in both focus and length (purely vocational, academic, short- and long-term certificates, associate degrees). This creates a complicated decision making environment in which students must weigh a number of potential options using a range of criteria (Scott-Clayton, 2011; Rosenbaum, Deil-Amen & Person, 2006). In order to improve the labor market outcomes of community college students, it is important to understand how they navigate this complex decision.

Third, community college students have traditionally persisted and graduated at relatively low rates. While the vast majority of students in community colleges have the intention of earning a bachelors degree when they start, very few actually do (Rosenbaum & Rosenbaum, 2013). For this reason, it may be more efficient for many students to aim for a relatively fast transition to the labor market with a one or two year degree or certificate that would enhance their earnings and job opportunities. This high probability of not completing a bachelors degree creates a different decision making environment than in four-year schools and necessitates conceptualizing the effect of labor market information anew.

Fourth, the training that occurs in community colleges is tied to a wider range of labor market outcomes than four-year training, and returns are more heterogeneous across two-year degrees and certificates

than they are across four-year degrees. The average returns to an associate degree or community college certificate are positive (Bailey & Belfield, 2011). However, a number of recent studies have shown that these effects vary greatly by field, with some degrees yielding insignificant earnings returns and others, often degrees in health-related fields, yielding large positive returns (Stevens et al, 2015; Bahr, 2015; Dadgar & Weiss, 2012; Jepsen, Troske & Coomes, 2014; Jacobson, LaLonde and Sullivan, 2005). Additionally, the labor market returns to a community college award go beyond salary; the effects on probability of employment and on hours worked is at least as significant as the effect on wages (Dadgar & Weiss, 2012; Jacobson, LaLonde and Sullivan, 2005; Marcotte et al, 2005).

Second, previous literature has mostly examined students' beliefs about wages. As noted above, for certain certificates and associate degrees, the labor market benefits might be on the margin of employment or the number of hours worked, rather than affecting hourly rate. In this study we examine the accuracy of students' knowledge labor market returns in terms of both probability and stability employment in addition to wages. Recent empirical work indicates that while college students can generally accurately rank the returns to various major categories and levels of awards (Arcidiacono, Hotz & Kang, 2010; Huntington-Klein, 2015), many students make significant errors in estimating returns to various degrees (Betts, 1996; Arcidiacono, Hotz & Kang, 2010). In addition, there is important heterogeneity; students tend to get more accurate over time (students in their fourth year offer more accurate predications than students in their first year) (Zafar, 2011; Betts, 1996), students from lower income families tend to underestimate the returns to schooling (Attanasio and Kaufmann, 2012; Betts, 1996), students with higher GPAs make smaller errors (Betts, 1996), and there is significant variation in accuracy across majors (Wiswall and Zafar, 2015b).

While investigating beliefs about returns to various degrees is interesting, if students don't use this information to make curricular decisions, it has few practical implications. A number of studies have attempted to decompose the effects of various factors that students use to make decisions. Most studies have found that expected enjoyment is the biggest driver of choice (Beffy et al, 2012; Wiswall and Zafar, 2015a; Stinebrickner & Stinebrickner, 2014) and that ability (comparative advantage) is an important consideration (Arcidiacono et al, 2010). Zafar (2009) finds that non-pecuniary outcomes explain about 45% of choice behavior for males and 75% for females.Most recent literature finds that the effect of expected earnings on major choice is small but significant. Wiswall and Zafar (2015a) show that a 1% increase in beliefs about self earnings in a major increases the log odds of graduating in that major by 2%. However, beliefs about self earnings are correlated with unobserved reasons why students prefer a certain major: when using experimental variation in beliefs about self earnings, a 1% increase in beliefs about earnings in a given major only increases the log odds ratio of graduating in that major by 0.28%.

In this study, we surveyed 376 students at two community colleges in California's Bay Area. We ask students about their knowledge of labor market outcomes, their curricular plans, and how they would respond to specific information about labor market outcomes in different fields of study. We examine how community college students differ from students at selective four-year schools. Importantly, we are the first study to examine a range of labor market outcomes (beyond salary), so we can examine which specific labor market outcomes are most important to students.

Methodology and Results

Our data come from an original survey administered at two community colleges in California's Bay Area in the winter of 2014. To increase response rates, we administered the survey in person in courses (using paper and pencil). We sent a request to administer the survey to course instructors via the departmental representatives to the faculty senate. Due to the nature of the survey questions, we targeted academic (not strictly pre-vocational) classes with no pre-requisites that enrolled mostly students in their first year.

Our sample of 12 classes consisted of courses that fit our sampling criteria and had instructors who were willing to use 30-40 minutes of class time for the survey. The classes were in a number of disciplines, including psychology, environmental science, language arts and biology. A member of the research team (Rachel Baker) administered the survey in each class and was present to read instructions and answer questions. The 12 classes had a total enrollment of about 470 and daily attendance of about 80%, so we obtained responses from 376 students. In each class, no students who were present opted out of the survey. Students took an average of 25 minutes to complete the survey. We provided an incentive of two $25 Amazon.com gift cards to each class and raffled the gift cards off when all students were finished with the survey. We also gave each participating instructor a $25 Amazon.com gift card.

Due to our sampling strategy, the students in our sample are more transfer- and academically-oriented than the average community college student. Sixty-four percent of the students in our sample stated that their most likely outcome was transfer (as opposed to earning an associates degree or certificate). The students in our sample were also younger than the mean community college student (mean age 23), and almost a quarter of the students in our sample were in their first term of college. We will return to the implications of these sample characteristics for the interpretation of our results in the discussion section.

Table 1: Student Descriptives presents descriptive information about the students who are included in the sample.

Table 1: Student Descriptives

Survey Summary Statistics	mean
Age (years)	23.472
Self-reported family income is < $50,000	0.430
No parent with college degree	0.438
Student is in first term	0.241
Self-reported HS GPA is ≥ B	0.733
Latino	0.243
White	0.293
Asian	0.508
Black	0.037
Pacific Islander	0.035
Student lists as most likely award:	
Transfer	0.641
AA	0.135
Cert	0.112
No Degree	0.112
Student lists as most likely broad major field:	
Science	0.378
Business	0.173
Language Arts	0.138
Humanities	0.311
Expectations about awards:	
Expected Salary	$44,689

Exp. Prob. of having a job	0.435
Exp. Stab. of employment	0.532
Prob. of enjoyment	0.532
Predicted grades	4.1/5
N	376

The survey, available in Appendix A, had four main sections: (1) students' self-reported probabilities of choosing each of four broad major fields and their expectations about enjoyment, grades, and labor market outcomes in each of these fields[1]; (2) the same information about the three specific majors that students state they are most likely to choose; (3) experimental questions in which we randomly assign hypothetical labor market information about two broad majors to students and ask them how this changes their probability of choosing a given major; and (4) multiple choice questions in which we ask students where they get information about expected salaries for majors and which factors they value when choosing a major. Additionally, we collected background demographic information from each student and linked survey responses to administrative transcript and application data. In this paper, we will be focusing on sections (1) and (3).

To assess students' accuracy in estimating the outcomes associated with various degrees and certificates, we collected data from the California Employment Development Department (EDD) Labor Market Information Division. For 2006-2013 graduates who earned each award offered at the two community colleges in our sample (e.g. AA in Music Technology in 2007, certificate in Network Administration in 2010), we collected data on the probability of employment six months after graduation (proportion of graduates who had positive wages in either of the two quarters after graduation), the mean salary three years after graduation (all adjusted to the 2013 consumer price index), and the stability of employment for graduates in the three years after graduation (number of quarters with positive wages/12 quarters). One important factor that sets this study apart from most previous studies is that we ask students about their expectations for students from their own college and compare their responses to this data (rather than comparing their responses to data on all graduates in the country or to data on students from different areas of study). This is an important improvement on past work, particularly in the context of community colleges, where the local labor market is particularly important.

[1] One methodological note is important to include here. On the survey (available in Appendix A), we asked for students' expectations about the labor market outcomes associated with earning an *associates degree* in each field. We did not ask for the labor market outcomes associated with transferring and then earning a *bachelors* degree in each field (in fact, we explicitly told students NOT to answer the question with students who successfully transfer an earn a BA/BS in mind). This, of course, affects the interpretation of our results, but we felt this was the most appropriate course of action for a few reasons. First, estimating labor market outcomes for students who transfer from a two- to four-year college is a function of a number of factors: probability of admission to a four-year school, probability of finishing a four-year school, selectivity and curriculum of both the two- and four-year schools, etc. Second, the time horizon necessary for estimating such returns is necessarily protracted—students will not be entering the labor force for at least four (and likely five or six) years. Finally, while the majority of our students stated that they intended to transfer and earn a bachelors degree, evidence from these schools, and community colleges more generally, indicates that most of these students will not transfer and those who do might not earn a four-year degree. The labor market outcomes associated with earning an associates degree is both simpler to estimate and more plausibly relevant for the students we sampled.

Descriptive summary results

Seventy-seven percent of students in our sample report that they are considering majors in more than one broad major field. On average, students are considering 2.63 fields with non-zero probability (1/3 of students are considering all four broad fields). Many students report 0 or very low probabilities of majoring in Language Arts, and Business & Technology[2] (for each of these two broad majors, almost half of students state that there is less than a 10% probability that they will select it).

[2] This could be a function of the sample of classes in which we administered the survey.

Table 2 : Students' beliefs of labor market outcomes

	Average Salary[a]		Belief of Salary[b]		Prob. of Employment[c]		Belief of Prob. of Employ.[d]		Percent of Time with a Job[e]		Belief of Stability of Employ.[f]	
	M	Rank	M	Rank	M	Rank	M	Rank	M	Rank	M	Rank
Science, Math & Engineering	46,300	2	51,919	2	0.615	2	0.466	2	0.611	2	0.599	1
	(27,395)		(35,501)		(0.211)		(0.256)		(0.196)		(0.587)	
Business, Comp. Sci. & Tech.	51,473	1	52,149	1	0.652	1	0.498	1	0.641	1	0.590	2
	(17,885)		(33,326)		(0.186)		(0.235)		(0.150)		(0.248)	
Arts & Language	28,820	4	34,850	4	0.485	4	0.369	4	0.473	4	0.462	4
	(13,635)		(19,480)		(0.135)		(0.221)		(0.131)		(0.246)	
Humanities & Social Sciences	33,180	3	39,702	3	0.537	3	0.406	3	0.529	3	0.503	3
	(12,005)		(26,629)		(0.148)		(0.228)		(0.143)		(0.251)	

Notes: All labor market information comes from the California Employment Development Department, Labor Market Information Division and represents 2006-2010 graduates from two community colleges in Northern California. [ace] Mean annual salary of graduates three years after graduation, in 2013 dollars; percent of graduates who are employed six months after graduation; fraction of quarters that graduates have non-zero earnings in the three years after graduation. [bdf] Students were asked: Average annual salary a recent graduate from CCD with an AA/AS in this field (who doesn't continue to a BA/BS) will make 3 years after graduation; probability a graduate will have a job six months after graduation; percent of time a graduate will be with a job in the first three years after graduation.

In Table 2, we see that students in our sample have broadly accurate views of the average labor market outcomes of graduates in various fields. They generally correctly rank fields in all outcomes (salary, probability of employment, and stability of employment), which is similar to Zafar's (2012) finding for students knowledge of relative salaries.

We find that students generally overestimate expected salaries, which matches what Hastings et al (2015) find with Chilean students, and is different from what Zafar (2011) found at a selective U.S. college. The only field in which they don't overestimate is Business, Computer Science & Technology,. On the other hand, students overestimate the most (in % terms) the salaries in Arts & Languages.[3] In all fields, students underestimate the probability of being employed. The degree of underestimation is remarkably consistent across fields—on average, students think the probability of being employed is about 75% of what it actually is. Students also underestimate the average stability of employment (percentage of the time with an income), but not nearly as much as they underestimate the probability of being employed. Overall, students overestimate salaries and underestimate the employment outcomes of awards.

There is a relatively wide distribution of students' beliefs about their own outcomes as compared to others' outcomes. Students' expected outcomes for themselves are higher than the population on average (10% higher for probability of having and stability of a job, 4% higher for salary), but there is a wide range, as shown by Figure 1, which plots the distribution of the difference between own outcomes beliefs and other students outcomes beliefs.

[3] One methodological note is important here. Our measure of the "true" salary is restricted to those graduates who have positive earnings in a given quarter, and thus included graduates who had positive earnings but did not work full-time for the whole quarter. Students in our survey may have been thinking of someone who is employed full-time for the full year, which could explain why they overestimate salary.

Figure 1: Expectations for Self vs. Others

Errors in beliefs about labor market outcomes

To examine students' errors in beliefs about labor market outcomes we used a similar measure as Zafar (2011) and Betts (1996):

$$error_{if} = \frac{s_{if} - s_{obs,f}}{s_{obs,f}} * 100$$

Where s_{if} is student *i*'s estimate of the labor market outcome of field *f* and $s_{obs,f}$ is the observed labor market outcome for field *f.* This measure represents the percent error in the student's belief relative to the actual outcome: for example, a value of 10 for salary error means that the student believes the salary to be 10% higher than it actually is. We constructed two measures for the error in beliefs: (1) error measure defined above, (2) absolute value of the error measure defined above. Since errors can be both positive and negative, a mean error close to zero does not necessarily indicate uniformly low errors. Reporting the absolute value of errors in addition to the mean error allows us to examine a measure of the dispersion of errors.

Table 3: Distribution of Errors and Absolute Value of Errors

	Mean	25th percentile	Median	75th percentile
			Error	
Salary	13.5	-30.6	4.1	38.8
Probability of Employment	-24.0	-58.8	-23.3	7.4
Stability of Employment	-4.3	-36.6	-5.5	26.7
			Absolute Error	
Salary	47.0	13.6	35.2	56.8
Probability of Employment	40.0	17.5	38.1	58.8
Stability of Employment	38.3	14.5	32.3	56.0

In Table 3 we see that on average, students overestimate salary by 13.5% and underestimate both probability and stability of employment, by 24% and 4.3% resepectively. The absolute errors indicate that students generally make large errors; 50% of students make errors larger than 30% for each of the labor market outcomes.

Table 4: Median Errors and Absolute Value of Error by Major

	Business	Humanities	Language & Arts	Science
			Error	
Salary	-2.9	5.5	4.1	8.0
Probability of Employment	-23.3	-25.5	-38.1	-18.8
Stability of Employment	-6.4	-5.5	5.6	-18.2
			Absolute Error	
Salary	32.0	35.6	38.8	35.2
Probability of Employment	23.3	44.1	38.1	35.0
Stability of Employment	24.8	32.3	36.6	30.9

Table 4Error! Reference source not found. shows that students' errors differ by major field. Students' errors are the largest, on average, for humanities and the smallest for business. Students are more likely to underestimate the labor market outcomes associated with business than they are for other fields.

Regression Outcomes

We examine student errors in two ways: asking first if certain groups of students have particularly large errors and asking second if certain groups of majors are associated with larger or smaller errors. We first use a model that examines differences between groups of students. We use the following model:

$$Y_{i,j,bm} = \boldsymbol{\Gamma_{bm}\beta_1} + \mathbf{X_i\beta_2} + \beta_4 own_{bm,i} + \varepsilon_i \quad (1)$$

$Y_{i,j,bm}$ is student *i*'s error in predicting labor market outcome *j* in broad major category *bm*. $\boldsymbol{\Gamma_{bm}}$ is a vector of broad-major fixed effects, $\mathbf{X}_i$ is a vector of student-level covariates which includes a dummy variable indicating if a student is from a low income family, a dummy variable for gender, and a dummy

variable indicating if the student is in his/her first term, and $own_{bm,i}$ and a dummy variable is a dummy equal to one if broad major *bm* is the intended major of student *i*. Standard errors are clustered at the student level. We estimate this model six times: for error and absolute value of error for each of the three labor market outcomes (stability and probability of employment and expected salary). The coefficients of interest is $\boldsymbol{\beta_2}$**.** That is, for a particular labor market outcome, within a broad major field, do certain groups of students have larger or smaller errors?

In addition, we estimated a model that included student fixed effects. Thus, the results from this model express the relative error for a given labor market outcome for a student. This student fixed effects model allows us to ask: do students systematically make larger or smaller errors for certain subjects or for certain labor market outcomes? We predicted two outcomes: (1) error measure as defined above, (2) absolute value of the error measure defined above. We use the model below:

$$Y_{i,bm} = \boldsymbol{\Gamma_{bm}\beta_1} + \boldsymbol{\Theta_{outcome}\beta_2} + \boldsymbol{\phi_i\beta_3} + \beta_4 own_{bm,i} + \varepsilon_i \quad (2)$$

Where each term is the same as defined above, $\boldsymbol{\Theta_{outcome}}$ is a vector of dummy variables for each labor market outcome (expected salary, probability of employment, stability of employment), and $\boldsymbol{\phi_i}$ is a vector of student fixed effects.

The results from model 1 are presented in **Error! Reference source not found.** below.

	Salary		Prob. of Employ.		Stab. of Employ.	
	% Error	|% Error|	% Error	|% Error|	% Error	|% Error|
Low Income	5.7057	6.2176	-6.2072	4.5211*	-2.1294	-0.9153
	(7.8733)	(5.8909)	(4.0932)	(2.3615)	(5.1506)	(3.4223)
Female	-8.0773	4.2466	2.0368	-0.5228	-1.8945	4.9655
	(7.2837)	(5.3630)	(4.0802)	(2.3492)	(4.9109)	(3.2043)
First Term	9.5481	17.4074**	-3.5417	3.0486	-6.6470	-4.4768
	(10.8579)	(8.1647)	(4.7938)	(2.8071)	(5.0778)	(3.1791)
Intended Major	9.7176**	3.5495	6.6093***	-3.7389***	4.1830	-6.5145**
	(4.0045)	(3.6694)	(1.9760)	(1.3850)	(3.4821)	(3.0853)
Constant	8.6512	37.5259***	-26.1322***	39.9803***	-1.1887	43.2329***
	(6.2830)	(4.5982)	(3.9879)	(2.3647)	(7.3769)	(6.4344)
Field Fixed Effects	X	X	X	X	X	X
Observations	1,064	1,064	1,142	1,142	1,210	1,210
R-squared	0.0214	0.0213	0.0116	0.0275	0.0043	0.0125

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Low income students are more likely than their higher income peers to have large errors in estimating the probability of employment (fourth column of **Error! Reference source not found.**), though these errors

are not systematically over- or under-estimates. Low- and high-income students do not have significantly different expectations about salary, which is different from what Hastings et al (2015) found. The difference with Hastings et al. (2015) may be explained by the fact that we consider a sample of relatively disadvantaged students while Hastings et al study the whole population of college-bound Chilean students. Students in their first term make significantly larger errors in estimating salary than students who have been enrolled longer (**Error! Reference source not found.**, second column). Their errors are not systematically over- or under-estimates. Students are more accurate in estimating labor market outcomes (stability and probability of employment) in their intended major than all other majors, similar to what Arcidiacono et al (2012) found. Students are more likely to overestimate the salary in their intended major as compared to other majors[4] (first column).

Why do students overestimate salary in their intended major? Students may correctly think that they will make more in their intended major than students who do not choose this same major. However, we do not compare students' beliefs about their *own* salary with their beliefs about the salary for other students in any given major, nor do we ask them to compare their beliefs about their own salary in their intended major as compared to other majors. Instead, we are asking students about the salary of *past graduates* from their college in a range of majors. Thus, comparative advantage cannot explain intended major overestimation. Instead, it is more likely that being overoptimistic about salary makes students more likely to prefer a certain major. We will explore the determinants of major choice – salary among them – below.

The results from model (2), exploring the heterogeneity in errors by major and labor market outcomes are presented in Table 5 (for reference, unconditional errors for each broad major category are shown in Table 4).

Table 5: Predicting Errors in Labor Market Outcome Estimates, Student Fixed Effects

	% Error	|% Error|

[4] Differences in errors in estimation are presented visually in the Appendix B in kernel density plots.

Business/CS	-2.7851	-7.2918***
	(2.5226)	(2.0593)
Arts & Lang. Arts	4.6116*	-0.0710
	(2.5340)	(2.0686)
Hum & Soc. Sci.	2.7257	-0.4588
	(2.4971)	(2.0385)
Prob. Of Employment	-36.0296***	-5.7012***
	(2.2236)	(1.8152)
Stability of Employment	-16.6109***	-8.9726***
	(2.1849)	(1.7836)
Intended Major	6.5463***	-2.6477
	(2.0774)	(1.6958)
Constant	9.7618***	49.2940***
	(2.3434)	(1.9130)
Student Fixed Effects	X	X
Observations	3,646	3,646
R-squared	0.3474	0.2222

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
Omitted Broad Major is Sci, Math & Eng, Omitted LMO is salary. Unit of observation is at the student-by-broad major-by-outcome level.

Students have smaller errors in estimating the average labor market returns to Business/CS than they do estimating the labor market returns to science, math and engineering (the omitted category). On average, students overestimate the labor market outcomes for Arts & Language Arts degrees. Students have smaller errors in estimating the probability and stability of employment than they do in estimating expected salary. However, the errors students make in predicting probability and stability of employment are more likely to be underestimates. While students are no more accurate in estimating the labor market outcomes for their own major, they are more likely to overestimate outcomes in their own field.

Overall, we find that students tend to correctly rank majors but overestimate salaries (by 13%) and underestimate the probability of employment (by 25%). Furthermore, low income students make larger errors in estimating the probability of employment. We now move on to examining the impact of students' beliefs about labor market outcomes on their major choice.

Determinants of Major Choice

Non-experimental results

First, we examine the relationships between choice and students' estimates of labor market outcomes, ability and enjoyment. Summary statistics for the variables shown in this correlation table can be found in Table 1.

Table 6: Correlations between Probability of Choice and Estimates of Outcomes

	Prob. of choosing	Expected Salary	Exp. Prob. of having a job	Exp. Stab. of employment	Predicted enjoyment	Predicted grades
Prob. of choosing	1					
Expected Salary	.0921 *	1				
Exp. Prob. of having a job	.1042 **	.1792 ***	1			
Exp. Stab. of employment	.0966 **	.1449 ***	.6613 ***	1		
Prob. of enjoyment	.6326 ***	0.0398	.0726 *	0.0617	1	
Predicted grades	.4806 ***	-0.0118	0.0539	0.0575	.5657 ***	1

Table 6 shows that the probability of choice is significantly correlated with all expected outcomes. Labor market outcomes (salary, probability and stability of having a job) are significantly positively correlated with each other. The belief about salary is not correlated with beliefs about enjoyment or ability; this is in contrast to the finding of Wiswall and Zafar (2015a) that taste for majors is correlated with salary expectations. On the other hand, the belief about having a job is correlated with the belief about enjoyment.

To examine how these beliefs predict the probability of choosing a given field, we estimate the following model based on Blass, Lach, and Manski (2010), and also used by Wiswall and Zafar (2015a):

$$\left(ln\pi_{k,i} - ln\pi_{h,i}\right) = \beta_0 + \beta_1\left(lnw_{k,i} - lnw_{h,i}\right) + \beta_2 X_{k,i} + \varepsilon_{k,i} \quad (3)$$

where $\pi_{k,i}$ is the stated probability for student i to major in field k. The subscript h stands for humanities, as everything is relative to humanities. The key explanatory variable is $lnw_{k,i} - lnw_{h,i}$, i.e. the difference in belief about salary of past graduates in this field relative to humanities. Thus, the variation we use to identify β_1 is both the true difference in the labor market outcomes between field *k* and humanities and students' errors in estimating this difference.[5]

In some specifications, we also add differences in beliefs about having a job, job stability (both shown in Table 7), and predicted enjoyment and average grade (shown in Table 8).We also extend our baseline specification in two ways: adding a vector of individual controls ($X_{k,i}$, including gender, race, measures of SES, and high school GPA) and adding a vector of student fixed effects.[6]

[5] The reason why everything must be expressed relative to a baseline choice is that the econometric model we use here is an extension of the multinomial logit (Blass, Lach, and Manski 2010). In the standard logit, there are only two choices, so the reference choice is easily determined as "the other choice." However, in a multinomial logit, there are three or more unordered choices. Therefore, a reference choice must be used as the default choice to which other choices are being compared.

[6] We also estimated models that included fixed effects for the broad majors. These models produced very similar results and we do not present them here (results available upon request). When adding broad major fixed effects, we are taking away any common component that makes a major more attractive to all students relative to

Individual controls account for the propensity of certain types of students to choose a major other than humanities. For example, a negative coefficient on female would mean that females are less likely to choose something other than humanities. To the extent that certain types of students make systematic errors about the labor market outcomes of different majors, this could lead to bias in the coefficients on the labor market outcomes if we do not control for student type. For example, if we assume that females systematically overestimate the labor market outcomes for humanities, this could explain their choices. In this case, controlling for gender will weaken the relationship between labor market outcomes and major choice. (Appendix E shows the estimated relationship between various individual characteristics and major choice).

The results from the student fixed effects model express the relative relationship between a labor market outcome and probability of choosing a major for a student. This student fixed effects model allows us to control for heterogeneity in individual students' preference for other majors relative to humanities. A similar logic can be applied as the one discussed above for female students. That is, if some individual students have a greater preference for humanities vs. other majors, this could lead them to overestimate the labor market outcomes of humanities relative to other majors. In such a scenario, we may overestimate the importance of labor market outcomes in major choice. Introducing student fixed effects allows us to control for student heterogeneity in the preference for other majors relative to humanities. The fixed effects estimate informs us about the choice between business, language and arts, and science after taking into account a student's general preference for humanities relative to these other majors.

Table 7: Relationship between Major Choice and Predicted Labor Market Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
Predicted Salary	0.6931**		0.4833	0.4638	0.3655	0.7352
	(0.2977)		(0.3072)	(0.3058)	(0.4429)	(0.4741)
Pred. Prob. of Employment		0.4041***	0.4208**	0.3057	0.3478	0.2010
		(0.1465)	(0.1975)	(0.2343)	(0.2833)	(0.3230)
Pred. Stab. of Employment				0.1694		
				(0.1639)		
Constant	-0.1334	-0.0216	-0.1332	-0.1301	-1.8865	0.7039***
	(0.1461)	(0.1376)	(0.1505)	(0.1500)	(1.5026)	(0.2173)
Individual Controls					X	
Student Fixed Effects						X
Observations	772	854	738	738	676	738
R-squared	0.0085	0.0109	0.0152	0.0169	0.0520	0.5847

Robust standard errors clustered at the student level are shown in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
Unit of observation is at the student-by-broad major level.

humanities. It is straightforward to see that if all students agreed on the labor market outcomes of a certain major, we could not estimate the impact of labor market outcomes separately from the major fixed effects. Thus, when using broad major fixed effects, we are living off of students' estimation errors. Our estimation is different from Wiswall and Zafar (2015b) because our main specification does not have self-beliefs on the right-hand side but beliefs about the outcomes of past graduates. Therefore, the heterogeneity in beliefs across individuals about labor market outcomes for a given major is necessarily due to errors.

In the Table 7, columns 1 and 2, we can see that, when we predict probability of choosing a major as a function of either salary or the probability of employment, each predictor is positive and statistically significant. When salary and the probability of employment are included together (column 3), only the probability of employment is statistically significant, but the point estimate on salary is of a similar magnitude: the estimates imply that a 10% change in salary or chance of having a job is associated with a 4 to 5% change in the probability of majoring in a given broad field. If we include all three labor market outcomes together (column 4), none of them is statistically significant. Also, when we control for individual characteristics (column 5) or student fixed effects (column 6), the impact of labor market outcomes becomes insignificant but the point estimates remain very similar.[7]

In Table 8, we repeat the same specifications but we also control for two key determinants of major choice: beliefs about enjoyment and average grades. The estimated relationship between various individual characteristics and major choice is shown in Appendix E.

Table 8: Relationship between Major Choice, Labor Market Outcomes and Enjoyment & Ability

	(1)	(2)	(3)	(4)	(5)	(6)
Predicted Salary	0.4749*		0.4223	0.6112*	0.2315	1.3204***
	(0.2514)		(0.2597)	(0.3156)	(0.3620)	(0.3908)
Pred. Prob. of Employment		0.1051	0.1742	-0.0941	0.0673	0.0561
		(0.1322)	(0.1777)	(0.2729)	(0.2323)	(0.3155)
Pred. Stab. of Employment				0.1876		
				(0.1957)		
Pred. Enjoyment	0.7521***	0.7869***	0.7708***	0.8335***	0.7599***	0.8683***
	(0.0560)	(0.0538)	(0.0556)	(0.0846)	(0.0705)	(0.0738)
Predicted Grades	0.8577***	0.7911***	0.8806***	0.7329***	1.0041***	0.7424***
	(0.1410)	(0.1331)	(0.1433)	(0.1959)	(0.1825)	(0.2105)
# Fam. & Friends w/ this Major				0.1125		
				(0.1808)		
Individual Controls					X	
Student Fixed Effects						X
Constant	0.2651**	0.3741***	0.2776**	0.2004	-0.0781	0.8251***
	(0.1300)	(0.1228)	(0.1348)	(0.1704)	(1.1797)	(0.1846)
Observations	617	691	593	325	544	593
R-squared	0.4060	0.3882	0.4179	0.4157	0.4638	0.7678

Robust standard errors clustered at the student level are shown in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
Unit of observation is at the student-by-broad major level.

[7] We also estimated a model similar to the one shown in Table 7, column 3 that included an interaction between predicted salary and predicted probability of employment. The interaction term was significant and positive, and the sign and significance (and general magnitude) of the coefficients on the salary and probability of employment terms remained roughly the same.

Predicted enjoyment and estimated grades are significant predictors; across specifications, a 10% increase in either enjoyment or grades leads to about an 8% increase in the probability of majoring in a broad field relative to humanities. Salary is a significant determinant of major choice (column 1), while the probability of employment is not (column 2), once we control for enjoyment and grades. The attenuation of the coefficient on the probability of employment is consistent with the fact that the belief about the probability of employment is correlated with the belief about enjoyment (Table 6). When both salary and having a job are included together, neither of them is significant (column 3).[8] Interestingly, when we control for student fixed effects (col. 6), the coefficient on predicted salary becomes larger and more significant. This result suggests that, after accounting for predicted enjoyment and grades, students who have a high probability of choosing humanities are not much more likely to predict a high wage for humanities relative to other majors. Thus, after eliminating the between student variation by using individual fixed effects, we find a stronger effect of salary on major choice.

Overall, we find that enjoyment and grades are the most important determinants of major choice (enjoyment is even more important than grades, as can be assessed by an R-squared that is twice as large when we include only enjoyment vs. only grades as explanatory variables; results not shown here). Labor market outcomes are likely to also matter, but it is difficult to precisely estimate their impact once we control for enjoyment and grades. What is clear is that, even though the average effect of labor market outcomes on major choice may be as high as half the impact of enjoyment, labor market outcomes do not explain much of the variance in major choice, as can be inferred from the very small R-squared in Table 7 compared to Table 8.

Experimental

In this section, we explore the effect of labor market outcomes on major choice by randomly varying students' beliefs about salary and the probability of employment in business and humanities. In our experiment, we present hypothetical labor market outcomes to students. There are two versions of the hypothetical labor market outcomes that were randomly assigned to students (described below, and presented graphically in Appendix D). We instruct students to act as if these outcomes were the real outcomes of past graduates.

Specifically, in the survey (see Appendix A), students are asked to recall and write down their beliefs about the probability of being employed, their expected salary, and their probability of choosing Business, Comp. Sci. & Technology. They are then given, on the same page, two different hypothetical scenarios with respect to the employment opportunities and salary in Business, Comp. Sci. & Technology. For each scenario, corresponding to a specific employment rate and salary in the field of Business, Comp. Sci. & Technology, students report their probability of choosing this major. The same procedure is repeated on the next page for Humanities, Education and Behavioral/Social Sciences.

[8] Of note we also control for the number of family and friends who majored in this field relative to humanities (column 4). This determinant of choice is not significant and makes the sample size shrink, so we only include it once.

In all, students saw four hypothetical scenarios: two for Business, Computer Science & Technology and two for Humanities, Education and Behavioral/Social Sciences. In order to separately identify the effects of expected salary and the effects of expected probability of employment, we use a factorial design. That is, each student saw all possible combinations of high and low estimates of the probability of employment (85-90% and 35-40%, respectively) and high and low estimates of salary ($75-80,000 and $30-$35,000, respectively). Each student was exposed to all four conditions: high employment, high salary; high employment, low salary; low employment, low salary; low employment, high salary. However, each student did not see all four conditions for each of the two majors. This design is depicted graphically in Appendix D.

The experiment allows us to impose randomly assigned beliefs on students, and therefore eliminates the source of bias due to correlation between students' beliefs about labor market outcomes and other determinants of major choice.

We first run this specification[9]:

$$ln\pi'_{k,i} = \beta_0 + \beta_1 lnw'_{k,i} + \epsilon'_{k,i} \quad (4)$$

Where $\pi_{k,i}$ is the probability for student i to major in field k. The key explanatory variable is $lnw'_{k,i}$, the expected labor market outcome for major *k* (salary (column (1), probability of employment (column (2) or both (column (3) in Table 9 and

[9] In the specification using non-experimental data, we had used a generalization of the ordered logit because students had to choose between several different majors with different labor market outcomes. Identification came from the variation across majors in probability of choosing and in expected labor market outcomes. Here, for the experimental results, the students report probability of choice given variation in labor market outcomes for the *same* major. In Appendix D we present results where we re-analyze the experimental data using methods more similar to what we used for the non-experimental data. That is, we predict the difference in probabilities of choosing majors using the difference in stated labor market outcomes. The results are not qualitatively different from what we present here.

Table 10). We run this specification separately for each of the two major groups: Business, Computer Science & Technology, and Humanities, Education and Behavioral/Social Sciences. Because this belief is randomly assigned, it should not be correlated with any omitted factors. We also add two additional specifications where we control for students' previously stated beliefs about salary and employment, as well as previously stated probability of choosing each broad major (from the observational analyses described above, which they were prompted to re-enter in the experimental tables).[10]

The impact of salary on major choice is positive and highly significant based on our experiment: column 1 in Error! Reference source not found. and 11 shows that a 1% increase in salary leads to a 1.4% to 1.8% increase in the probability of choosing a major. The effects are larger for humanities than for business, but the difference is not significant (results from a joint regression including an interaction between business and salary not shown). The impact of the probability of employment when included alone is positive but insignificant (col. 2). When salary and the probability of employment are included together, the impact of the probability of employment becomes larger and significant for humanities majors, implying that a 1% increase in the probability of employment leads to a 0.46% increase in the probability of choosing a major.[11]

Labor market outcomes thus have a large impact on the probability of choosing a major according to our experimental estimates. While the effects seem large, their magnitude is within the range of what was found in the prior literature. For example, Wiswall and Zafar (2015a) show found effects of a 1% increase in earnings that vary between 0.3% and 2%. Our experimental estimates suggest that the true impact of labor market outcomes is towards the higher end of this range.

Table 9: Experimental Estimates of Effect of Labor Market Outcomes on Major Choice: Business, CS, and Technology

	(1)	(2)	(3)	(4)	(5)
"True" salary	1.4244***		1.3903***	1.4540***	1.5003***
	(0.2735)		(0.2767)	(0.2888)	(0.2473)
"True" Prob. Employment		0.5569	0.3647	0.3880	0.4016
		(0.3417)	(0.3362)	(0.3511)	(0.3006)
Prev. Belief of Salary				-0.2329	0.0040
				(0.2702)	(0.2371)
Prev. Belief of Prob. Employ.				0.1065	-0.1634
				(0.2547)	(0.2235)
Prev. Prob of Choosing					0.4639***
					(0.0367)
Constant	17.9108***	-2.2720***	17.3465***	15.3494***	16.7223***
	(2.9632)	(0.2197)	(3.0301)	(4.3134)	(3.7039)

[10] We also tried a specification that includes an interaction between the "true" salary and "true" probability of employment. We find that this interaction is very small and not statistically significant; students do not seem to disproportionately prefer majors with high salary and probability of employment.
[11] In separate regressions we examine if "true" salary has differential effects for students based on their previous probability of choosing this major. In Appendix E we present results from these models, which show that students who previously stated there was zero chance they would select this major seem to be most affected by this new salary information.

Observations	431	431	431	376	362
R-squared	0.0595	0.0062	0.0621	0.0721	0.3434

Robust standard errors, clustered at the student level, are in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Observations are at the student-by-scenario level.

Table 10: Experimental Estimates of Effect of Labor Market Outcomes on Major Choice: Humanities, Education and Behavioral/Social Science

	(1)	(2)	(3)	(4)	(5)
"True" salary	1.8166***		1.9043***	1.9834***	2.0498***
	(0.2850)		(0.2863)	(0.2933)	(0.2562)
"True" Prob. Employment		0.1861	0.4625*	0.5442**	0.5557**
		(0.2614)	(0.2506)	(0.2565)	(0.2241)
Prev. Belief of Salary				-0.0552	-0.0651
				(0.2411)	(0.2169)
Prev. Belief of Prob. Employ.				-0.2947**	-0.4622***
				(0.1492)	(0.1331)
Prev. Prob of Choosing					0.4341***
					(0.0430)
Constant	21.7554***	-1.8889***	22.4405***	22.9385***	22.3808***
	(3.1365)	(0.1941)	(3.1355)	(4.0630)	(3.5470)
Observations	410	410	410	361	345
R-squared	0.0906	0.0012	0.0980	0.1212	0.3755

Robust standard errors, clustered at the student level, are in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Observations are at the student-by-scenario level.

When we add controls to a true experiment, it should not affect the size of the estimates on the variable that is randomly assigned. This is indeed what happens in Table 9 &

Table 10 for true salary (compare coefficients in column 1 and columns 4-5). It is also remarkable that the initial belief about salary no longer matters conditional on true belief (column 4), which is a way of validating that we succeeded in fully changing students' beliefs. Indeed, if we had only updated the beliefs to some limited amount, we would expect both the true salary and the past belief to matter (positively) for student choice.

The initial probability of choosing a major has a positive and highly significant impact on hypothetical major choice after the experiment, and also triples the R-squared (Table 9 &

Table 10, column 5). This is consistent with the fact that there are other important determinants of major choice beyond salary, so people who are inclined to choose a certain major are still inclined to choose it even after accounting for new beliefs about salary.

Experimental vs. non-experimental

The experimental estimate of the impact of salary on major choice is much larger than the non-experimental estimate.[12] In this section, we attempt to explain why the experimental impact of salary on major choice is greater than the nonexperimental impact. We do not find evidence to support four possible explanations. First, it is not the case that the difference is due to the fact that the experiment only deals with humanities and business majors while the observational data considers all majors. Second, the difference is not due to differences in modelling strategies between the experimental and non-experimental analyses (relative vs. absolute change). We provide evidence concerning these two explanations in Appendix F.

Third, of the variables we measured on the survey, we did not find a variable that is negatively correlated with earnings beliefs and is an important determinant of major choice. The variables we measured were exhaustive based on prior literature, and include all that we think are important determinants of major choice. The explanation therefore does not seem to be an omitted variable bias.

A fourth explanation that we do not find support for is more psychological: by only varying labor market outcomes, we make those a lot more salient in our experimental intervention, and we are thus perhaps overestimating their impact. However, two factors make this explanation unlikely. First, the fact that the probability of employment is not such a strong determinant of major choice in the experiment, both in absolute terms and relative to the non-experimental data, even though it was listed before salary in our scenarios, makes this psychological explanation less likely. Second, we explicitly remind people of their original stated probability of choosing this major. This implicit anchoring should make respondents more likely to stick to what they first said[13], and makes it less likely that we are overestimating the impact of labor market outcomes on major choice in the experiment relative to the non-experimental estimates.

Instead, we find support for an explanation based on students' uncertainty. From a Bayesian perspective, if students are more uncertain about some of the determinants of major choice, they should put less weight on these determinants. For example, if students are more uncertain about labor market outcomes than about how much they would enjoy the major, they should put less weight on labor market outcomes than on enjoyment when choosing a major. In the experiment, we provide the "true" labor market

[12] While the estimates are qualitatively different, the 95% confidence interval for the effect of salary on major choice in the non-experimental and experimental estimates do overlap. At the same time, the point estimates from the experimental estimates (for both humanities and business) fall outside the confidence interval of the non-experimental estimate.

[13] Consistent with this interpretation, the original probability of choosing a major has a strong and positive effect on the probability of choosing this major in the experiment in Table 9 and

Table 10.

outcomes, thus removing uncertainty and increasing the estimated impact of labor market outcomes on major choice. This could therefore explain why the experimental estimates of the impact of labor market outcomes on major choice are larger than the non-experimental estimates.

To test this uncertainty hypothesis, we first calculate for each student the percent error (as described above). We take the absolute value of the error and add up the errors for each student. This sum of errors tells us which students make the largest mistakes; these students are likely to be the least certain about their salary predictions, and thus their belief about salary should matter less to their major choice. In Table 11 below, we use the observational data and run an interaction model between the salary belief and the sum of errors (col. 2). This shows that the impact of salary is indeed larger for those who make smaller errors because the point estimate of salary is now larger than in column 1. In column 3, we divide the students in below the median sum error and above the median sum error, thus creating the "large error" dummy. We can see that students who make large errors have a much lower coefficient on salary than students who make small errors, and the interaction is highly statistically significant. Furthermore, for students with small errors, the impact of salary belief on major choice is of essentially the same size as our experimental estimate (1.8 v 1.7). These results can thus provide an account of why experimental results yield a higher impact of salary than the non-experimental results: in the non-experimental case, students who are uncertain about labor market outcomes are likely to put less weight on them when choosing their majors.

Table 11: Relationship between Student Errors and Role of Salary in Major Choice

	(1)	(2)	(3)
Belief of Salary	0.6931**	0.9759**	1.8182***
	(0.2977)	(0.4823)	(0.5392)
Sum of Salary Errors		-0.0011	
		(0.0008)	
Sum(error)*Sal. Belief		-0.0009	
		(0.0014)	
Error>p50(Error)			-0.3867
			(0.2911)

Large Error*Sal. Belief			-1.3993**
			(0.6379)
Constant	-0.1334	0.0582	0.0154
	(0.1461)	(0.2036)	(0.1997)
Observations	772	772	772
R-squared	0.0085	0.0130	0.0198

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Conclusion

In this paper, we provided new evidence about the role of labor market outcomes in determining major choice among community college students. We find that students have some information about labor market outcomes but this information is limited. Students correctly rank the labor market outcomes of broad majors on average, but they make large errors. In particular, students systematically overestimate salaries (by 13%) and underestimate employment outcomes (by almost 25%). Furthermore, lower income students are more likely to make mistakes in estimating the probability of employment.

We then examine the determinants of major choice among community college students. We find that course enjoyment and grades are the most important determinants. Labor market outcomes also play a role, but this role is underestimated in non-experimental data. Using experimental data, we find that a 1% increase in salary is associated with an almost 2% increase in the probability of choosing a major, while a 1% increase in the probability of employment is associated with about a 0.5% increase in the probability of choosing a major. We find evidence consistent with the greater impact of labor market outcomes in our experimental data being driven by students' lack of information at baseline. Indeed, if students are uncertain about labor market outcomes, it can be rational to put less weight on these labor market outcomes when choosing a major.

Our results suggest that providing better information about labor market outcomes has the potential to significantly affect major choice among community college students. We also find that students put the most weight on course enjoyment when choosing a major. Thus, increasing the salience of labor market outcomes may also help students improve their labor market outcomes.

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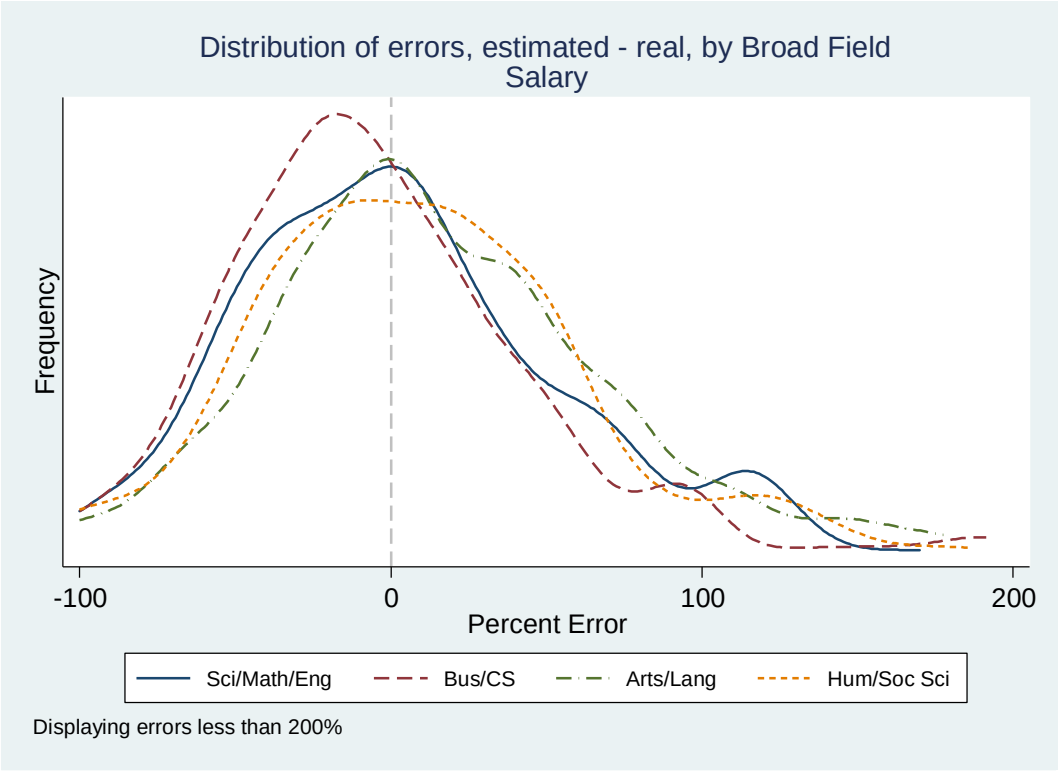
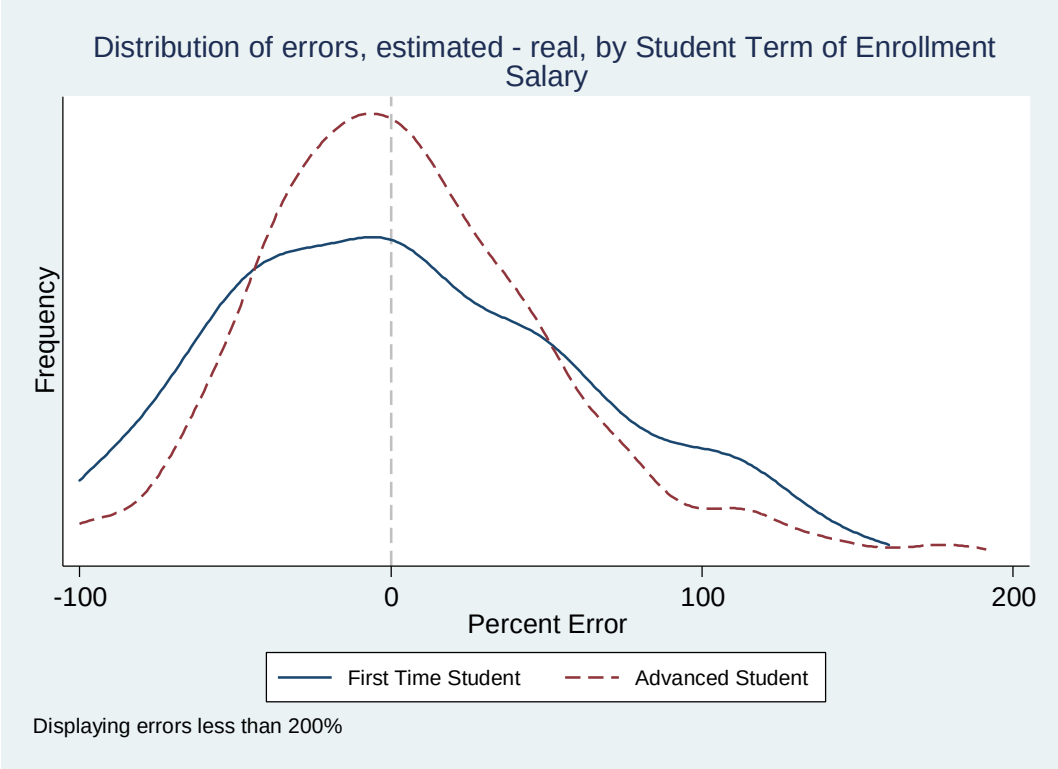
Appendix A: Student Survey

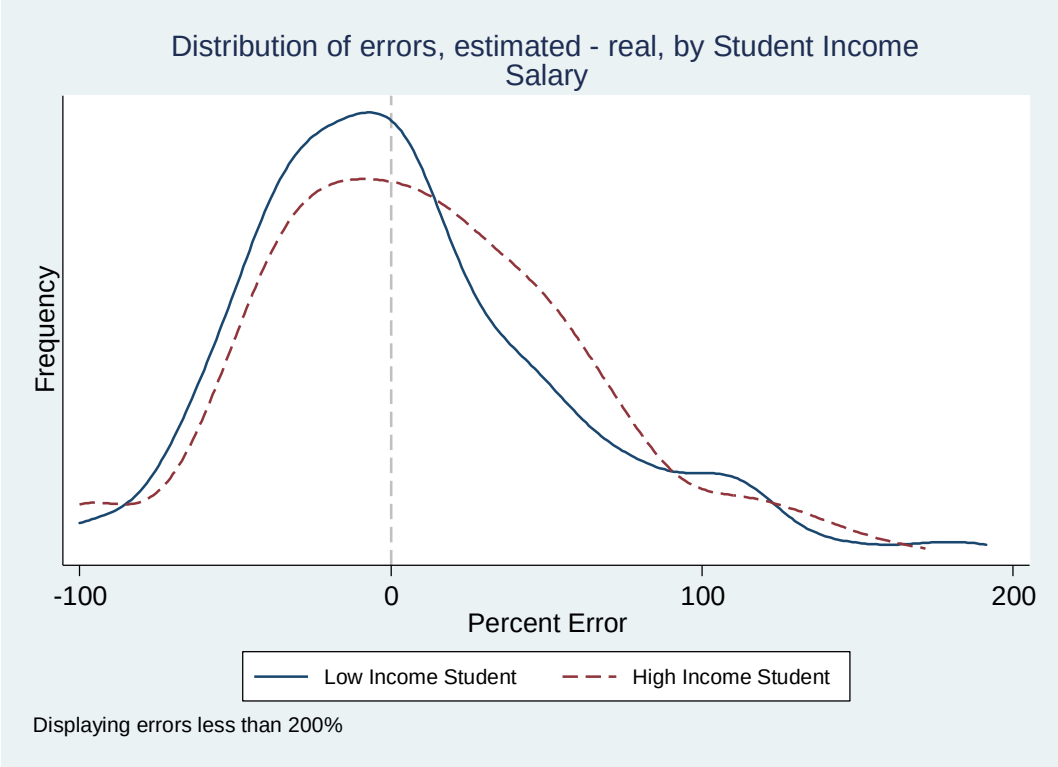
(in attached document)

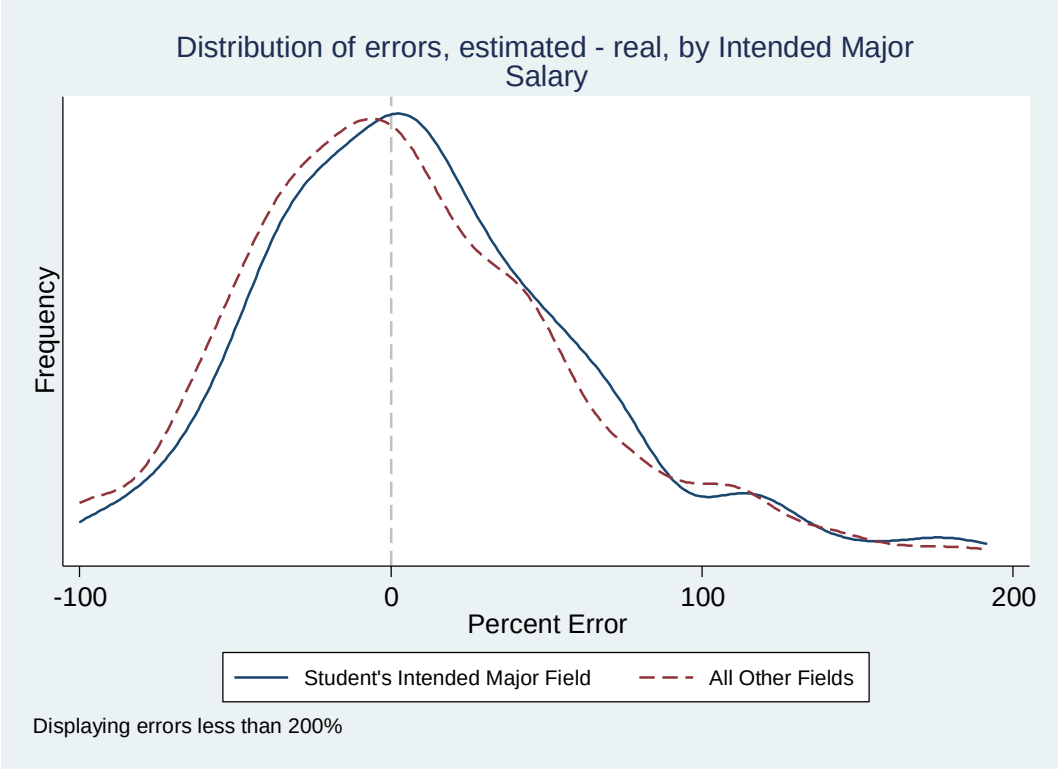
Appendix B: Students' Errors in labor market outcomes expectations

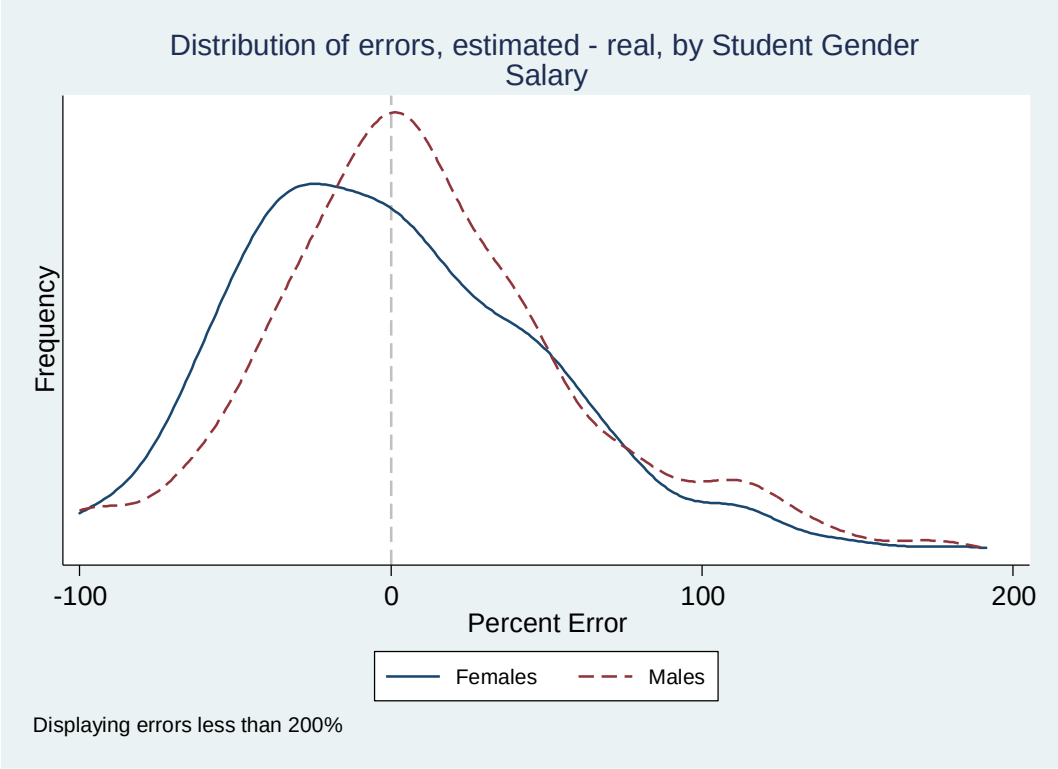


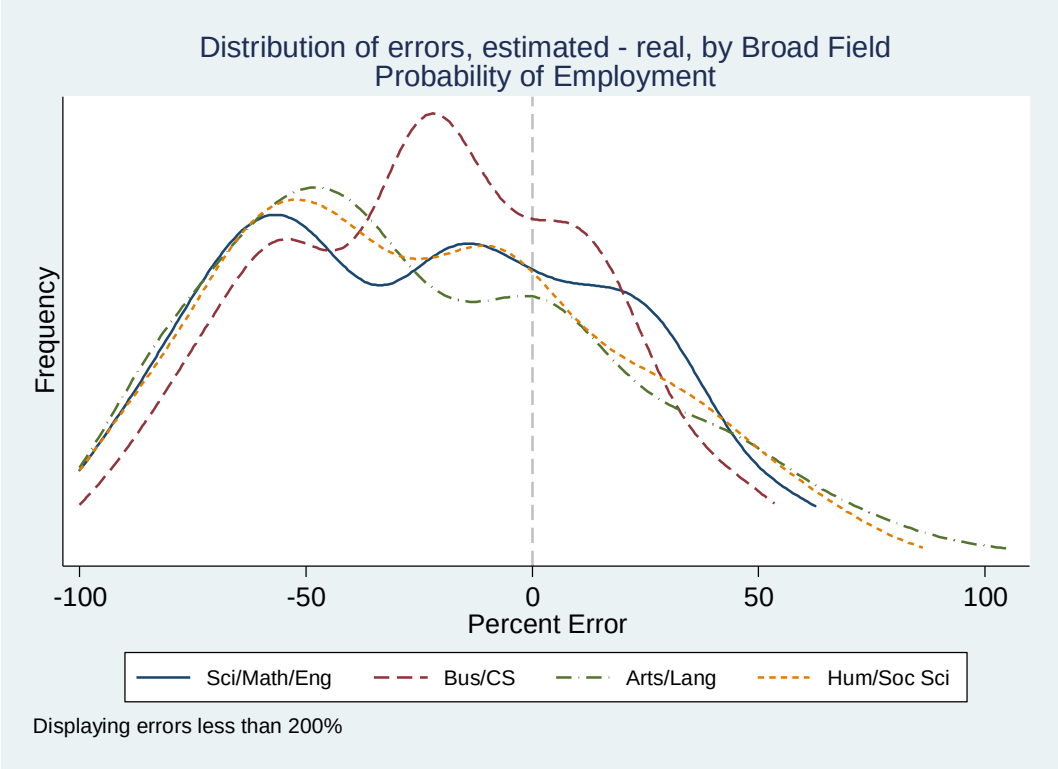
Notes: Interestingly, the mode of the distribution is around zero for all fields but Business/CS where it is below 0. At the same time, there is a substantial fraction of students who over-predict in each field. For business/CS the mode being lower and the over-prediction together results in a correct estimate on average.

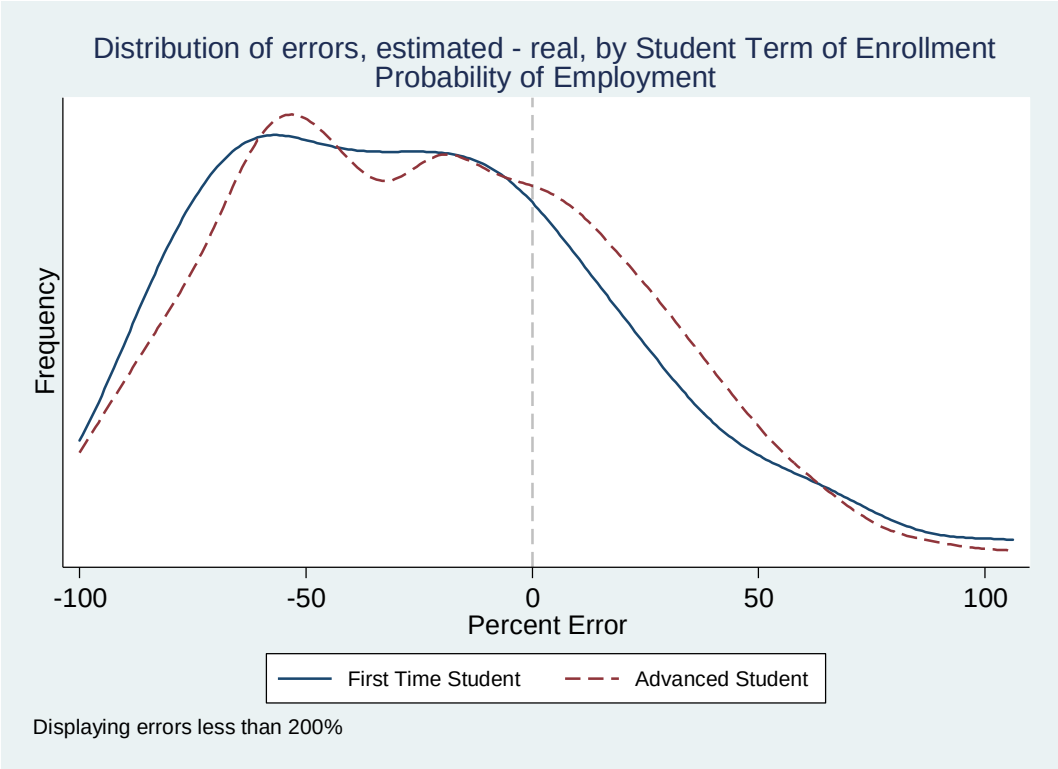

Distribution of errors, estimated - real, by Student Term of Enrollment
Salary
Frequency
-100
0
100
200
Percent Error
First Time Student
Advanced Student
Displaying errors less than 200%

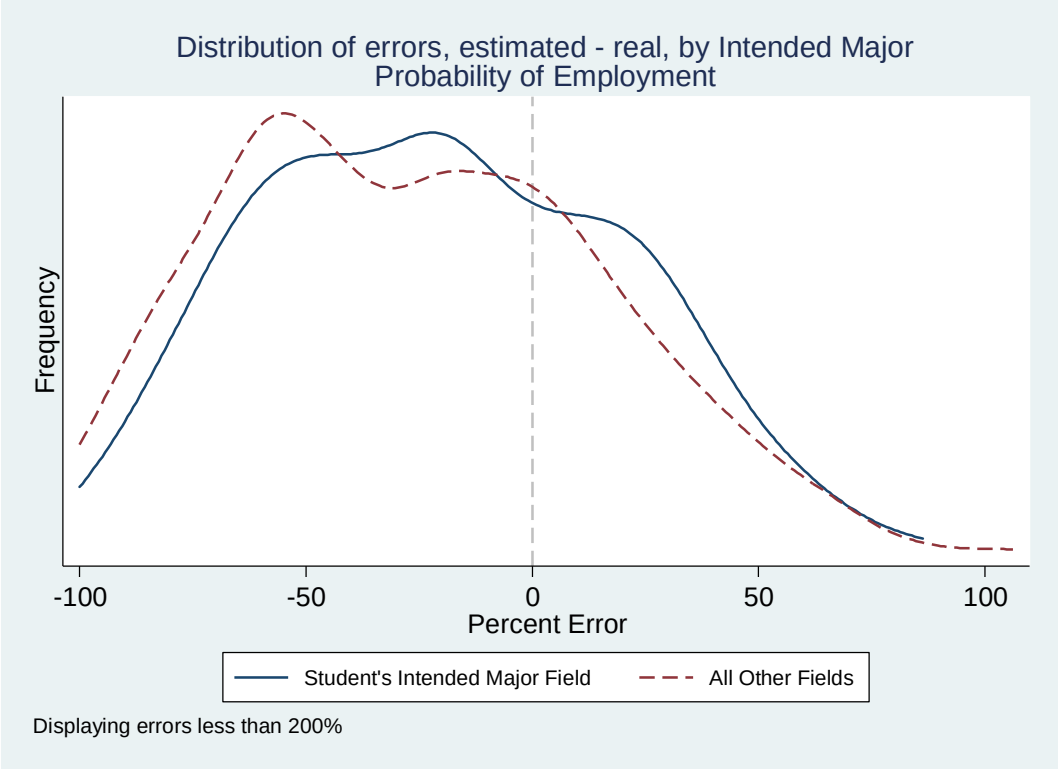

Distribution of errors, estimated - real, by Student Income
Salary
Frequency
-100
0
100
200
Percent Error
Low Income Student
High Income Student
Displaying errors less than 200%

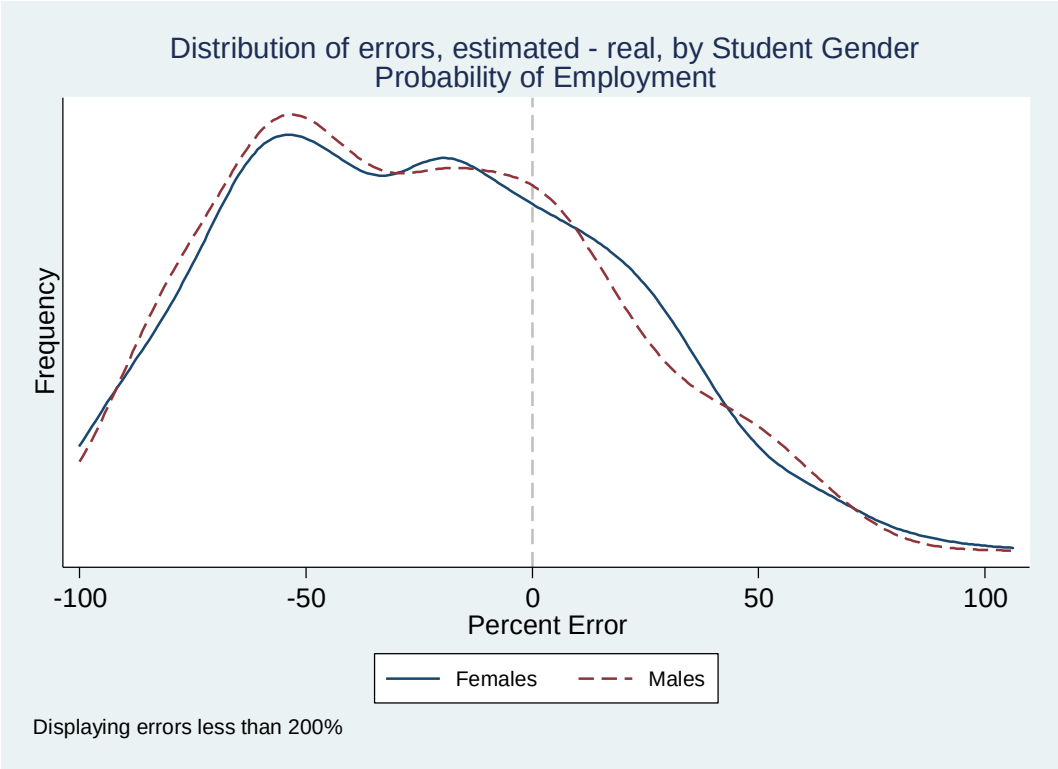

Distribution of errors, estimated - real, by Intended Major
Salary
Frequency
-100
0
100
200
Percent Error
Student's Intended Major Field
All Other Fields
Displaying errors less than 200%

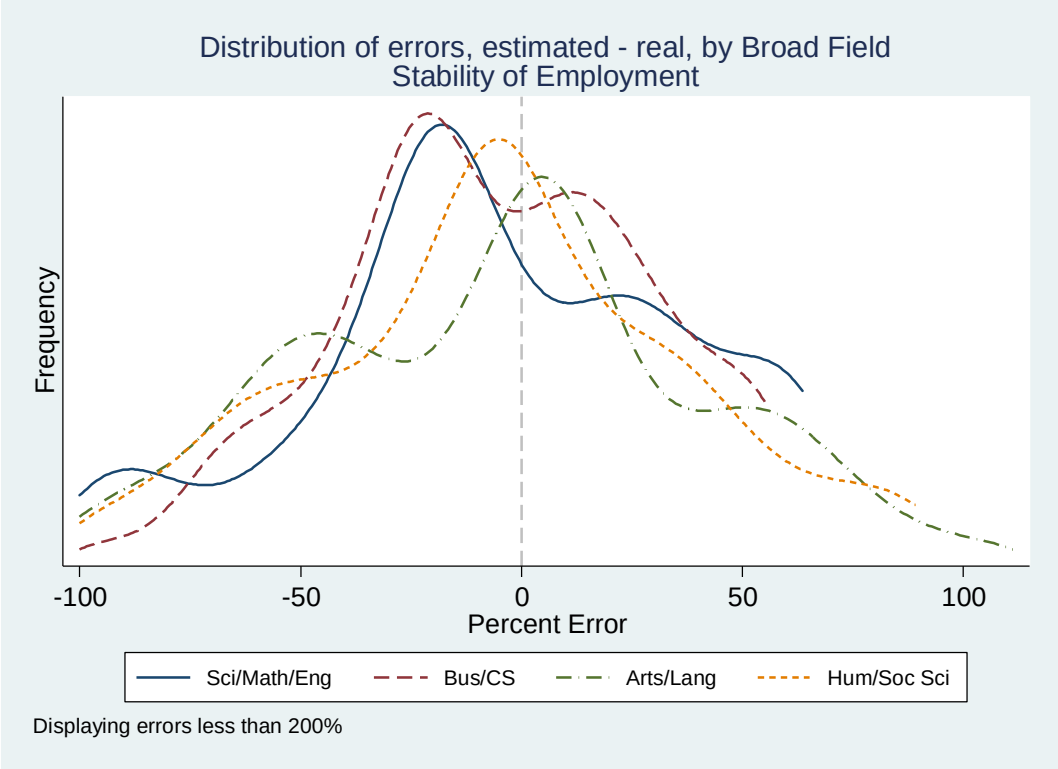

Distribution of errors, estimated - real, by Student Gender
Salary
Frequency
-100
0
100
200
Percent Error
Females
Males
Displaying errors less than 200%

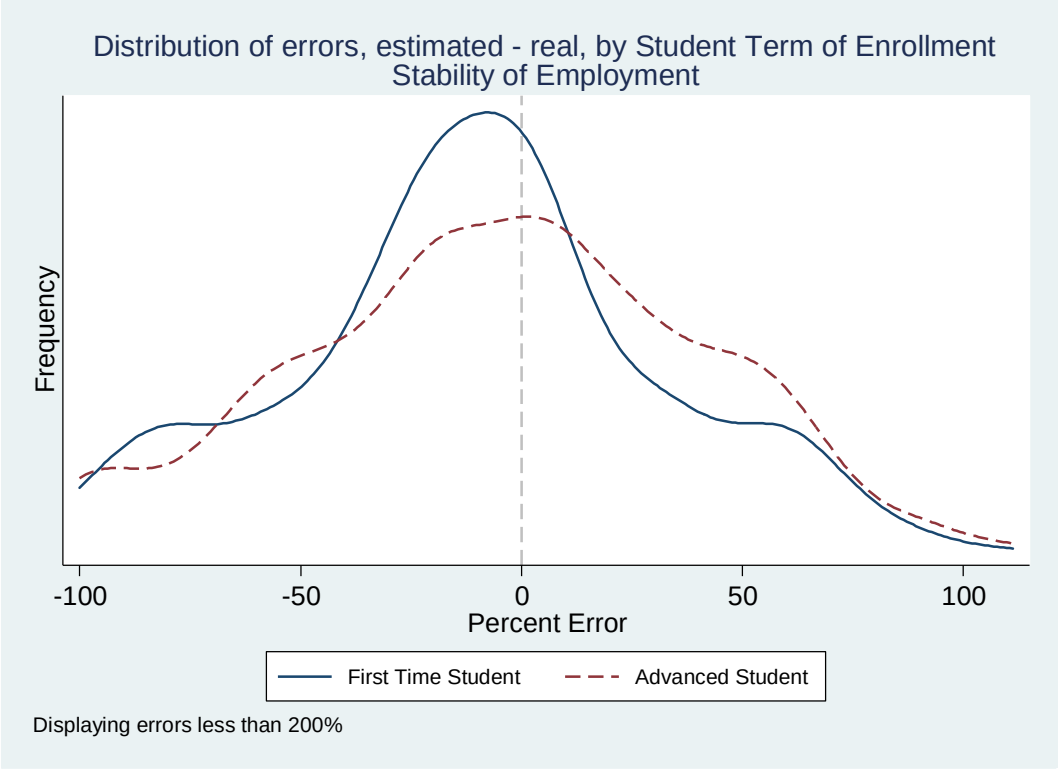

Distribution of errors, estimated - real, by Broad Field
Probability of Employment
Frequency
-100
-50
0
50
100
Percent Error
Sci/Math/Eng
Bus/CS
Arts/Lang
Hum/Soc Sci
Displaying errors less than 200%

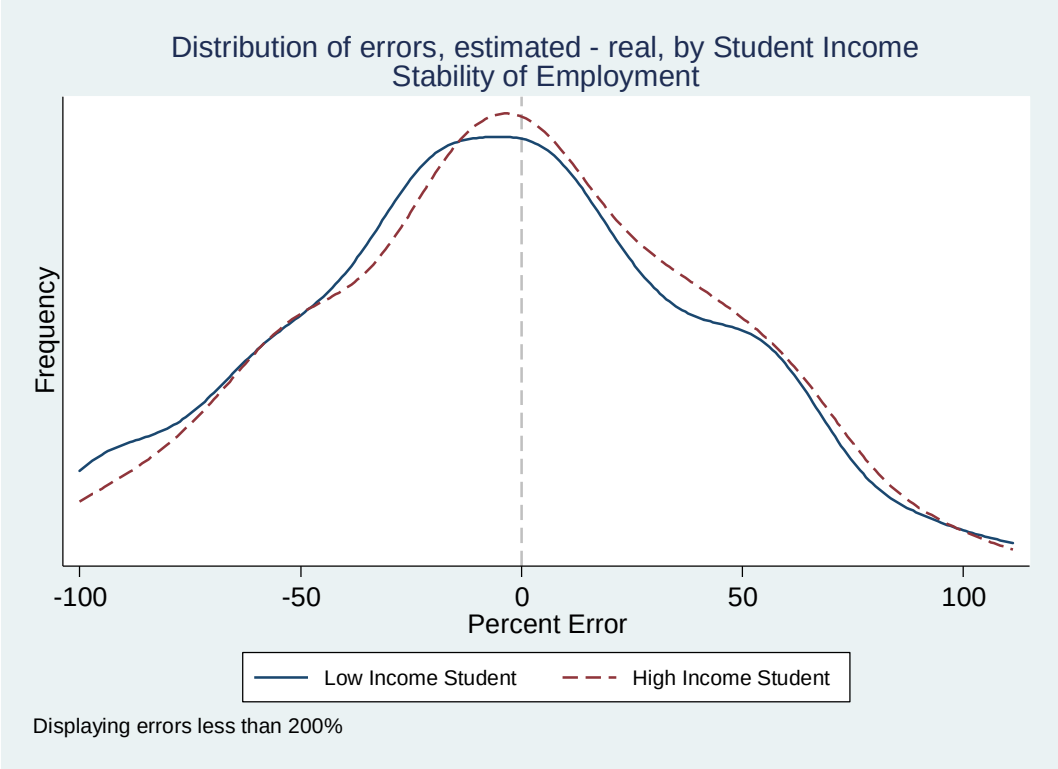

Distribution of errors, estimated - real, by Student Term of Enrollment
Probability of Employment
Frequency
-100
-50
0
50
100
Percent Error
First Time Student
Advanced Student
Displaying errors less than 200%

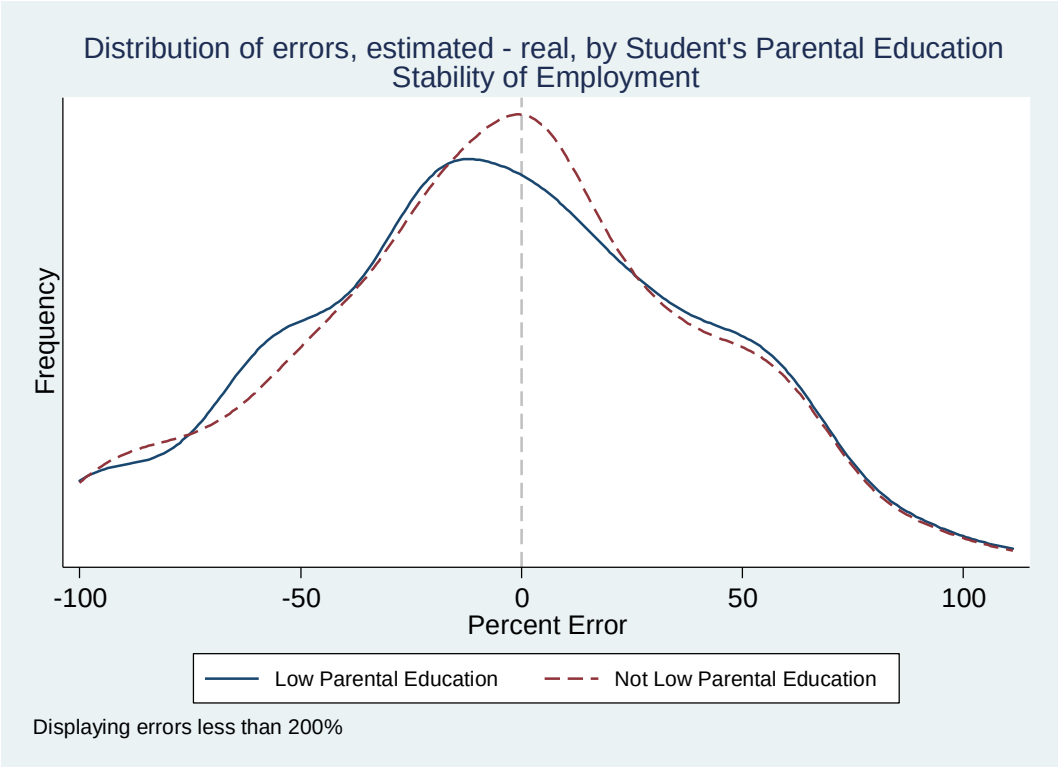

Distribution of errors, estimated - real, by Intended Major
Probability of Employment
Frequency
-100
-50
0
50
100
Percent Error
Student's Intended Major Field
All Other Fields
Displaying errors less than 200%

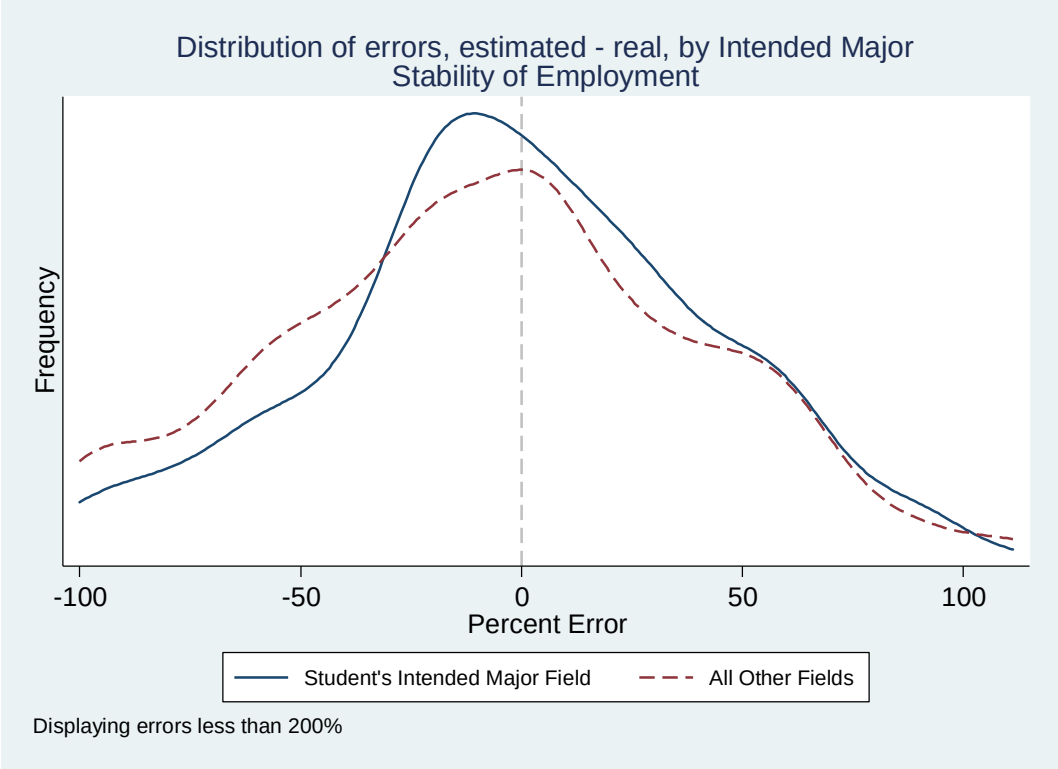

Distribution of errors, estimated - real, by Student Gender
Probability of Employment
Frequency
-100
-50
0
50
100
Percent Error
Females
Males
Displaying errors less than 200%

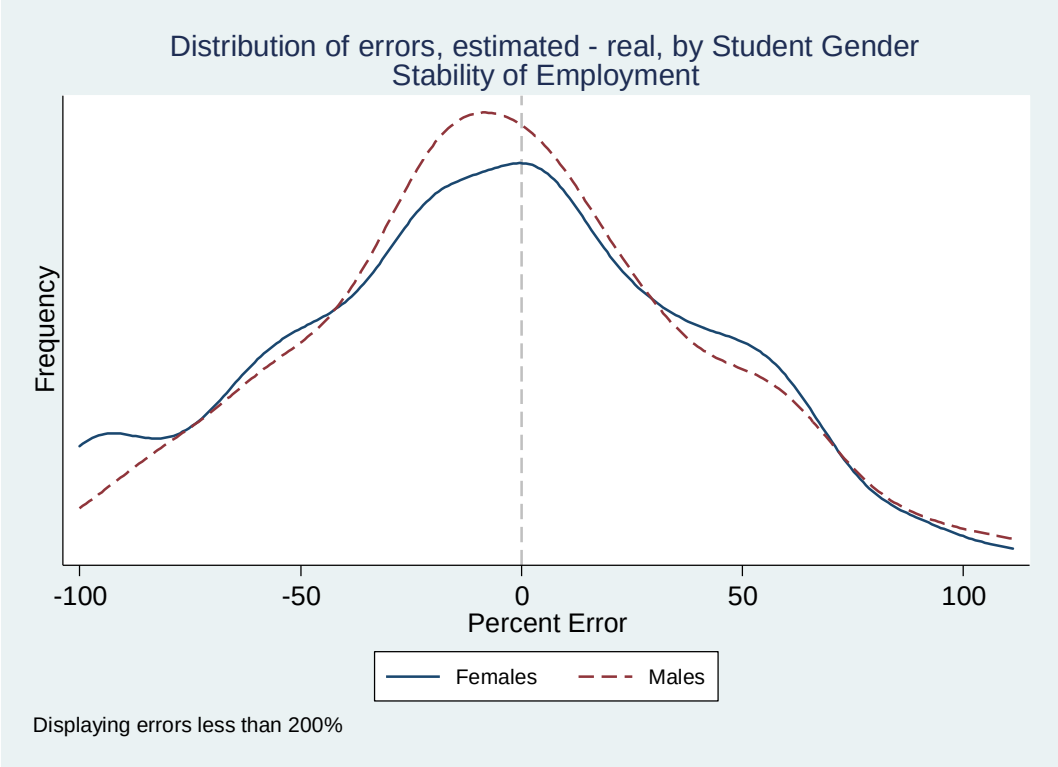

Distribution of errors, estimated - real, by Broad Field
Stability of Employment
Frequency
-100
-50
0
50
100
Percent Error
Sci/Math/Eng
Bus/CS
Arts/Lang
Hum/Soc Sci
Displaying errors less than 200%


Distribution of errors, estimated - real, by Student Term of Enrollment
Stability of Employment
Frequency
-100
-50
0
50
100
Percent Error
First Time Student
Advanced Student
Displaying errors less than 200%


Distribution of errors, estimated - real, by Student Income Stability of Employment
Frequency
-100
-50
0
50
100
Percent Error
Low Income Student
High Income Student
Displaying errors less than 200%


Distribution of errors, estimated - real, by Student's Parental Education Stability of Employment
Frequency
-100
-50
0
50
100
Percent Error
Low Parental Education
Not Low Parental Education
Displaying errors less than 200%


Distribution of errors, estimated - real, by Intended Major
Stability of Employment
Frequency
-100
-50
0
50
100
Percent Error
Student's Intended Major Field
All Other Fields
Displaying errors less than 200%


Distribution of errors, estimated - real, by Student Gender
Stability of Employment
Frequency
-100
-50
0
50
100
Percent Error
Females
Males
Displaying errors less than 200%

Appendix C: Relationship Between Major Choice and Labor Market Outcomes with Covariates

	(1)	(2)	(3)	(4)	(5)
Predicted Salary	0.6931**		0.4833	0.4638	0.2329
	(0.2977)		(0.3072)	(0.3058)	(0.4622)
Pred. Prob. of Employment		0.4041***	0.4208**	0.3057	0.2779
		(0.1465)	(0.1975)	(0.2343)	(0.2752)
Pred. Stab. of Employment				0.1694	
				(0.1639)	
Female					-0.7256*
					(0.4343)
Hispanic					-0.6593
					(0.5444)
Asian					-0.0043
					(0.4633)
Black					0.9363
					(1.4442)
Pacific Islander					-1.1480
					(0.8785)
Other Race					0.8021
					(0.6399)
Low Income					-0.0135
					(0.4517)
No Parent with College Degree					-0.0578
					(0.4497)
HS GPA = F					1.3123***
					(0.4367)
HS GPA = D					0.5712
					(0.9695)
HS GPA = C					1.3442*
					(0.6984)
HS GPA = B					1.7046***
					(0.5625)
HS GPA = A					2.4731***
					(0.6455)
Constant	-0.1334	-0.0216	-0.1332	-0.1301	-1.4269**
	(0.1461)	(0.1376)	(0.1505)	(0.1500)	(0.6419)
Observations	772	854	738	738	620
R-squared	0.0085	0.0109	0.0152	0.0169	0.0399

Robust standard errors clustered at the student level are shown in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Unit of observation is at the student-by-broad major level.

	(1)	(2)	(3)	(4)	(5)
Predicted Salary	0.4749*		0.4223	0.6112*	0.1914
	(0.2514)		(0.2597)	(0.3156)	(0.3952)
Pred. Prob. of Employment		0.1051	0.1742	-0.0941	0.0450
		(0.1322)	(0.1777)	(0.2729)	(0.2321)
Pred. Stab. of Employment				0.1876	
				(0.1957)	
fri_and_fam_rel				0.1125	
				(0.1808)	
Predicted Enjoyment	0.7521***	0.7869***	0.7708***	0.8335***	0.7889***
	(0.0560)	(0.0538)	(0.0556)	(0.0846)	(0.0729)
Predicted Grades	0.8577***	0.7911***	0.8806***	0.7329***	0.9110***
	(0.1410)	(0.1331)	(0.1433)	(0.1959)	(0.2007)
Female					0.0491
					(0.3547)
Hispanic					-0.9074**
					(0.4597)
Asian					-0.5615
					(0.4018)
Black					-4.4342***
					(0.5341)
Pacific Islander					-1.2553
					(0.8005)
Other Race					-0.4632
					(0.6286)
Low Income					0.4288
					(0.3714)
No Parent with College Degree					-0.0884
					(0.3626)
HS GPA = F					-0.0444
					(0.4420)
HS GPA = D					2.0948***
					(0.5850)
HS GPA = C					1.2878**
					(0.5280)
HS GPA = B					1.0689**
					(0.5088)
HS GPA = A					1.4391***
					(0.4814)
Constant	0.2651**	0.3741***	0.2776**	0.2004	-0.4938
	(0.1300)	(0.1228)	(0.1348)	(0.1704)	(0.5721)
Observations	617	691	593	325	505
R-squared	0.4060	0.3882	0.4179	0.4157	0.4486

Robust standard errors clustered at the student level are shown in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Unit of observation is at the student-by-broad major level.

Appendix D: Experimental Design

Form A				
	Business, Comp. Sci. & Tech.		Humanities, Education, Social Sci.	
Prob. Of Employment	Low	High	Low	High
Salary	High	Low	Low	High

Form B				
	Business, Comp. Sci. & Tech.		Humanities, Education, Social Sci.	
Prob. Of Employment	Low	High	Low	High
Salary	Low	High	High	Low

Appendix E: Which students react most to information?

In the main text we examined the effects of the provision of experimentally manipulated "true" labor market outcomes on students' stated probability of choosing a given major. In this appendix we examine of the effects of information vary by students' initial probability of choosing a given major. We accomplish this with the following model:

$$ln\pi'_{k,i} = \beta_0 + \beta_1 lnw'_{k,i} + \boldsymbol{\theta_{prev.prob.}\beta_2} + \boldsymbol{\delta_{prev.prob} * lnw'_{k,i}\,\beta_3} + \epsilon'_{k,i} \quad \text{(C1)}$$

Where $\pi_{k,i}$ is the probability for student i to major in field k. $lnw'_{k,i}$, is the expected labor market outcome for major *k* (salary (column (1), probability of employment (column (2) or both (column (3) in Table E1 and C2). We also include a vector of dummy variables that indicate no, low (<30%), medium (>= 30% and <= 50%) and high (>50%) previous probabilities ($\boldsymbol{\theta_{prev.prob.}}$) and a vector of these dummies interacted with the experimentally manipulated labor market outcomes ($\boldsymbol{\delta_{prev.prob} * lnw'_{k,i}\,\beta_3}$). Thus, the estimated coefficients β_3 gives an indication of if the effect of the "true" salary differs between students who previously stated no, low, medium, or high probability of choosing a given major. In some models (columns 4-6), we add students' prior beliefs about expected salary and probability of employment. We run these analyses separately for the business (Table C1) and humanities (Table C2) experiments.

In both tables we see that the effects of labor market information seem to be greatest for students who previously stated that there was zero chance they would choose this field; the interaction between a dummy for membership in this group and information about "true" salary are large and significant for humanities (Table E2) and large and sometimes significant for business (Table E1). In the case of the humanities major, the effects of labor market information are significantly greater for students who previously had a low probability of selecting this major. This is not true for the business major. The results do not qualitatively change with the addition of students' previous beliefs about salary and probability of employment.

Table E1—Effects of Salary on Choice, by Initial Probability, Business

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	hyp_per_char	hyp_per_char	hyp_per_char	hyp_per_char	hyp_per_char	hyp_per_chan
ln_true_salary	0.9664**		0.9638*	0.8330**		0.8061**
	(0.4817)		(0.4969)	(0.3605)		(0.3297)
no_chXln_true_salary	1.0191		0.9433	1.3115**		1.2676**
	(0.6355)		(0.6540)	(0.5616)		(0.5542)
lo_chXln_true_salary	-0.1671		-0.1689	0.0179		0.0949
	(0.7065)		(0.7208)	(0.6083)		(0.5646)
med_chXln_true_salary	-0.2051		-0.2573	-0.0552		-0.1437
	(0.5975)		(0.5824)	(0.4412)		(0.4003)
no_chance	-13.2880*	-1.7277***	-12.1439*	-16.7882***	-1.9482***	-15.9942***
	(6.8784)	(0.5266)	(7.0481)	(6.0795)	(0.5358)	(6.1284)
low_chance	1.1052	-0.5118	1.2403	-1.0462	-0.4215	-1.5462
	(7.6568)	(0.5824)	(7.8048)	(6.6106)	(0.5743)	(6.1468)
med_chance	2.5178	0.6385	3.2394	0.7683	0.8156**	2.0351
	(6.4984)	(0.4635)	(6.1875)	(4.8423)	(0.4083)	(4.4828)
ln_true_prob_employ		-0.1396	-0.0360		-0.0954	-0.2281
		(0.5991)	(0.6031)		(0.6053)	(0.4008)
no_chXln_true_prob_employ		1.0979	0.6079		0.9895	0.8732
		(0.7975)	(0.7944)		(0.8169)	(0.6737)
lo_chXln_true_prob_employ		0.3469	0.2140		0.2770	0.4227
		(0.8761)	(0.8756)		(0.8745)	(0.6863)
med_chXln_true_prob_employ		0.6197	0.2952		0.5030	0.5054
		(0.7435)	(0.7072)		(0.6739)	(0.4866)
ln_salary				-0.1171		0.0014
				(0.2177)		(0.2337)
ln_have_a_job					-0.0749	-0.2178
					(0.2424)	(0.2299)
Constant	-11.7627**	-1.4280***	-11.7541**	-8.7484*	-1.4703***	-9.9923**
	(5.2307)	(0.3952)	(5.2938)	(4.4564)	(0.4403)	(4.4061)
Observations	431	431	431	392	402	376
R-squared	0.2499	0.1914	0.2534	0.3164	0.2370	0.3504
Robust standard errors in parentheses						
*** p<0.01, ** p<0.05, * p<0.1						

Table E2-- Effects of Salary on Choice, by Initial Probability, Humanities

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	hyp_per_char	hyp_per_char	hyp_per_char	hyp_per_char	hyp_per_char	hyp_per_chan
ln_true_salary	0.8373**		0.8159**	0.7536**		0.6608*
	(0.3316)		(0.4007)	(0.3381)		(0.3860)
no_chXln_true_salary	1.9470***		2.1407***	2.3752***		2.6597***
	(0.6598)		(0.6844)	(0.6795)		(0.6834)
lo_chXln_true_salary	1.1907**		1.1854**	1.2184**		1.2739**
	(0.5228)		(0.5669)	(0.5177)		(0.5526)
med_chXln_true_salary	0.3691		0.4007	0.2707		0.4536
	(0.6548)		(0.7322)	(0.6267)		(0.6429)
no_chance	-23.8803***	-2.2292***	-25.4056***	-28.5206***	-2.2879***	-31.0687***
	(7.2236)	(0.4744)	(7.4341)	(7.4372)	(0.4777)	(7.4515)
low_chance	-13.7479**	-0.2870	-13.3575**	-13.9665**	-0.3505	-14.2078**
	(5.8467)	(0.3750)	(6.2287)	(5.7750)	(0.3748)	(6.0703)
med_chance	-4.6911	-0.6153	-4.9753	-3.4125	-0.2183	-5.1433
	(7.2062)	(0.4664)	(7.8548)	(6.9006)	(0.3926)	(6.8994)
ln_true_prob_employ		-0.2844	-0.0595		-0.2488	-0.2026
		(0.2986)	(0.3519)		(0.2988)	(0.3380)
no_chXln_true_prob_employ		0.8178	1.0054*		0.8788	1.2781**
		(0.6166)	(0.5998)		(0.6279)	(0.5982)
lo_chXln_true_prob_employ		0.8789*	0.5744		0.8813*	0.8789*
		(0.4968)	(0.4970)		(0.5020)	(0.4837)
med_chXln_true_prob_employ		0.1026	0.1019		0.3202	0.4279
		(0.5899)	(0.6415)		(0.5064)	(0.5628)
ln_salary				-0.2381		-0.0933
				(0.2177)		(0.2217)
ln_have_a_job					-0.4896***	-0.4922***
					(0.1322)	(0.1379)
Constant	-9.8974***	-0.9569***	-9.6996**	-6.4994	-1.4046***	-7.5500
	(3.6784)	(0.2436)	(4.2876)	(4.2818)	(0.2898)	(4.6797)
Observations	410	410	410	373	387	361
R-squared	0.3053	0.2041	0.3179	0.3384	0.2476	0.3933
Robust standard errors in parentheses						
*** p<0.01, ** p<0.05, * p<0.1						

Appendix F: exploring the differences between the experimental vs. non-experimental impact of labor market outcomes on major choice

In this appendix we present examine two potential explanations for why the results from the experimental analyses differ from the results from the non-experimental analyses. In both cases, we do not find satisfactory explanations for the differences in results.

Relative vs. absolute probability of choosing a major

First, we examine if the differences are due to modelling decisions. Similar to our strategy for the non-experimental estimates, in this section we predict the difference in probabilities of selecting a major using differences in experimentally assigned labor market outcomes.

$$\left(ln\pi_{b,i} - ln\pi_{h,i}\right) = \beta_0 + \beta_1(lnw_b - lnw_h) + \varepsilon_{k,i}$$

where $\pi_{b,i}$ is the probability student i assigns to majoring in business. The subscript h stands for humanities as everything is relative to humanities. The key explanatory variable is $lnw_b - lnw_h$, i.e. the difference in salary relative to humanities.

Table D1:

	(1)	(2)	(3)
VARIABLES	n_hyp_per_ch	n_hyp_per_ch	n_hyp_per_ch
rel_ln_true_salary	1.6568***		1.6728***
	(0.1672)		(0.1682)
rel_ln_true_prob_employ		-1.5060	0.9204
		(1.7057)	(1.5368)
Constant	-0.4221***	-0.5417***	-0.4557***
	(0.1475)	(0.1724)	(0.1528)
Observations	397	397	397
R-squared	0.1991	0.0020	0.1998
Robust standard errors in parentheses			
*** p<0.01, ** p<0.05, * p<0.1			

The results in Table D1 make it clear that the large estimated differences in effects between the non-experimental and experimental results are not due to the different specifications.

Focusing on humanities and business in the non-experimental data

In the experiment, we ask students about probability of majoring in only business and humanities majors, whereas in the non-experimental section we ask students about all four categories of majors. Thus, it could be that the difference in results are due to the different categories. We examine this possibility below.

In Table F2 we break the non-experimental results by major category. In the first four columns in Table F2, we regress the log probability of choosing that major on the log salary in the major. We can see that differences in beliefs about salary in a single major across students are not a big predictor of major choice, as salary is never significant. Furthermore, for business and language and arts, the point estimate is also close to zero. The strongest evidence for a role of beliefs is for science, where students with 10% higher estimates of salary in science are 26% more likely to major in science; but this estimate is still not statistically significant.

In columns 5-7, we regress the probability of majoring in that field relative to humanities. This is now asking if the probability of majoring in a certain field is influenced by relative beliefs. The point estimates are now more definitely positive, showing that students who have higher gaps in salary between a major and humanities are relatively more likely to major in that. Still, only the science vs. humanities contrast is statistically significant.

Table F2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	bus	hum	langarts	sci	bus	langarts	sci
log_salary	-0.0259	0.1160	0.0109	0.2551			
	(0.2127)	(0.2307)	(0.2289)	(0.2017)			
log_salary_rel					0.2424	0.2967	1.0836**
					(0.5095)	(0.6092)	(0.4957)
Constant	-3.8711*	-4.6891*	-4.1501*	-5.0767**	-0.7202**	-0.4679**	0.7906***
	(2.2711)	(2.4088)	(2.3661)	(2.1586)	(0.2971)	(0.2119)	(0.2947)
Observations	266	264	263	269	258	258	256
R-squared	0.0001	0.0012	0.0000	0.0065	0.0010	0.0016	0.0175
Robust standard errors in parentheses							
*** p<0.01, ** p<0.05, * p<0.1							

It is also interesting to note how low the R-squared is in the table, indicating that different beliefs about salary across students are not important drivers of major choice, but relative beliefs explain major choice better than absolute beliefs. There is thus strong evidence that the differences between the experimental and non-experimental results is not driven by the different categories of majors that we ask about.

How can we understand the fact that choices relative to humanities are better predicted than absolute choices? In some way, it makes sense that differences in beliefs explain more than absolute beliefs,

because students are choosing between majors, so saying that a student believes business earns a lot without telling us how much the student thinks other majors earn is leaving out an important part of the picture.

We then repeat **Error! Reference source not found.** but add controls for enjoyment and grades. **Error! Reference source not found.** below shows the results. The R-squared has increased quite a bit compared to **Error! Reference source not found.**, and the explanatory power again appears greater in relative terms. In this case, salary is not significant, except when considering science in isolation.

Table F3

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	bus	hum	langarts	sci	bus	langarts	sci
log_salary	0.1120	0.1573	0.0050	0.2575*			
	(0.1992)	(0.2265)	(0.3143)	(0.1440)			
log_enjoy	0.5976***	0.6587***	0.6765***	0.6770***			
	(0.0627)	(0.0829)	(0.0533)	(0.1002)			
avg_grade	0.4995***	0.0769	0.3269*	0.7611***			
	(0.1652)	(0.2204)	(0.1802)	(0.2201)			
log_salary_rel					0.1111	0.1845	0.3553
					(0.4392)	(0.5513)	(0.3684)
log_enjoy_rel					0.6987***	0.6312***	0.8173***
					(0.0879)	(0.1450)	(0.0739)
avg_grade_rel					0.9502***	1.0621***	0.8154***
					(0.2277)	(0.3012)	(0.2249)
Constant	-5.7947***	-4.3187*	-4.2906	-7.2254***	0.3104	-0.3395*	0.9408***
	(2.1871)	(2.2891)	(3.2510)	(1.9512)	(0.2836)	(0.1980)	(0.2371)
Observations	226	224	217	244	205	205	207
R-squared	0.3079	0.2086	0.2255	0.3729	0.4613	0.2810	0.4319
Robust standard errors							
*** p<0.01, ** p<0.05,							

While we learned interesting things here, it is clear that the discrepancy between the experimental and nonexperimental results is not because the experimental results focus on business and humanities alone; indeed, these fields are not really special compared to other fields when looking at nonexperimental data.

Understanding the bias in nonexperimental estimates due to the correlation of beliefs about labor market outcomes with other determinants of major choice

The basic explanation here is that people who hold higher salary beliefs about some majors relative to others may also hold other unfavorable beliefs (e.g. about enjoyment and grades), which dampens the effect of salary on their choice.

Based on **Error! Reference source not found.** below, it appears that it is the enjoyment factor that dampens the impact of salary on major choice, while just controlling for grades does not change the effect of salary on major choice. Interestingly, controlling for both grade and enjoyment (col. 4) leaves a greater impact of salary on major choice than just controlling for enjoyment. The fact that the enjoyment factor dampens the coefficient on salary is interesting in light of the positive but insignificant (P-val=0.28) correlation between enjoyment and salary beliefs (as shown in results for broad majors above). It appears that some of the positive effect of salary on choice loads onto enjoyment.

Table F4

	(1)	(2)	(3)	(4)
VARIABLES	prob_no_0	prob_no_0	prob_no_0	prob_no_01
log_salary_rel	0.6931**	0.3758	0.6720**	0.4749*
	(0.2977)	(0.2347)	(0.2843)	(0.2514)
log_enjoy_rel		0.9472***		0.7521***
		(0.0371)		(0.0560)
avg_grade_rel			1.8734***	0.8577***
			(0.1108)	(0.1410)
Constant	-0.1334	0.0080	0.3389**	0.2651**
	(0.1461)	(0.1212)	(0.1414)	(0.1300)
Observations	772	692	620	617
R-squared	0.0085	0.4032	0.2638	0.4060
Robust standard erro				
*** p<0.01, ** p<0.05				

The coefficient on salary is biased by omitted variables that determine choice and are correlated either positively or negatively with salary. If we trust our experimental estimates, we must infer that salary is correlated with some determinants that have a negative impact on choosing a certain major. However, these determinants are not grades since controlling for grades doesn't change the impact of salary, and it's not about enjoyment either since controlling for enjoyment rather decreases the impact of salary (if we control for the variable that is responsible for the downward bias in the salary coefficient, the salary coefficient should go up, nor down, hence the inference that enjoyment is not such a variable).