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Modeling college major choices using elicited measures of expectations and counterfactuals[☆]

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ABSTRACT

The choice of a college major plays a critical role in determining the future earnings of college graduates. Students make their college major decisions in part due to the future earnings streams associated with the different majors. We survey students about what their expected earnings would be both in the major they have chosen *and* in counterfactual majors. We also elicit students' subjective assessments of their abilities in chosen and counterfactual majors. We estimate a model of college major choice that incorporates these subjective expectations and assessments. We show that both expected earnings and students' abilities in the different majors are important determinants of a student's choice of a college major. We also consider how differences in students' forecasts about what the average Duke student would earn in different majors versus what they expect they would earn both influence one's choice of a college major. In particular, our estimates suggest that 7.8% of students would switch majors if they had the same expectations about the average returns to different majors and differed only in their perceived comparative advantages across these majors.

1. Introduction

Numerous studies have documented large differences in earnings across different college majors.[1] For example, Grogger and Eide (1995) find that one-quarter of the change in the college wage premium for men was driven by a shift from low-paying to high-paying majors. And James et al. (1989, p. 252) argue that "while sending your child to Harvard appears to be a good investment, sending him to your local state university to major in Engineering, to take lots of math, and preferably to attain a high GPA, is an even better private investment". Given these large earnings differences across majors, economists have analyzed the extent to which students sort into majors as a function of such differences.[2] At the same time, differences in student ability and aptitudes also have been found to influence choice of college majors. For example, Turner and Brown (1999) provide evidence of ability sorting across majors by SAT scores, and Paglin and Rufolo (1990) argue that the difference in the mathematical ability is the main reason for the difference in the major choice and earnings between male and female.[3]

In this paper, we examine the factors that influence college major choice. Borrowing from standard economic models of schooling decisions (Becker, 1993; Ben-Porath, 1967; Mincer, 1974), we model the choice of a college major by comparing the returns to different majors with the costs associated with completing them. As noted above, economists typically focus on the expected earnings streams that result from different educational choices to measure their returns. In the context of majors, such earnings streams are, themselves, associated with

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1 See Daymont and Andrisani (1984), Hamermesh and Donald (2008), Grogger and Eide (1995), James et al. (1989), Loury (1997) and Loury and Garman (1995).

2 See, for example, Arcidiacono (2004), Arcidiacono (2005) and Montmarquette et al. (2002).

3 We note that this ability sorting explanation seems less able to explain the underrepresentation of women in more lucrative majors, as researchers (Friedman, 1989; Goldin et al., 2006) have found that the gender gap in math and science aptitude is small and has decreased for several decades.

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alternative careers, or occupations, that majoring in a particular subject make more or less likely. For example, majoring in biology (or pre-med) is likely to affect one's chances of becoming a medical doctor and realizing the earnings stream associated with a career in medicine. With respect to the costs of schooling, economic models tend to focus on a student's ability or abilities to complete years of schooling more efficiently and effectively. Finally, some models of schooling decisions emphasize the consumption value of education, as students may enjoy the content of courses in some majors more than others *and/or* find the career paths associated with particular majors to be more enjoyable than others.

One of the key problems in implementing and assessing models of educational choices, including that for majors, is the lack of data on the constructs of such models. In particular, one typically does not directly observe students' forecasts of the earnings they expect to receive from alternative majors or about what students' abilities would be in alternative majors. Rather, economists typically have data on the earnings streams associated with different majors that are actually chosen. After dealing with selection issues, economists need to make strong assumptions about how students form expectations for earnings across these different educational paths in order to estimate their choice models.[4]Furthermore, researchers often have only limited information on students' relative abilities outside their chosen majors. Again, assumptions must be invoked for what a student's ability would be in majors not chosen.

To address the issue of measuring students' expectations of earning across different major–career combinations, we conducted a survey of male undergraduates at Duke University. We elicited from each student the probabilities that he would be in particular careers in the future as well as the earnings he might expect to earn in them. Students were asked these questions both for the major they actually chose and for the other majors they could have chosen but did not, i.e., for their *counterfactual* majors. In addition, we asked students to provide information about their relative abilities in their own and all other possible majors. We describe the survey we conducted and present a brief description of expectations data it yielded in Section 2, focusing on the sorting patterns on both expected earnings and ability.

Based on a simple characterizations of the data from our survey, we find evidence of sorting on the basis of both expected earnings and ability. With the exception of the lowest paying majors, most students state that their expected earnings are highest (or second highest) in the major they actually chose. At the same time, the majority of students indicate that they expect their earnings to be higher or at least as high if they had majored (or are majoring) in economics. Furthermore, we find clear evidence of ability sorting, as the students in our study are much more likely to state that they are more able (more competitive) in the major that they choose relative to the ones they did not.

To disentangle the relative importance of ability and expected earnings on the choice of major, we formulate and estimate a model of major choice while also allowing for different preferences over careers. The model and some of its variants are described in Section 3, and the resulting estimates are discussed in Section 4. Our model-based estimates clearly indicate that expected earnings do matter for student's choice of major, even after controlling for ability and career preferences. For example, a one standard deviation increase in expected earnings of business careers shifts the fraction of students choosing economics from 19.7% to 22.9%, a sixteen percent increase. Although there is sorting on expected earnings, our evidence indicates that students prefer majors that they are good (or more able) at, a finding consistent with those in Arcidiacono (2004). Equalizing student abilities across majors would drop the fraction of humanities majors from 9.3% to 5.9% while increasing the fraction of economics majors to 23.8%.

The use of subjective expectations data analyzing choice models inevitably raises questions about their accuracy and variability. In the context of this paper, students' reported expectations of future earnings are likely to differ because students differ in what they know about the labor market opportunities and earnings potentials for different majors and careers. In a survey of students at an elite public university, Betts (1996) found that students had fairly diverse beliefs in what they thought the average starting and mid-career salaries were in different careers and with different majors (e.g., engineering). Betts found that this variability and the discrepancies between student estimates and actual starting and mid-career salaries in the US were systematically related to the student's family background, year in college, and own field of study. To assess the "reasonableness" of the elicited earnings expectations we elicited, in Section 2.2 we present a comparison of what students in our survey would expect to earn in the first year after graduation given their chosen major with data on reported starting salaries of Duke seniors in 2007. As we show, there are not large differences in the medians of earnings across these two surveys.

But, for the reasons noted above, students may make very different forecasts of what they would earn with different majors and in different careers because of the information they have about these jobs and careers and about labor markets in general. In an attempt to indirectly measure these differences in information, we asked the students in our study to provide us with what they would expect the average Duke student to earn in different careers with different majors. By using the average Duke student as the referent person in these elicitations, we seek to separate out the informational differences students may have about labor markets from differences in their forecasts due to their perceived *comparative advantages* across these careers/majors. We summarize our findings for this set of elicitations in Section 2.3. We then use these data in Section 5, along with our estimates for our models of major choice, to answer the following hypothetical question: How would the choice of college majors at Duke change if the only source of their differences in expected earnings were due to differences in their expected comparative advantage in different majors? We outline a set of assumptions about our data that allow us to eliminate differences across students in their forecasts about the average Duke students that might arise because of the heterogeneity in information about labor markets and careers across students, and estimate how it would have changed students' choice of a major.

The approach taken in this paper fits into a growing literature on the use of subjective expectations.[5] More recently, work has begun to incorporate subjective expectations into models of choice behavior.[6] Our work builds on the recent literature of Delavande (2008), Attanasio and Kaufmann (2009), Stinebrickner and Stinebrickner (2010b), and Zafar (2008, 2011), who use counterfactual expectations of choice models.

Of particular relevance for our work is Zafar (2011), who also examines counterfactual expectations and the choice of major. Zafar (2008) focuses on gender differences in the choice of major while Zafar (2011) examines how expectations change over time regarding major fit and the probability of graduating conditional on major choice. In contrast to our findings, Zafar's work finds

4 See Manski (1993a,b) for more on this point.

5 This literature begins with the seminal work of Manski (1993a) and Dominitz and Manski (1996, 1997). Also see Manski (2004).

6 See van der Klaauw (2000), van der Klaauw and Wolpin (2008) and Blass et al. (2010). For an early discussion on incorporating subjective expectations into choice models, see Manski (1999) and Wolpin (1999).

no significant evidence of expected earning affecting the choice of major, leaving no role for informational differences on market returns to affect the choice of major. While Zafar's study was informative for the design of our survey, there are differences between the designs of his study and ours. First, in order to obtain more accurate measures of the students' expected earnings across majors, we asked students for their expected earnings for various major *and* subsequent career combinations, whereas Zafar asked students to provide these expectations conditional only on majors.[7] Second, we drew a larger sample than Zafar and limited it to one gender (males) in an attempt to minimize the potential for finding insignificant effects of expected income, or other measures, on students' choice of a major due to low statistical power in estimation.[8] Third, we included students from all classes (i.e., freshmen, sophomores, juniors, and seniors), whereas Zafar only included sophomores in his study. Zafar imposed this restriction because of his concern about the potential problem of "cognitive dissonance", i.e., upper-classmen might report systematically higher expected earnings for their chosen majors relative to reports for majors they did not choose in order to justify their particular choice of a major. As we discuss below, we find little evidence consistent with this pattern in our data.

2. Data from survey of Duke undergraduates

We administered a survey of male undergraduate students at Duke University between February and April in 2009. Gender was the only restriction on sample recruitment; students from any major, class, or race were eligible to participate in the survey. We recruited our sample members by posting flyers about our study around the Duke campus. Surveys were administered on computers in a designated room in Duke's Student Union. All students who completed the survey were paid $20. Our sample consists of 173 students who completed our survey.[9]

In our survey, we collected data on students' background characteristics and their current or intended major. Table 1 presents a summary of the characteristics of our sample and compares them with the corresponding characteristics of the male undergraduate population at Duke. Due to the large number of majors offered at Duke University, we divided the majors into six broad groups: natural science, humanities, engineering, social sciences, economics, and policy. The classification system of the majors is reported in the Appendix.[10] Those who had already declared their majors were asked to provide us with their current major; those who have not declared were asked to provide us with their intended major.

While our sampling strategy was not systematically random, one can see from Table 1 that our sample corresponds fairly closely to the Duke male undergraduate student body. Our sample includes slightly more Asians and fewer Latinos and Blacks than are at Duke. It also appears that a higher percentage of our sample receives some financial aid than is the case in the Duke student body, although the 22.0% figure for the student body is based on aid provided by Duke, whereas the higher percentage of students receiving financial aid (40.5%) is likely due to the fact that our survey asked about receipt of financial aid, regardless of source. Finally, our sample is slightly tilted towards upper-classmen. Duke has very low dropout rates, so the share for each class should be approximately 25%.

Table 1
Sample descriptive statistics.

	Sample	Duke male Study body[a]
Current/intended major[b]		
Science	17.9%	14.8%
Humanities	9.3%	9.4%
Engineering	19.1%	20.7%
Social Sciences	17.9%	18.8%
Economics	19.7%	18.0%
Public policy	16.2%	18.0%
Class/Year at Duke:		
Under-classmen		
Freshman	20.8%	
Sophomore	20.2%	
Upper-classmen		
Junior	27.2%	
Senior	31.8%	
Characteristics of students:		
White	66.5%	66.0%
Asian	20.2%	16.6%
Latino	4.6%	8.3%
Black	4.0%	5.9%
Other	4.6%	3.0%
US citizen	94.8%	94.1%
Receives financial aid[c]	40.5%	22.0%
Sample size	173	

[a] The information on the Duke male population is drawn from a recent student survey done by the Campus Life and Learning (CLL) Project at Duke University. See Arcidiacono et al. (2009) for a detailed description of the CLL dataset.

[b] Respondents were asked to choose one of the six choices (science, humanities, engineering, social science, economics, policy) in response to the questions: "What is your current field of study? If you have not declared your major, what is your intended field of study?".

[c] For the Duke male study body, the proportion receiving financial aid includes those who received need-based, merit or athletic aid in school year 2008–2009. Source: Duke Undergraduate Financial Aid Office.

2.1. Expectations about future careers

In our survey, we elicited students' expectations about future careers and how much they expected to earn in them. For each of the groups of majors listed in the Appendix, we asked students to give the probability that they would enter a particular career/occupation and the income they would expect to receive in that career 10 years after graduation. We used the following six broad career groups to characterize possible careers: science/technology, health, business, government/non-profit, education, and law. These groups were based on the distribution of the careers that the Duke undergraduates have historically entered after they graduated. Table 2 gives the sample means, taken over the full sample ($N = 173$), for P_{ijk}, the probability that student i would pursue career k given that he majored in major j, and Y_{ijk10}, the income this student would expect to earn 10 years after graduation if he were to major in major j and pursue career k.[11]

7 We made this adaptation to our design based on feedback from focus groups of students on whom we tested in an initial version of our survey. Members of these groups complained that it was difficult for them to answer questions about expected earnings for different majors because they felt earnings for a given major would greatly vary across the careers one might enter from that major.

8 Zafar's sample consisted of 161 students, of which 92 were women and 69 were men. We gathered data on 173 students, all of whom were men, giving us a sample that is over 2.5 times larger than that used by Zafar to estimate his college choice model for men.

9 The questionnaire we used in our survey is discussed further in Kang (2009), and a copy of it can be found at www.econ.duke.edu/~vjh3/working_papers/college_major_questionnaire.pdf.

10 There are four different schools at Duke in which undergraduates are enrolled: Trinity College (college of arts and sciences), Pratt School of Engineering, Nicholas School of the Environment, and Sanford School of Public Policy.

11 For the respondents whose probabilities for each major j did not add up to 1 or 100, their stated probabilities were proportionally adjusted so that the sum of

Table 2
Elicited expected incomes (10 years out) and elicited probabilities of going into various careers and majors.

If majored in:	If career in: Science	Health	Business	Government	Education	Law
A. Probability of going into career[a]						
Science	0.352	0.319	0.120	0.070	0.068	0.070
Humanities	0.067	0.122	0.235	0.145	0.230	0.200
Engineering	0.411	0.194	0.190	0.072	0.065	0.068
Social Sciences	0.091	0.139	0.246	0.193	0.128	0.204
Economics	0.067	0.076	0.515	0.154	0.062	0.125
Policy	0.054	0.113	0.228	0.317	0.075	0.214
B. Expected income 10 years out[b]						
Science	106,156	162,000	138,121	93,965	72,590	143,694
Humanities	77,994	122,769	130,618	90,971	70,936	147,087
Engineering	118,012	152,462	153,318	97,017	74,746	165,422
Social Sciences	81,942	122,393	142,676	95,532	71,000	149,965
Economics	91,023	126,769	192,306	101,957	78,283	158,254
Policy	86,052	123,382	156,705	103,653	71,925	164,809

[a] To elicit career probabilities, students were asked: "Suppose you majored in each of the following academic fields [Sciences, Humanities, Engineering, Social Sciences, Economics, Public Policy]. What are the probabilities that you will pursue the following career field [science, health, business, government/non-profit, education, law] *AFTER* majoring in this academic field.".
[b] To elicit expected earnings associated with different careers and majors, students were asked: "For the following questions regarding future income, please answer them in pre-tax, per-year, US dollar term, ignoring the inflation effect. Suppose you majored in the following academic field. How much do you think you will make working in the following career 10 years after graduation?" We assume that respondents reported their answers as means.

There are several noteworthy patterns in Table 2 with respect to the expectations elicited about careers from our sample of undergraduates. First, there are marked differences in the probabilities of entering the six careers across the various majors. Some careers appear to be tied to certain majors, whereas other careers are less so. For example, if students were to major in the (natural) Sciences or Engineering, the probability of going into Science or Health related careers is fairly high, compared to if the students were to major in one of the other fields. A similar pattern occurs for entering a career in the field of Education, which is more likely if a student were to major in the Humanities compared to other majors. In contrast, the probabilities of going into a Business career are relatively high for all majors. This is especially true for being an economics major, where students indicate that the probability of going to a Business career is over 50%, which is substantially higher than the career probabilities found for any of the other majors. Second, student expectations about the earnings in careers 10 years out differ across majors. For example, majoring in science or engineering was perceived to lead to higher earnings in science and health careers while perceived earnings in business were higher if a student's major was economics.

The sample means presented in Table 2 are calculated over all students in the sample, regardless of whether they are majoring (or intending to major) in a particular field and of what class they are in. We now consider how the elicited expectations differed by a student's class/year at Duke and by whether the student actually chose the hypothetical major. With respect to both dimensions, we might expect differences by one's major and class/year in the information students have about different careers. For example, under-classmen might have less information about careers than do upper-classmen, since the latter group is closer to graduation and, thus, may be devoting more time to learn about their future prospects. Similarly, students who were majoring in a particular field may have a better idea about the earnings potential of careers more closely related to their field of study than would be the case for non-majors. It also may be the case that students who major in a field expect that they have a major-specific *absolute advantage* in certain careers, because of their major-specific abilities. In Table 3, we present the differences in the means for expected earnings (10 years out) for the various major–career combinations between students who majored in the particular career versus those who did not (non-majors) and between upper-classmen and under-classmen. We also display in this table results for hypothesis tests of differences between these groups in student earnings expectations.

While there is no clear pattern to differences in-majors versus non-majors and upper-classmen versus under-classmen for most of the various careers and major fields, there are a couple of notable exceptions. First, students who are currently majoring in Policy have markedly higher income expectations than students majoring in other fields for all careers but those in Health. Furthermore, several of these differences are statistically significant. For example, Policy majors expect to earn more than 50% higher salaries ($84,171) if they enter the field of Law than if non-majors were to enter the same field having majored in Policy. Second, we find that upper-classmen, regardless of their major, expect to earn *less* if they enter either a Science or Education career than do under-classmen, with differences for Education careers being statistically significant. The two patterns just cited may be due to systematic differences in the tastes and/or abilities of Policy majors or in upper-classmen versus under-classmen with respect to Education careers. But, a potentially more plausible explanation is that there are differences in information between groups – e.g., upper-classmen may have more information than under-classmen about the low earnings of careers in Education careers based on the former group's greater preparations for life-after-college – and these differences lead to systematically *different forecasts*. Below, we present some results concerning students' expected earnings for the average Duke student that are quite consistent with the differences-in-forecasts explanation.

If there are systematic differences in information regarding future careers between in-majors and non-majors and between upper-classmen and under-classmen as suggested by Table 3, the information differences should also be reflected in the career choice probabilities. In Table 4, we present a comparison of the means of major–career combination choice probabilities between different major and class groups. There are a few notable differences between the major–career choice probabilities both by the major chosen (first panel) and by a student's class (second

P_{ijk} over k was equal to 1 for each student. 9.8% of the respondents showed "poor" understanding of probabilities, i.e., their career choice probabilities did not sum up to 1 or 100 for less than four majors out of six.

Table 3
Differences by own major versus non-major and upper-classmen versus under-classmen in elicited expected incomes (10 years out) for alternative careers and majors[a].

Major	If career in:					
	Science	Health	Business	Government	Education	Law
A. In-major versus non-major						
Science	−2391	54,745**	48,663***	14,426	−2,565	20,652
Humanities	−9153	1977	−2059	2993	−68	−6087
Engineering	−19,074	−24,200	−14,922	−20,467	−7175	−39,465
Social Sciences	267	−1736	−234	1592	−9511	−13,949
Economics	−12,438	−2567	−5433	−10,672	−13,421	3271
Policy	36,455***	−1265	16,501	27,813	36,053***	84,171***
B. Upper-classmen versus under-classmen						
Science	−20,733*	−13,473	12,461	−10,140	−13,835*	5452
Humanities	−14,223	−3235	−2295	−8219	−18,621*	649
Engineering	−10,921	−267	26,076*	−10,696	−12,376	50,857
Social Sciences	−12,257	−2630	4850	−9728	−15,050**	−9471
Economics	−3520	5771	6205	−21,227	−9863	9437
Policy	−12,716	−786	−15,956	−16,402	−14,747*	4311

[a] Test results for between-group differences in means of expected income.
* Significantly different at 10%.
** Significantly different at 5%.
*** Significantly different at 1%.

Table 4
Differences by own major versus non-major and upper-classmen versus under-classmen in career choice probabilities for alternative careers and majors[a].

Major	If career in:					
	Science	Health	Business	Government	Education	Law
A. In-major versus non-major						
Science	−3.48%	8.59%*	−3.86%	−2.62%*	4.69%***	−3.32%
Humanities	−1.61%	3.32%	−11.64%***	−0.69%	3.85%	6.78%
Engineering	−1.16%	−1.66%	3.53%	−1.63%	−0.67%	1.58%
Social Sciences	4.33%*	1.34%	−2.98%	−7.00%**	−0.11%	4.42%
Economics	0.02%	0.97%	8.33%*	−5.41%**	−3.39%**	−0.52%
Policy	−3.78%**	−7.20%**	3.92%	−4.93%	−2.37%	14.35%***
B. Upper-classmen versus under-classmen						
Science	−1.12%	7.71%**	−1.53%	−0.78%	−0.26%	−4.02%**
Humanities	−0.86%	−2.43%	3.43%	3.17%*	−0.54%	−2.78%
Engineering	−1.91%	3.37%	0.36%	−0.42%	0.41%	−1.81%
Social Sciences	0.90%	0.81%	−4.04%	−0.28%	2.82%	−0.21%
Economics	−1.98%	2.34%	1.95%	−1.41%	2.01%	−2.90%
Policy	1.34%	3.46%	−8.56%***	6.32%*	2.31%*	−4.87%

[a] Test results for between-group differences in means of choice probability.
* Significantly different at 10%.
** Significantly different at 5%.
*** Significantly different at 1%.

panel). For instance, those majoring in science are 8.59% more likely to choose health-related careers given a science major than those not majoring in science, and those majoring in policy are 14.35% more likely to pursue a career in law given a policy major compared to those not majoring in policy. These observations are consistent with our earlier explanation on the differences in income expectations; "in-major" students and upper-classmen may have systematically different career choice patterns due to more information about careers than their counterparts.

We use the elicited earnings expectations and career probabilities for alternative major–career combinations to form Y_{ij10}, student i's major-specific expected earnings 10 years after graduation, given by

$$Y_{ij10} = \sum_{k=1}^{K} P_{ijk} Y_{ijk10}. \tag{1}$$

Sample means for these major-specific expected earnings are given in Table 5. Unlike the sample means presented in Table 2, the sample means in Table 5 are for students who *are majoring* in, or *intend to major* in, each of the major fields. The theoretical model of college major choice in Section 3 hypothesizes that students are more likely to major in fields in which they have a *comparative* expected earnings advantage. Looking along the diagonals in Panel A of Table 5, we do see evidence of income sorting in choice of majors. For all but those whose "own major" is in the field of Humanities, students expect that the earnings in their own major is the highest, or second highest, compared to all of the other majors. This pattern is seen in Panel B of Table 5, which records the proportion of students who indicate that the expected earnings in their own major is the highest, or at least as high, compared to the majors they did not choose.[12]

At the same time, we also find that the majority of students would expect that they would have their highest, or at least as high, earnings if they majored in Economics, regardless of their actual major. Looking back at the career probabilities and expected incomes for different major–career combinations in Table 2, it is clear that this finding is driven by the combination of the high

12 Some students gave the same expected earnings for two or more majors. As a result, 17.3% of the students had two or more majors with the highest expected earning.

Table 5
Elicited expected incomes (10 years out), conditional on pursuing alternative majors by own major[a].

Own major	If majored in:					
	Science	Humanities	Engineering	Social Sciences	Economics	Policy
A. Expected annual income, 10 years out						
Science	169,385	138,856	157,489	148,483	197,043	154,981
Humanities	120,158	115,786	119,484	129,314	135,255	112,377
Engineering	111,982	97,326	122,416	102,250	148,880	100,569
Social Sciences	121,610	101,150	120,308	125,578	144,877	117,820
Economics	130,839	112,475	133,916	119,021	160,488	125,676
Policy	152,761	139,314	162,677	149,457	187,109	180,350
B. Proportion of students where expected inc is at least as high in own major						
Science	0.419	0.097	0.226	0.194	0.581	0.129
Humanities	0.063	0.188	0.188	0.063	0.500	0.000
Engineering	0.242	0.152	0.242	0.091	0.545	0.061
Social Sciences	0.097	0.032	0.419	0.161	0.645	0.226
Economics	0.147	0.147	0.206	0.118	0.647	0.147
Policy	0.357	0.143	0.321	0.214	0.571	0.214

[a] There is one observation for every student in every cell. Here we do not condition on a student's own major. See text for how expected incomes were calculated using information elicited from students.

expected incomes that all students associate with Business careers and, more importantly, the fact that students think majoring in Economics is much more likely to lead to a career in Business (probability = 0.515) relative to all other majors. As a result, the majority of students expect that they would have an *absolute income* advantage if they were to major in Economics, even though only slightly less than 20% of Duke male undergraduates have chosen to do so. Thus, while we do find evidence in our data of income sorting in the choice of college majors, it appears that there are other factors that influence students' decisions. Below, we consider one of them, namely, students' abilities to complete various majors at Duke.

2.2. Comparison between the elicited expected income and objective income data

In this section, we present a brief comparison between the subjective expectations on future earnings that we elicited in our survey with the observed income levels of recent Duke graduates. This comparison allows us to assess whether students have reasonable expectations regarding their future earnings streams.

The data we have on the observed earnings is from the 2007 Duke Senior Exit Survey.[13] The Exit Survey contains information on: (1) respondents' majors; (2) whether they accepted job offers, are attending graduate education, or seeking employment; and (3) salary levels if they accepted job offers. As the Duke Exit Survey data only has information on the major that is actually chosen, it closely resembles typical earnings data used in the literature. The 2007 Exit Survey had 1146 respondents, of which 346 reported the salary levels they were to earn in the first year after graduation.[14] We compare these earnings data with data that we elicited from students in our survey about the earnings they would expect to receive in the first year after they graduate if they were in different majors and careers. While the latter income expectations measures are not the ones discussed above or used to estimate our model of college major choice below, they more closely correspond to the data on observed earnings in the Duke Exit Survey. Furthermore, in order to further minimize the differences between the two sources of data, we imposed the following restrictions on the data from our sample. We only use the expectations data obtained from upper-classmen (i.e., juniors and seniors) and only include the elicited earnings expectations for the majors that the students in our survey actually chose.

Table 6
Comparison of upper-classmen's subjective earnings expectations first year after graduation and reported staring salary of Duke class of 2007[a].

Major chosen	Expected earnings from our survey		Reported salary from exit survey		p-value[b]
	Median	Share	Median	Share	
Science	43,750	16.7%	40,000	9.5%	0.96
Humanities	46,250	7.8%	49,500	6.9%	0.46
Engineering	60,000	20.6%	60,000	21.1%	0.45
Social Sciences	48,400	18.6%	42,500	17.6%	0.21
Economics	60,000	22.5%	60,000	26.0%	0.69
Policy	47,000	13.7%	45,000	18.8%	0.47
Sample		102		346	

[a] "Expected earnings" corresponds to the subjective expectation on earnings first year after college, elicited from our 2009 survey. "Reported salary" corresponds to the starting salary, self-reported by graduating seniors in Spring 2007.
[b] p-values are computed by nonparametric Mann–Whitney U-test, with the null hypothesis that the exit survey data and our survey data are from populations with the same distribution.

Table 6 presents a comparison of the medians of the subjective earnings expectations and observed earnings of Duke students in their first year after graduation. In all six major groups, the two earnings measures are fairly similar in magnitude. There is no difference in the median earnings across the two samples for engineering and economics majors. The corresponding differences are larger for Science ($3750) and Social Sciences majors ($5900). The two datasets have roughly the same share of students who chose each major, although there are fewer policy majors and more science majors in our survey compared to the Duke Exit Survey. Finally, the p-values in the final column of Table 6 indicate that we cannot reject the null hypothesis that the earnings distribution in the two surveys are equal at conventional levels of significance. In sum, this comparison suggests that our (upper-classmen) survey respondents, on average, have fairly reasonable accurate expectations about what they are likely to earn one year after graduation with their chosen major.[15]

However, the findings from this comparison need not characterize the accuracy of student's earnings expectations for majors

13 The 2007 Duke Senior Exit Survey was administered by Duke Career Center.

14 We focus on the students working in the US labor market and exclude respondents with job offers abroad.

15 In contrast, comparing the expectations of under-classmen to those from the exit survey shows significant differences in five of the six careers, and in each case expectations of the under-classmen were higher than what was realized in the exit survey.

Table 7
Elicited expected incomes (10 years out) for average Duke student in alternative majors and careers by student's own major.

If majored in:	If in Career:					
	Science	Health	Business	Government	Education	Law
Science	110,607	166,988	124,133	77,815	71,873	109,994
Humanities	74,578	116,965	128,410	89,618	77,983	139,566
Engineering	120,925	153,295	141,162	80,168	68,919	135,786
Social Sciences	80,283	112,809	133,110	88,618	74,618	136,191
Economics	79,509	107,335	176,566	91,988	69,440	137,509
Policy	74,145	106,948	134,301	99,295	71,162	143,173

Table 8
Differences in elicited expected incomes (10 years out) for average Duke student by own major versus non-major and upper-classmen versus under-classmen[a].

Major	Career					
	Science	Health	Business	Government	Education	Law
A. In-Major versus Non-Major						
Sciences	9675	42,380	13,436	−16,006	−13,286	204
Humanities	−1257	−18,350	−1003	−2334	−3355	3232
Engineering	−22,487	−30,096	−13,418	−6573	−1098	−27,932
Social Sciences	−9227	−13,169	−26,465	−13,723	−21,072**	−26,760*
Economics	3540	3683	17,269	4297	3955	17,743
Policy	44,271***	35,173**	13,831	33,396***	38,029***	56,082***
B. Upper-classmen versus Under-Classmen						
Sciences	−21,426*	19,760	6,771	−11,947	−17,750*	1209
Humanities	−14,499	9855	4232	−17,632*	−32,279***	−19
Engineering	−15,703	18,488	24,521*	−7838	−15,975*	46,745
Social Sciences	−8573	11,167	12,847	−22,266**	−14,932*	5364
Economics	1364	13,659	24,969	−13,302	−21,948**	4040
Policy	−9573	11,545	−4435	−9127	−21,297**	−2095

[a] Test results for between-group differences in means of expected income.
* Significantly different at 10%.
** Significantly different at 5%.
*** Significantly different at 1%.

they did *not* choose.[16] As such, this comparison does not allow us to determine whether students differ in their earnings forecasts across majors because of differences in their perceptions of how well they would do in the labor market with different majors or whether they simply do not know much about the labor market prospects associated with these majors. In the next section, we describe some information we elicited from students in an attempt to get at the latter distinction.

2.3. Expectations for the "average" Duke student

Students can differ in their forecasts of future expected earnings in different careers and majors precisely because they differ in their abilities to succeed in different majors and, subsequently, in various careers. But, as noted in the Introduction, students' expectations about the future also can differ because they make errors in their forecasts of future earnings. Without waiting for 10 years to find out their actual earnings and career choices, we cannot directly measure the extent of these errors or assess their properties. But we can determine the *relative* properties of students' forecasts by asking all students to make forecasts about the future for a similar event or person. In our survey, we asked each student to provide us with their assessments of what the "average" Duke [male] undergraduate would earn in different major–career combinations to parallel the questions we asked of students about their expectations about their own future earnings. In particular, we asked:

> *Suppose an average Duke student majored in [Sciences, Humanities, Engineering, Social Sciences, Economics, Public Policy]. How much do you think he will make working in the following careers [Science, Health, Business, Government, Education, Law] 10 years after graduation?*

Let Y^{AV}_{ijk10} denote student i's answer to how much the average Duke student would earn in career k conditional on majoring in field j 10 years after graduation. To see how expected earnings for the average student varies at the major–career level, we report the sample averages of students' expected earnings for the average Duke student, i.e., $\overline{Y}^{AV}_{jk10} = \frac{1}{N}\sum_{i=1}^{N} Y^{AV}_{ijk10}$, in Table 7. In general, the expected earnings for the average Duke student for the different major–career combinations are similar to the corresponding student expectations about their own future earnings in Table 2.

Following on the findings of Betts (1996), we examine how the expectations for the future earnings of the average Duke student differed between majors and non-majors and between upper-classmen and under-classmen. The results of these comparisons are reported in Table 8. The structure of Table 8 parallels Table 3. While most of the differences in means between majors and non-majors and upper-classmen and under-classmen are not that sizable or statistically different at conventional levels of significance, there are some notable exceptions. In particular, Policy majors consistently have higher forecasts of expected earnings for the average Duke student compared to students who are not Policy majors. Furthermore, upper-classmen consistently have lower forecasts of the expected earnings that the average Duke student would have in Education careers than do under-classmen. Recall that we found in Table 3 differences in the same direction for the corresponding comparisons of students' expectations about what their *own earnings* would be and that these differences in that table also were statistically significant. Taken together, these findings strongly suggest that there are differences across students in the information they have about different careers and the labor market. As such, these informational

[16] These findings also may not apply to forecasting earnings 10 years after graduation.

Table 9
Elicited rankings of student's ability if he pursued alternative majors by own major[a].

Own major	If majored in:					
	Science	Humanities	Engineering	Social Sciences	Economics	Policy
A. Ability ratings						
Science	4.000	3.548	2.710	3.548	2.871	2.774
Humanities	2.625	4.438	1.750	3.750	2.500	3.375
Engineering	3.576	3.000	3.909	3.182	3.242	2.818
Social Sciences	2.806	3.419	2.129	4.000	2.677	2.935
Economics	3.412	3.176	2.353	3.412	3.794	3.206
Policy	2.536	3.536	1.821	3.786	2.893	4.286
All majors	3.225	3.428	2.532	3.590	3.058	3.197
B. Proportion of students for whom highest ability rating would be in this major						
Science	0.774	0.387	0.194	0.484	0.194	0.226
Humanities	0.125	0.938	0.063	0.375	0.125	0.313
Engineering	0.424	0.242	0.697	0.242	0.333	0.121
Social Sciences	0.161	0.290	0.129	0.677	0.194	0.194
Economics	0.324	0.235	0.206	0.324	0.588	0.235
Public policy	0.179	0.321	0.071	0.500	0.107	0.821

[a] Students were asked: "Rate your competitiveness relative to your peers at Duke in academic field *j*", using a 5-point scale with 1 = much worse, 3 = average, 5 = much better.

differences may have a non-trivial effect on what major a student chooses. We explicitly try to quantify this influence in Section 5.

2.4. Assessments of abilities in alternative majors

Finally, we discuss the measures we elicited from students about their perceived abilities for each of the major fields. In our survey, we asked each student to rate their competitiveness relative to their peers at Duke in each of the six majors. All else being equal, we would expect students to sort to the major in which they have a *comparative ability advantage*. In Table 9 we see clear evidence of such advantage. Looking along the diagonals of either Panel A, which gives the average student ability ratings in their own major, or of Panel B, which gives the proportion of students that had the highest ability rating in their own major, one sees strong evidence of sorting by ability in choice of major fields. Furthermore, ability sorting in choice of a major appears to be stronger than sorting on expected future earnings. In particular, note that the proportion of students with their highest ability rating in their own major (the diagonal elements of Panel B) are much higher than the proportion of students that have their highest expected earnings in their own major (the diagonal elements of Panel B in Table 5).

The ability ratings of students also appear consistent with one's sense of the difficulty of the curriculums for the different majors. Looking at the average ratings taken over all majors for each of the major fields, we find that the average student finds Engineering the most challenging field (2.532), followed by Economics (3.058), while the average student finds that Social Sciences (3.590) and Humanities (3.428) are the least difficult majors.

3. Empirical model of college major choice

In this section, we lay out an empirical model of college major choice in order to examine the interplay of students' ability, expected income, and preferences over majors and careers. We based our data collection on a model of how students made their college major decisions. We provide an explicit characterization of that model, as well as a specification of the process generating students' expected future earnings associated with alternative careers and majors that require expectations data on earnings for only one point in students' futures.

In modeling a student's college major choice, we make a number of simplifying assumptions. First, we assume that a student's choice of major is a one-shot decision, i.e., we do not allow students to change their majors.[17] Second, in order to simplify our analysis, we ignore the possibility that students may continue their education by seeking post-baccalaureate degrees.[18] Third, we assume that, once students have made their major decisions, they do not choose their careers upon graduation, but rather face a lottery over alternative careers, where the probabilities of being assigned to particular careers depend upon their choice of major. Let P_{ijk} denote the probability of i being assigned career k conditional on choosing major j. Once student i realizes his draw on a career, he makes no further decisions[19] and reaps the benefits of his choice of major and the outcome of his career assignment. These benefits come in the form of the consumption he can realize in each remaining period of his lifetime and, as we describe below, preferences over careers.

3.1. Earnings and consumption

In deciding on their college major, students are assumed to compare the expected utility from future consumption associated with alternative major–career combinations. Let C_{ijkt} denote the consumption individual i would realize in period t if he had chosen major j and had entered career k. Let the per-period utility be proportional to $\ln C_{ijkt}$. We also assume that there is no saving, so that $Y_{ijkt} = C_{ijkt}$.[20] These assumptions imply that the expected

[17] In reality, students may change their majors over the course of their college careers. As discussed in Kang (2009), we did ask students about any changes they made in their major since coming to Duke. Less than 20% of the (male) students in our survey had changed their majors, with most of these changes reported by upper-classmen (juniors and seniors).

[18] We asked students about their plans for continuing their education and we found that almost all of the Duke students we surveyed (91%) planned to seek an advanced degree. Given this high percentage, we do not try to model attending graduate school in this paper. However, we expect that students factored in graduate school in the probabilities and expected earnings we elicited from them about careers (e.g., a career in Law is likely to require going to law school).

[19] With respect to careers, we asked students to provide expectations about broad careers, rather than narrow occupations, in an attempt to mitigate planned occupation switching.

[20] An alternative assumption that yields the same reduced form is that individuals are able to perfectly consumption smooth. In this case, we also can have probabilities of employment that differ by major. See Arcidiacono (2005) for a discussion.

present discounted value of the utility of consumption associated with major j, v_{ij}^C, is given by

$$v_{ij}^C \equiv \alpha \sum_{k=1}^{K} \sum_{t=1}^{T} \beta^t P_{ijk} E \ln(C_{ijkt}) = \alpha \sum_{k=1}^{K} \sum_{t=1}^{T} \beta^t P_{ijk} E \ln(Y_{ijkt}), \quad (2)$$

where β is the rate of time preference and α is the (utility) value of log consumption, and we normalize the price of consumption to 1. Then a student's optimal choice of a major, $j_i^\dagger$, is determined by the following decision rule:

$$j_i^\dagger = \arg\max_j v_{ij}^C. \quad (3)$$

We next lay out a set of assumptions on the process generating earnings and what students know about its future values that also allows us to express v_{ij}^C in (2) solely as a function of the measures of career probabilities (P_{ijk}) and the expected earnings as of 10 years after graduation ($t = 10$) that we elicited from students for each possible major j. Let Y_{ijkt} be given by

$$Y_{ijkt} = \exp(\mu_{ijk} + g_{jt} + \epsilon_{ijkt}), \quad (4)$$

where μ_{ijk} is a time-invariant, individual-specific component of earnings for major j and career k, g_{jt} is a growth rate which is major-specific but neither career or individual specific,[21] and ϵ_{ijkt} is a mean-zero transitory error term. At the time they make their college major decisions, students are assumed to know μ_{ijk} and g_{jt}, but not ϵ_{ijkt}, for all j and k. It follows from (4) and these assumptions that a student's subjective expectation about what his earnings will be for the various major–career combinations in future years, $\hat{Y}_{ijkt}$, is given by

$$\hat{Y}_{ijkt} = E[\exp(\mu_{ijk} + g_{jt} + \epsilon_{ijkt})] = \exp(\mu_{ijk} + g_{jt}) E[\exp(\epsilon_{ijkt})]. \quad (5)$$

Finally, we assume that $E[\exp(\epsilon_{ijkt})] = E[\exp(\epsilon_{ijk't'})]$ is the same for all students (i) and careers (k, k') in each time period. It follows from these assumptions that a student's expected utility from choosing major j, v_{ij}^C, can be written as the following function of $\hat{Y}_{ijk10}$:

$$v_{ij}^C = \alpha^* \sum_{k=1}^{K} P_{ijk} \ln \hat{Y}_{ijk10} + \phi_j^*, \quad (6)$$

where α^* and ϕ_j^* are given by

$$\alpha^* = \frac{\alpha(\beta - \beta^T)}{1 - \beta} \quad (7)$$

$$\phi_j^* = \alpha \sum_{t=1}^{T} \beta^t \left(g_{jt} - g_{j10} - \ln(E[\exp(\epsilon_{ijK10})]) \right), \quad (8)$$

where, since $E[\exp(\epsilon_{ijk10})] = E[\exp(\epsilon_{ijk'10})]$, we have expressed the last line relative to career K.

In our initial empirical model we assume that college major payoffs are equal to v_{ij}^C in (6) plus an individual-specific and major-specific preference component, η_{ij}, that is unobserved by the econometrician, so that

$$v_{ij} = \phi_j^* + \alpha^* \sum_{k=1}^{K} P_{ijk} \ln \hat{Y}_{ijk10} + \eta_{ij}. \quad (9)$$

3.2. Utility while in college

Assuming that the payoffs from different majors depend only on expected lifetime consumption (income) ignores the role that coursework and other requirements play in one's choice of a college major. Individuals may also base their choice of a major on the difficulty of a major's coursework and their ability to complete it.[22] To get at the role of difficulty of majors and students' abilities to complete them, we control for students' assessments of their relative abilities in the each of the majors, A_{ij}, that we elicited in our survey. In particular, we model the observed utility of the major choice while in school as $u_{ij} = \gamma_j + A_{ij}\theta$, so that v_{ij} becomes

$$v_{ij} = \gamma_j^* + A_{ij}\theta + \alpha^* \sum_{k=1}^{K} P_{ijk} \ln \hat{Y}_{ijk10} + \eta_{ij}, \quad (10)$$

where $\gamma_j^* = \gamma_j + \phi_j^*$.

3.3. Career preferences

Finally, we allow for differences in preferences over careers themselves in some of our specifications of our college choice model. Normalizing the preferences for the first $K - 1$ careers relative to career K yields the following payoff to student i for major j:

$$v_{ij} = \gamma_j^* + A_{ij}\theta + \alpha^* \sum_{k=1}^{K} P_{ijk} \ln \hat{Y}_{ijk10} + \sum_{k=1}^{K-1} P_{ijk} \delta_k^* + \eta_{ij}. \quad (11)$$

We note that the career-specific preferences also may be picking up differences in growth rates across majors. In particular, if we assume that major–career specific growth rates in earnings can be written as $g_{jk} = g_j + g_k$, then δ_k^* can be decomposed into the actual preference for the career, δ_k, plus a function of the difference in growth rates between career k and career K:

$$\delta_k^* = \delta_k + \sum_{t=1}^{T} \beta^t \left(g_{kt} - g_{k10} - g_{Kt} + g_{k10} \right).$$

3.4. Estimation

Assuming that students choose their college major so as to maximize their expected utility, let $d_{ij} = 1$ when $j = \arg\max_{j'} v_{ij'}$, and zero otherwise. To simplify the estimation, we assume that the unobserved preferences for particular majors, η_{ij}, follow a Type I extreme value distribution. Letting $\bar{v}_{ij}$ denote v_{ij} net of η_{ij}, the probability that individual i chooses major j, p_{ij}, is

$$p_{ij} = \frac{\exp(\bar{v}_{ij})}{\sum_{j=1}^{J} \exp(\bar{v}_{ij})}. \quad (12)$$

Given data on observed major choices (or intended major choices) by the students in our sample, the log likelihood for the data is given by

$$L = \sum_i \sum_j 1[d_{ij} = 1] \log[p_{ij}], \quad (13)$$

where 1[ ] is the indicator function.

4. Results

Table 10 presents estimates for the three alternative specifications of a multinomial logit model of students' college major

[21] Below we will show that the model generalizes to cases where the growth rate on earnings is additive in career and major: $g_{jkt} = g_{jt} + g_{kt}$.

[22] A student's ability to do the coursework in a major is likely to translate into what earnings they can expect in later life with that major.

Table 10
Multinomial logit estimates of major choice[a].

	Coeff.	St. error	Coeff.	St. error	Coeff.	St. error
Natural Science	0.060	(0.264)	0.066	(0.304)	−0.436	(0.408)
Humanities	−0.364	(0.319)	−0.694	(0.351)	−1.299	(0.417)
Engineering	0.082	(0.261)	0.540	(0.316)	0.112	(0.422)
Social Sciences	0.182	(0.265)	−0.118	(0.294)	−0.421	(0.315)
Economics	−0.105	(0.268)	0.167	(0.299)	0.053	(0.356)
Expected ln earnings	1.612	(0.389)	1.690	(0.466)	1.463	(0.514)
$A_{ij} = 3$			1.110	(0.360)	1.162	(0.369)
$A_{ij} = 4$			2.130	(0.352)	2.102	(0.361)
$A_{ij} = 5$			3.538	(0.376)	3.592	(0.388)
Science career					−1.146	(0.847)
Health career					−0.511	(0.835)
Business career					−1.176	(0.799)
Government career					−4.225	(1.244)
Education career					0.069	(1.284)
Log likelihood	296.1		223.8		216.4	

[a] $N = 173$. The omitted major category is public policy. The omitted career category is law.

Table 11
The effects of changes in expected earnings and abilities on probabilities of college major choices[a].

	Base	Equal abilities	Equal earnings	1 Std. dev. Increase in Y of science career	1 Std. dev. Increase in Y of business career	1 Std. dev. Increase in Y of all majors
Natural Science	0.179	0.166	0.178	0.189	0.162	0.259
Humanities	0.093	0.059	0.109	0.086	0.091	0.150
Engineering	0.191	0.271	0.190	0.211	0.186	0.266
Social Sciences	0.179	0.122	0.197	0.174	0.172	0.268
Economics	0.197	0.238	0.166	0.186	0.229	0.293
Public policy	0.162	0.144	0.160	0.154	0.161	0.232

[a] Forecasts used the multinomial logit estimates from the last column in Table 10. The last three columns refer to one standard deviation increases. The last column shows major choices when earnings for that major were increased holding earnings in the other majors constant.

choices corresponding to the major-specific payoff functions in (9)–(11), respectively. For all three specifications, we find that the coefficient on expected log earnings 10 years out, $\hat{Y}_{ijk10}$, is positive and significantly different from zero. Consistent with Arcidiacono (2004), we also find that students' comparative advantage in their abilities in different majors plays a very important role in choice of a major, over and above the earnings they expect to receive from different majors.[23] For example, moving from a 4 to a 5 on the self-assessed ability scale is equivalent to an 86% increase in earnings. Finally, we find much less evidence that preferences for specific careers influence students' major choices. The one exception to this is the effect of a career in the government, which is statistically significant and very negative in the multinomial logit estimates.[24]

Using the multinomial logit estimates from the last column of Table 10, we examine the effect of expected log earnings and abilities on major choice. These results are presented in Table 11. The first column of this table displays the baseline probability of choosing each of the majors. In the second and third columns, we use the parameter estimates to forecast choice behavior when abilities and earnings, respectively, are the same across majors. When abilities are set equal, large shifts occur as individuals move away from the Humanities and the Social Sciences and into Engineering, with some movement also into the Economics major. This occurs because earnings now play a greater role in sorting and because students' beliefs about their ability to perform well in Engineering are much lower than their beliefs about their abilities to perform well in other majors. In contrast, when earnings are set equal, the share of individuals choosing Humanities and Social Sciences majors increases by 17% and 10%, respectively, with the share choosing Economics as a major falling by 16%. The overall distribution across majors when earnings are equal, however, still leaves no major drawing more than 20% of the students.

The fourth and fifth columns of Table 11 show the effects of one standard deviation increases in the earnings of Science and Business careers, respectively. These standard deviation increases are calculated separately for each major using the sample distribution. Increasing earnings in Science careers results in shifts from all the other majors to Natural Science and Engineering majors. The share of individuals choosing Natural Science and Engineering majors increases by 5.5% and 10%, respectively, from a one standard deviation increase in earnings from Science careers.

23 In our estimation, we aggregated the indicators with two lowest ability ranks, $A_{ij} = 1$ and $A_{ij} = 2$, as we had very few such observations, particularly in the majors actually chosen by respondents. For example, only 3.2% of Science majors and 3.6% of Policy majors responded that their ability rank in the chosen major is equal to 1 or 2.

24 Similar to Zafar (2008), we also elicited more information from the students in our sample than just their choice (or expected choice) of major. In particular, we asked them to provide their full preference orderings over all of the majors. These data can be used to estimate the parameters of the alternative specifications of the payoff functions, v_{ij}, in (9)–(11) via a rank-ordered, or exploded, logit model. Let $r_i = (r_{i1}, r_{i2}, \ldots, r_{im}, \ldots, r_{iJ})'$, where r_{im} denotes the major that student i ranked as the mth highest of the J majors. Then it follows that the probability of observing student i's rankings of majors, r_i, is given by

$$p(r_i) \equiv Pr(v_{ir_{i1}} > v_{ir_{i2}} > \cdots > v_{ir_{iJ}}) = \prod_{j=1}^{J-1} \frac{\exp(\bar{v}_{ir_{ij}})}{\sum_{l=j}^{J} \exp(\bar{v}_{ir_{il}})}, \quad (14)$$

and the log likelihood for the data is

$$L = \sum_i \log[p(r_i)]. \quad (15)$$

While the coefficient on earnings was positive and significant, it was much smaller in magnitude. We believe this was because of the wording of the question, as close to 20% of individuals reported a most preferred major that was not the major they chose.

Table 12
Multinomial logit estimates of major choice by class[a].

	Under-classmen		Upper-classmen		Under-classmen		Upper-classmen		Under-classmen		Upper-classmen	
	Coeff.	St. error	Coeff.	St. error	Coeff.	St. Error	Coeff.	St. error	Coeff.	St. error	Coeff.	St. error
Natural Science	0.011	(0.384)	0.118	(0.364)	−0.326	(0.432)	0.433	(0.432)	−0.804	(0.607)	−0.010	(0.591)
Humanities	−0.364	(0.453)	−0.372	(0.449)	−0.743	(0.510)	−0.641	(0.510)	−1.749	(0.649)	−0.864	(0.569)
Engineering	−0.158	(0.400)	0.273	(0.350)	−0.083	(0.461)	1.088	(0.461)	−0.437	(0.637)	0.653	(0.594)
Social Sciences	−0.018	(0.401)	0.343	(0.357)	−0.363	(0.452)	0.104	(0.452)	−0.734	(0.498)	−0.083	(0.429)
Economics	−0.419	(0.411)	0.134	(0.361)	−0.370	(0.453)	0.610	(0.453)	−0.504	(0.521)	0.606	(0.509)
Expected ln earnings	1.575	(0.625)	1.555	(0.500)	1.694	(0.708)	1.589	(0.708)	1.530	(0.804)	1.335	(0.706)
$A_{ij} = 3$					0.777	(0.562)	1.365	(0.562)	0.687	(0.583)	1.435	(0.481)
$A_{ij} = 4$					1.968	(0.546)	2.322	(0.546)	1.725	(0.565)	2.334	(0.474)
$A_{ij} = 5$					3.470	(0.599)	3.730	(0.599)	3.508	(0.623)	3.803	(0.513)
Science career									−1.419	(1.204)	−1.055	(1.329)
Health career									0.169	(1.150)	−1.187	(1.320)
Business career									−0.652	(1.075)	−1.745	(1.193)
Government career									−4.572	(2.040)	−3.817	(1.685)
Education career									2.169	(1.675)	−2.141	(1.958)
Log likelihood	122.5		172.7		94.9		126.1		89.0		122.8	

[a] $N = 173$. The omitted major category is public policy. The omitted career category is law.

In contrast, a one standard deviation increase in the earnings from Business careers leads to drops of 9.5% and 3% in the share of Natural Science and Engineering majors. This is coupled with a 16% increase in Economics majors. The last column of Table 11 shows the effects of a one standard deviation increase in expected earnings for a major as a whole, holding earnings in the other majors constant. Here the results are quite large. All majors see at least a 40% increase in the share choosing the particular major, with Humanities majors increasing by over 60%.

In Table 12, we present estimates for the alternative models separately for students who are under-classmen (i.e., freshmen and sophomores) and those who are upper-classmen (i.e., juniors and seniors). The only significant difference between under-classmen and upper-classmen is that the under-classmen prefer Education careers relatively more than do upper-classmen. (Recall that this pattern was found in Table 3 for the unadjusted differences between classes in expected earnings for different major–career combinations.) Note that the coefficients on expected log earnings are not only statistically significant for both under-classmen and upper-classmen, but they also are virtually identical in magnitude. In his study of the choice of college majors by students at Northwestern University, Zafar (2008) only interviewed sophomores because of a concern that asking upper-classmen about their choice of a major would raise issues of "cognitive dissonance", given that upper-classmen, compared to under-classmen, might be more inclined to tilt their responses about expected outcomes in favor of the majors they had chosen. Our estimates suggest that Zafar's concern does not seem to apply to the expected future earnings associated with chosen majors and their alternatives.

5. Forecasts of average returns and choice of major

As noted in Section 2.3, students may differ in their subjective expectations about what they would earn with different majors and in different careers not only because they differ in their abilities to succeed in them, but also because they differ in their forecasts of what the average returns to different majors would be. As we argued above, the latter differences could result from differences in information that students have about various careers and about labor markets in general. In what follows, we use the expectations we elicited from our sample about the average Duke student, along with the model estimates presented above, to address the following hypothetical question: How would the choice of college majors change if all students had the same forecasts of the average returns that a Duke student could expect in different majors? Below, we outline our strategy for eliminating differences across students in their forecasts of these average returns, and then present results from simulations to quantify how the elimination of these differences would affect the nature and distribution of college major choices.

5.1. Adjusting for heterogeneity in forecasts of average expected returns to majors

To characterize the possible sources of differences in students' expectations about future earnings, it is convenient to use a slightly different representation of $\hat{Y}_{ijk10}$ than the one in (5). In particular, let $\ln(\hat{Y}_{ijk10})$ be expressed as

$$\ln \hat{Y}_{ijk10} = \kappa_{jk10} + \zeta_{ijk10} + \lambda_{ijk10}, \tag{16}$$

where κ_{jk10} is the population *average expected return* to major j and career k for a Duke student in his earnings 10 years after graduation, ζ_{ijk10} is student i's deviation in his forecast from this average return, and λ_{ijk10} denotes the student's *perceived comparative advantage* in a particular major–career combination, measured in terms of earnings. We note that κ_{jk10} corresponds to the *average treatment effect* (ATE) for major j and career k,[25] where here the average is for the population of male Duke students. Students also could be wrong about what they are relatively good at (λ_{ijk10} may not reflect their actual comparative advantage), although our focus here is on the market premium for each major–career combination. Finally, we assume that the median of ζ_{ijk10} is zero, although, as we discuss below, this assumption can be relaxed and the following results will still hold.

We assume that student i's response to what he would expect the earnings of the average Duke student to be as of $t = 10$ for each major–career combination, Y^{AV}_{ijk10}, measures the following:

$$Y^{AV}_{ijk10} = \exp(\kappa_{jk10} + \zeta_{ijk10}). \tag{17}$$

Then it follows that an estimate of κ_{jk10} is given by the sample median of the students' log expectations of the average Duke student's earnings[26]:

$$\kappa_{jk10} = \ln Y^{MD}_{jk10} \equiv median(\ln(Y^{AV}_{ijk10})). \tag{18}$$

[25] See Heckman and Vytlacil (2007), Imbens and Wooldridge (2009) and Blundell and Costa Dias (2009) for definitions of this and other treatment effects and their identification requirements.

[26] We allow the estimates of κ_{jk10} to vary by whether the individual is an upper-classmen or not due to the timing of the survey being during the financial crisis and this possibly affecting cohorts differently. However, the estimates of switching behavior are similar when we restrict the premiums to be the same across the two groups.

Table 13
Consequences of heterogeneity in forecasts of average expected returns[a].

	All students	Students with $A_{ij} = 5$ in own major	Students with $A_{ij} < 5$ in own major
Percentage of students who would switch majors if no heterogeneity in average expected returns	7.8%	4.3%	10.1%
Percentage of students for whom $\zeta_{ij10} > 0$			
Own major	55.5%	58.0%	53.9%
Other majors	52.8%	53.3%	52.5%

[a] Forecasts used the multinomial logit estimates from the last column in Table 10. See (23) for the definition of ζ_{ij10}.

Given that $median(\zeta_{ijk10}) = 0$ implies that $median(\exp(\zeta_{ijk10})) = 1$, it follows that we can purge students' expectations about their earnings forecasts of ζ_{ijk10} as follows:

$$Y^*_{ijk10} = \hat{Y}_{ijk10} \exp(-\zeta_{ijk10}) = \frac{\hat{Y}_{ijk10} \exp(\kappa_{jk10})}{\exp(\kappa_{jk10} + \zeta_{ijk10})} = \frac{\hat{Y}_{ijk10} \exp(\ln Y^{MD}_{jk10})}{Y^{AV}_{ijk10}}, \tag{19}$$

where Y^*_{ijk10} is student i's earnings forecast for major j and career k for $t = 10$ based *solely* on his perceived comparative advantage (λ_{ijk10}) and the average expected return (κ_{jk10}) in that major and career.

The discussion above assumes that all individuals have a clear understanding of who the average Duke male student is and that the median of ζ_{ijk10} is zero for this population of students. These assumptions can be relaxed in the following manner. Suppose a student's beliefs about the labor market abilities of the average Duke student also are subject to error and that this error is the same across all major–career combinations. Denote this error by ξ_{i10}. Then Y^{AV}_{ijk10} becomes

$$Y^{AV}_{ijk10} = \exp(\kappa_{jk10} + \zeta_{ijk10} + \xi_{i10}), \tag{20}$$

implying that students either inflate or deflate their expected earnings of the average Duke student by the same percentage. Because the model structure is such that log earnings affect choices, percentage increases in earnings for all major/occupation combinations will not affect the choices. As a result, deviations of student expectations from the average expected return only influence the choice of one's major to the extent that these deviations are higher or lower than those from other major/occupation combinations. A similar argument implies that if the median of the ζ_{ijk10} is not zero but has the same value across major/career combinations, the above derivation of Y^*_{ijk10} still holds.

5.2. Choice of major with no heterogeneity in forecasts of average expected returns

How would students' choice of a major change if there were no heterogeneity in students' forecasts of the average expected returns in earnings for different major–career combinations? To address this question, we performed the following set of simulations.

First, recall the decision rule for student i's college major choice given in (3) and the major-specific payoff function in (11):

$$j^\dagger_i = \arg\max_j \gamma^*_j + A_{ij}\theta + \alpha^* \sum_{k=1}^{K} P_{ijk} \ln \hat{Y}_{ijk10} + \sum_{k=1}^{K-1} P_{ijk}\delta^*_k + \eta_{ij}. \tag{21}$$

Denoting student i's chosen major as $\hat{j}_i$, and using the parameter estimates reported in Table 10 for this specification of payoffs, we drew 100 sets of η values for each student such that student i's observed choice of major, $\hat{j}_i$, was consistent with the decision rule in (21). We then plugged these η_{ij} draws into (21), replacing the $\ln \hat{Y}_{ijk10}$ values with the corresponding values of $\ln Y^*_{ijk10}$, in order to characterize students' college major choices in the absence of heterogeneity about the average expected returns about majors and careers:

$$j^*_i = \arg\max_j \gamma^*_j + A_{ij}\theta + \alpha^* \sum_{k=1}^{K} P_{ijk} \ln Y^*_{ijk10} + \sum_{k=1}^{K-1} P_{ijk}\delta^*_k + \eta_{ij}, \tag{22}$$

where j^*_i denotes student i's choice of a major conditional on the $\ln Y^*_{ijk10}$. We repeated this evaluation for each set of draws of η_i and each student in our sample.

At the top of Table 13, we present tabulations of the incidence of major switching, i.e., $j^*_i \neq \hat{j}_i$, based on the above simulations. Overall, 7.8% of students would switch their major if there were no heterogeneity in the forecasts of the average expected returns to the various majors and careers. Among the 40% of students that ranked themselves at the top of the ability rankings in their own major ($A_{ij} = 5$),[27] only 4.3% would switch their majors if the only heterogeneity in their earnings forecasts were due to perceived comparative advantage in different majors and careers. But, among those students that assessed their ability in their chosen major to be lower ($A_{ij} < 5$), 10.1% would switch their major using earnings forecasts purged of heterogeneity in the average expected returns to majors and careers.

What accounts for this difference in the propensity to switch majors by students with differing abilities in their chosen major? One possibility is that the lower-ability group is more likely to be on the margin of switching majors because they have smaller differences in their abilities across the various majors. As a result, this group would be more likely to change their major due to small changes in their forecasts of expected returns across the various majors, regardless of their source. Alternatively, it is possible that the lower-ability group had more inaccurate – more heterogeneous – forecasts of average expected returns across majors than do higher-ability students. As a result, efforts to reduce or eliminate informational differences across students about these average expected returns would lead to more major switching by students with lower own-major abilities than those with higher ones, all else being equal. In the remainder of this section, we attempt to assess the relative importance of these two possible explanations.

To assess whether eliminating heterogeneity in forecasts of average expected returns would differentially improve the forecasts of students with lower ability in their chosen major, we examined the difference in log of students' forecasts of expected earnings for each major, with and without heterogeneity in the average expected returns for each major/career combination.

[27] Note that for all majors the fraction who reported that they were at the top was less than 20%. However, those reporting abilities at the top for the chosen major were much higher at 40%.

More precisely, we calculated

$$\zeta_{ij10} \equiv \sum_{k=1}^{K} P_{ijk} \ln \hat{Y}_{ijk10} - \sum_{k=1}^{K} P_{ijk} \ln Y^*_{ij10}$$
$$= \sum_{k=1}^{K} P_{ijk}(\ln \hat{Y}_{ijk10} - \ln Y^*_{ijk10}) = \sum_{k=1}^{K} P_{ijk}\zeta_{ijk10}, \qquad (23)$$

i.e., the career-probability-weighted average deviations in students' forecasts of the average expected returns for major j. We then calculated the fraction of students whose earnings forecasts for a given major j were higher than if there were no heterogeneity in average expected returns, i.e., the fraction of students for whom $\zeta_{ij10} > 0$. These tabulations are presented at the bottom of Table 13 for all students, those who reported high and lower abilities in their chosen major, and by chosen majors ($j = \hat{j}$), and majors not chosen ($j \neq \hat{j}$).

Comparing the last two rows in Table 13, we first note that positive deviations in students' forecasts of the (weighted) average expected returns are more likely within students' chosen major compared to majors they did not choose, providing evidence that heterogeneity in forecasts of average expected returns does affect college major choices. However, the difference in the incidence of these higher earnings forecasts for students' chosen major and those not chosen is actually *greater* among students who report very high ability in their chosen major than those who report they are not as able in their major. If informational differences across students about the average expected returns for different majors was the primary factor accounting for the disparity across ability groups in the major switching recorded in the top row of Table 13, we should have found the opposite ordering with respect to improvements in earnings forecasts when heterogeneity in average expected returns is eliminated. Thus, it appears that the higher switching behavior observed for those with lower within-major ability occurs because these students are closer to the margin of choosing one major over another, not because their information about average expected returns for different majors is worse than that of their higher-ability counterparts.

Further evidence that the differences by students' own-major abilities in the incidence of major switching are not primarily driven by heterogeneity in forecasts of average returns can be seen by examining the correlations in the deviations in students' forecasts from average expected returns (ζ_{ij10}) across majors. Among students who reported high ability in their chosen major, the correlation in these deviations between their own major and the majors they did not choose was 0.58, while it was higher, at 0.79, for those who reported lower own-major abilities. Since it is relative earnings across majors that matter in our choice model, *higher* correlations of the ζ_{ij10} should result in *less* major switching if heterogeneity in forecasts of average returns were eliminated. But, as we have noted, we find that eliminating this heterogeneity among students with lower ability leads to *more* major switching compared to students with high ability in their major (see top row of Table 13), just the opposite of what the patterns in the correlations of the ζ_{ij10} would predict for our model.[28]

6. Conclusion

The choice of college major plays a critical role in determining the future earnings of college graduates. Economic models of educational choices suggest that students' college major decisions would be guided, in part, by the future earnings streams associated with the different majors. To examine the potential role of future expected earnings on these choices, we asked a sample of college students about their subjective expectations on the probabilities of entering different careers and the earnings associated with different careers conditional on both their own major as well as conditional on majors they did not choose, i.e., their counterfactual expectations.

The descriptive statistics and model estimates reveal that sorting occurs, both on expected earnings and on individual perceptions of their relative abilities to perform the coursework in particular majors. Our estimates imply that equalizing abilities would lead to a substantial increase in the number of students majoring in Economics and a drop in the number majoring in Humanities. In contrast, if we equalize expected earnings across majors, our estimates imply a sizeable increase in the number of students majoring in Humanities.

Students also were asked to make forecasts about what the average student at Duke would make in particular careers. We found that students are more likely to enter careers where they expected the average Duke student to earn more than what the average student in the sample expected. We used this data to purge students' forecasts of expected earnings in different majors of differences in their expectation for the average Duke student. We then examined how their choices of a college major would differ under this alternative earnings forecast. Our results indicate that adjusting for student differences in expectations about what the average Duke student would earn in different majors would lead to 7.8% of the students in our sample switching their majors. These findings suggest that it may be advantageous to provide college students with information about school-specific average earnings by major so that they can choose majors that better match their abilities and preferences.

The approach and findings of this paper about college major choice illustrates the potential for using counterfactual expectations in choice models. Using data on elicited probabilities of agents choosing different choice alternatives, as well as on expectations about the future payoffs associated with each of these alternatives, represents a potentially useful alternative to relying solely on data on *observed* discrete choices and payoffs – or their determinants – when estimating structural dynamic discrete choice models.[29]

The data we have collected here can also be used to examine preferences over different occupations. In particular, it is possible with these data to allow students' probabilities of entering alternative careers to be endogenously determined. Because we have elicited both expectations about future earnings as well as probabilities of choosing particular careers, we can disentangle the importance of both pecuniary and non-pecuniary components in the choice of career. In future work we also plan to conduct a panel study to see how individuals update their expectations over time. This would allow us to examine how students update their abilities to do the coursework, the expected earnings in the various careers, and their preferences over working in different careers.[30]

28 While not recorded in the paper, we also found that the median of students' earnings forecasts for the average Duke student was the same ($100,000) for those who ranked their abilities in their chosen major as high versus those who did not. The same pattern is true for 25th and 75th percentiles of students' elicited forecasts for the average Duke student.

29 See Manski (1993b), Hotz and Miller (1993), Hotz et al. (1994), and Arcidiacono and Miller (forthcoming), who use data from observed choices and payoffs to form conditional choice probabilities (CCPs) in the estimation of dynamic discrete choice models.

30 See Stinebrickner and Stinebrickner (2010a) for a study of how individuals update their subject beliefs about their classroom performance.

Appendix. Actual Majors at Duke and Major 'Groups'

The following is the list of majors at Duke and the six groups we used to classify them:

Science:	Engineering:
Biological Anthropology and Anatomy	Computer Science
Biology	Biomedical Engineering
Chemistry	Civil Engineering
Earth and Ocean Sciences	Electrical and Computer Engineering
Mathematics	Mechanical Engineering
Physics	
Humanities:	Social Sciences:
Art History	Cultural Anthropology
Asian and African Languages and Literature	History
Classical Civilization/Classical Languages	Linguistics
Dance	Psychology
English	Sociology
French Studies	Women's Studies
German	
International Comparative Studies	Economics:
Italian Studies	Economics
Literature	
Medieval and Renaissance Studies	Policy:
Music	Environmental Science and Policy
Philosophy	Political Science
Religion	Public Policy Studies
Spanish	
Theater Studies	
Visual Arts	

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