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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 student's choice of a college major. We also show that students' forecast errors with respect to expected earnings in different majors is potentially important, with our estimates suggesting that 7.5% of students would switch majors if they made no forecast errors.

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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, Nabeel, Conaty and To (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, 1964; 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 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 a student's expected earnings associated with alternative majors or in their abilities in different majors. Rather, economists typically have, at best, data on the earnings streams for 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. 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 students' expectations of earning across different major-career com-

[1] See Daymont and Andrisani (1984); Hamermesh and Donald (2008); Grogger and Eide (1995); James, Nabeel, Conaty and To (1989); Loury (1997); Loury and Garman (1995).

[2] See for example Arcidiacono (2004, 2005) and Montmarquette, Cannings and Mahseredjian (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, Katz and Kuziemko, 2006) have found that the gender gap in math and science aptitude is small and has decreased for several decades.

binations, we conducted a survey of male undergraduates at Duke University. We elicited from each student the probabilities he would be in particular careers in the future as well as they earnings he might expect to earn in them. Students were asked these questions both for the major they actually chose as well as 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.

An obvious potential concern with the elicitation of such information, especially with respect to their expectations about future careers and earnings associated with them, is the accuracy of these forecasts. Students may not have a very good idea of such phenomena, especially for majors they have not chosen, and, thus, their forecasts of earnings may be subject to forecast errors. Such errors may be more of an issue for students early in their college careers, i.e., freshmen and sophomores, relative to those who are closer to completing their degrees and closer to having to make career decisions, i.e., juniors and seniors. To get a sense of the importance of such forecast errors and how they may differ across students, we also elicited from students their expectations on how much the average Duke student would make in different major-career combinations. To the extent that all students have the same information about what careers associated with different majors would pay in the future, we should not find any differences in these expectations for the average Duke student, consistent with no forecast errors.[4]

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 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. 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 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, which is consistent with the findings 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%.

Expectations over future earnings are likely to be subject to forecast errors. For example, individuals have differing expectations regarding the market returns to particular fields. To understand how these expectations differ across students of different majors, we asked students what the average Duke student would make in different majors. These assessments suggest that students think the market premium is higher for their own major compared to those for majors they did not choose. We show under what assumptions we can purge the student's expected earnings of measurement error and use our model to forecast the major choices of the students with expected earnings free of the forecast error. We estimate that over 7.5% of students would

[4]Obviously, finding that students have the same assessments of the earnings and career expectations for the average Duke student also is consistent with all students having a common, but non-zero, forecast error.

switch majors if this forecast error was not present. Thus, our results suggest an important role for informational differences in modeling the choice of college major and, given our evidence of heterogeneity in the resulting forecast errors, of the importance of eliciting information on expectations from survey respondents.

Our work fits into a large and 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), Kaufman (2009), and Zafar (2008, 2009) who use counterfactual expectations of choice models. Of particular relevance to our work is Zafar (2008, 2009), who also examines counterfactual expectations and the choice of major. Zafar (2008) focuses on gender differences in the choice of major while Zafar (2009) examines the how expectations change over time regarding major fit and the probability of graduating conditional on major choice. Zafar's work finds no evidence of expected earning affecting the choice of major. Zafar's work was very informative in our own survey design. By linking majors to careers, we sought to obtain more accurate measures of the students' expected earnings across majors. In addition, we drew a larger sample than Zafar and limited it to one gender (men) 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.[7]

The rest of the paper proceeds as follows. In Section 2, we describe a simple model of major choice that motivates the survey design. In Section 3, we describe the data we collected in our survey and present a descriptive analysis of these data, showing the sorting patterns on both expected earnings and ability. In Section 4, we develop an empirical model of the choice of college major where expected income at only one point in time is sufficient for estimation. In Section 5, we present the estimation results and examine how changing abilities and earnings would affect the choice of major. In Section 6, we formulate a model of how to extract expectation error from expected earnings and then show how removing this error would affect major choice. Section 7 concludes the paper.

2 Modeling College Major Choice

To help motivate our data collection, we first sketch a model of college major choice. As implied by most models of human capital production (Ben-Porath, 1967), we assume that individuals specialize in college early in the life cycle and then enter working careers for the remainder of their lives. While in college, we assume that individuals choose from among J majors based upon the benefits and costs received while in college, as well as the subsequent returns in the labor market careers associated with the choice of a major. The in-college flow utility is a function of the i^{th} individual's abilities in a given major, A_{ij}, as well as their preferences for studying particular subjects, ξ_{ij}. Denote the in-school utility of individual i from choosing major j as

[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 Manski, Blass and Lach (forthcoming). For an early discussion on incorporating subjective expectations into choice models, see Manski (1999) and Wolpin (1999).

[7] 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.

$u(A_{ij}, \xi_{ij})$.

Students trade off this current utility with the expected value of future utility associated with choosing major j, EV_{ij}. This expected utility embeds a student's expectations about K possible careers that they may end up in, conditional on a given major and the expected payoffs from such careers. Let P_{ijk} denote the probability of ending up in career k, conditional on major j for the i^{th} individual and let EV_{ijk} denote the corresponding expected value of the career-specific value function. As for the expected payoffs from careers, we focus on the expected earnings associated with different major-career combinations, Y_{ijk}. Finally, we assume that the student chooses a major according to:

$$\arg\max_j u(A_{ij}, \xi_{ij}) + \beta \sum_k P_{ijk} EV_{ijk}(Y_{ijk}) \tag{1}$$

where β is the discount rate.

In our survey, we elicited from students their subjective expectations of each component of the above model of college major choice. Namely, we elicited measures of each student's abilities (A_{ij}), the probabilities of their entering alternative careers, conditional on their pursuing each of the J majors (P_{ijk}), as well as the corresponding earnings for each of the $J \times K$ major-career combinations (Y_{ijk}). We also asked students to provide us with direct assessments of their preference orderings over all of the J possible majors. In Section 4, we discuss how we use these orderings to produce one set of estimates of an empirical model of college major choice.

The above model of college choice abstracts from a number of considerations. First, we assume that students make a one-time decision about their college major. In fact, 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). Second, we ignore the possibility that students may continue their education by seeking post-baccalaureate degrees. Again, we asked students about their plans for continuing their educations 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.[8] 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). Third, the above 2-period model does not allow for the possibility that earnings in careers, and careers themselves, might be expected to change over a student's life cycle. 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. In what follows, we focus our attention on students' expected earnings 10 years out from graduation and, in Section 4, we outline a set of simplifying assumptions under which we only need a forecast for a single year in the future. Finally, we note that the above model assumes that, *per se*, careers are not chosen, but occur at random, conditional on the choice of a major. While not developed in this paper, the data we have gathered on career probabilities and expected earnings can be used to estimate a more general model of college major and career choice than is considered herein.

[8] Furthermore, the fact that most students in our sample plan to go to graduate school seriously compromises what we can learn from students' responses to our questions about their earnings expectations one year after graduating from Duke. Accordingly, we focus our analysis in this paper on students responses to questions about their expectations about earnings 10 years after graduating from Duke.

3 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 around the Duke campus about our study. 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 addition to data on career and income expectations, 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 Table 2.[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 is 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.

3.1 Expectations about Future Careers

In our survey, we elicited students' expectations about future careers and how much they expected to earn in them. We asked each student the probability that they would choose a particular career and the income they would expect to receive if they were in that career, conditional on their having majored in each of the majors listed in Table 2. 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. Sample means, taken over the full sample, for expected income 10 years after graduation and probabilities associated with the alternative careers, conditional on a student majoring in each possible field, are presented in Table 3.[11]

There are several interesting patterns in Table 3 with respect to the expectations elicited about careers from our sample of undergraduates. First, there are marked differences in the

[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 those respondents whose probabilities for each choice did not add up to 1 or 100, their stated probabilities were proportionally adjusted so that the sum of the probabilities associated with the career choices is 1.

Table 1: Sample Descriptive Statistics

	Sample	Duke Male Study Body[†]
Current/Intended Major[‡]		
Science	17.9%	14.8%
Humanities	9.3%	9.4%
Engineering	19.1%	20.7%
Social Science	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%
U.S. Citizen	94.8%	94.1%
Receives Financial Aid[§]	40.5%	22.0%
Sample Size	173	

[†] 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, Aucejo, Fang and Spenner (2009) for a detailed description of the CLL dataset.
[‡] 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?"
[§] 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.

Table 2: Major Groups and Actual Majors Offered at Duke University

Science	***Engineering***
Biological Anthropology and Anatomy	Computer Science
Biology	Biomedical Engineering
Chemistry	Civil Engineering
Earth & Ocean Sciences	Electrical & 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 & Renaissance Studies	***Policy***
Music	Environmental Science and Policy
Philosophy	Political Science
Religion	Public Policy Studies
Spanish	
Theater Studies	
Visual Arts	

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 .515, which is substantially higher than the career probabilities found for any of the other majors. The "link" between career and majors for the other careers falls somewhere between these two extremes. Second, student expectations about the earnings in careers 10 years out did not vary much across the major fields we asked them to condition their responses on. Put differently, students in our sample appear to view future earnings to be primarily determined by what career one enters, with little role for the major field in which one might have studied.

The sample means presented in Table 3 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. It is of interest to consider how the expectations elicited differed by a student's

Table 3: Elicited Expected Incomes (10 years out) and Elicited Probabilities of Going into Various Careers and Majors

	If Career in:					
If Majored in:	Science	Health	Business	Govt.	Education	Law
A. Probability of Going into Career †						
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 ‡						
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

† 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."

‡ 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, U.S. 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?"

class/year at Duke and by whether the student was majoring in a particular major or not. 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, underclassmen might have less information about careers than do upperclassmen, 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 an major-specific *absolute advantage* in certain careers, because of their major-specific abilities. In Table 4, we present the differences in the means for expected earnings (10 years out) for the various career-major combinations between students who majored in the particular career versus those who did not (non-majors) and between upper- 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 vs. non-majors and upper- vs. underclassmen for most of the various careers and major fields, there are a couple of notable exceptions in Table 4. 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

Table 4: Differences by Own Major vs. Non-Major and Upper- vs. Under-Classmen in Elicited Expected Incomes (10 years out) for Alternative Careers and Majors†

	If Career in:					
Major	Science	Health	Business	Govt.	Education	Law
A. In Major vs. Non-Major						
Science	-2,391	54,745**	48,663***	14,426	-2,565	20,652
Humanities	-9,153	1,977	-2,059	2,993	-68	-6,087
Engineering	-19,074	-24,200	-14,922	-20,467	-7,175	-39,465
Social Sciences	267	-1,736	-234	1,592	-9,511	-13,949
Economics	-12,438	-2,567	-5,433	-10,672	-13,421	3,271
Policy	36,455***	-1,265	16,501	27,813	36,053***	84,171***
B. Upper-Classmen vs. Under-Classmen						
Science	-20,733*	-13,473	12,461	-10,140	-13,835*	5,452
Humanities	-14,223	-3,235	-2,295	-8,219	-18,621*	649
Engineering	-10,921	-267	26,076*	-10,696	-12,376	50,857
Social Sciences	-12,257	-2,630	4,850	-9,728	-15,050**	-9,471
Economics	-3,520	5,771	6,205	-21,227	-9,863	9,437
Policy	-12,716	-786	-15,956	-16,402	-14,747*	4,311

† Test results for between-group differences in means of expected income: * significantly different at 10%; ** significantly different at 5%; *** significantly different at 1%.

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 upperclassmen, regardless of their major, expect to earn *less* if they enter either a Science or Education careers than do underclassmen, 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- versus underclassmen 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 underclassmen 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.

We use the earnings expectations and career probabilities that we elicited for the alternative career-major combinations to form major-specific expected earnings by computing the weighted averages of the career-major expected earnings, using the career probabilities associated with each specific major as weights. Sample means for these major-specific expected earnings, 10 years out, are given in Table 5. Unlike the sample means presented in Table 3, the sample means in Table 5 are for students who *are majoring* in or *intend to major* in each of the major fields. According to the theoretical model of college major choice outlined in Section 2, we would expect to find 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,

Table 5: Elicited Expected Incomes (10 Years Out), Conditional on Pursuing Alternative Majors by Own Major†

	If Majored in:					
Own Major	Science	Humanities	Engineering	Soc. Sci.	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. Prop. 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

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

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 of, earnings if they majored in Economics, regardless of their actual major. Looking back at the career probabilities and expected incomes for different career-major combinations in Table 3, it is clear that this finding is driven by the combination of the high 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 = .515) relative to all other majors. As a result, the majority of students expect to have an *absolute income* advantage to majoring 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. We consider one of them, a student's abilities in various majors, in the next section.

3.2 Assessments of Abilities in Alternative Majors

In our survey, we also elicited measures of students' perceived abilities for each of the major fields. In particular, we asked each student to rate their competitiveness relative to their peers at Duke in each of the six majors. All else equal, we would expect students to sort to the major in which they have a *comparative ability advantage*. In Table 6 we see clear evidence of

[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 6: Elicited Rankings of Student's Ability if he Pursued Alternative Majors by Own Major†

	If Majored in:					
Own Major	Science	Humanities	Engineering	Soc. Sci.	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. Prop. 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 Science	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

† 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.

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).

Finally, the ability ratings of students also appear consistent with one's sense of the difficulty of the curriculums across 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) and the average student finds that Social Science (3.590) and Humanities (3.428) are the least difficult majors.

3.3 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 forecast errors. Without waiting for ten years to find out their actual earnings (and career choices), we cannot get direct measures of such errors and examine

Table 7: Elicited Expected Incomes (10 years out) for Average Duke Student in Alternative Majors and Careers by Student's Own Major

	If in Career:					
If Majored in:	Science	Health	Business	Govt.	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

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 career-major 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 career-major combinations are similar to the corresponding student expectations about their own future earnings in Table 3. However, there are differences between the two sets of forecasts.

To provide a sense about the extent to which students' earnings expectations are subject to forecast errors, we compared the expected earnings for the average Duke student between majors and non-majors and between upper- and under-classmen. The results of these comparisons are reported in Table 8. The structure of Table 8 parallels Table 4. While most of the differences in means between majors and non-majors and upper- and under-classmen are not that sizeable 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 4 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 expectations about future earnings are, indeed, subject to forecast errors and that such errors are likely to influence students' choice of majors in non-trivial ways. We explicitly examine this influence in section 6, where we use

Table 8: Differences in Elicited Expected Incomes (10 years out) for Average Duke Student by Own Major vs. Non-Major and Upper- vs. Under-Classmen†

	Career					
Major	Science	Health	Business	Govt.	Education	Law
A. In Major vs. Non-Major						
Sciences	9,675	42,380	13,436	-16,006	-13,286	204
Humanities	-1,257	-18,350	-1,003	-2,334	-3,355	3,232
Engineering	-22,487	-30,096	-13,418	-6,573	-1,098	-27,932
Soc. Sci.	-9,227	-13,169	-26,465	-13,723	-21,072**	-26,760*
Economics	3,540	3,683	17,269	4,297	3,955	17,743
Policy	44,271***	35,173**	13,831	33,396***	38,029***	56,082***
B. Upper-Classmen vs. Under-Classmen						
Sciences	-21,426*	19,760	6,771	-11,947	-17,750*	1,209
Humanities	-14,499	9,855	4,232	-17,632*	-32,279***	-19
Engineering	-15,703	18,488	24,521*	-7,838	-15,975*	46,745
Soc. Sci.	-8,573	11,167	12,847	-22,266**	-14,932*	5,364
Economics	1,364	13,659	24,969	-13,302	-21,948**	4,040
Policy	-9,573	11,545	-4,435	-9,127	-21,297**	-2,095

† Test results for between-group differences in means of expected income: * significantly different at 10%; ** significantly different at 5%; *** significantly different at 1%.

students' expectations for the earnings of the average Duke student to eliminate such forecast errors from students' own expected earnings and examine how students' choice of majors would change in the absence of such errors.

4 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. As noted in Section 2, we based our data collection on a model of how students made their college major decisions. We now 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.

As noted in Section 2, 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. Furthermore, to simplify our analysis, 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. Following the notation in Section 2, let P_{ijk} denote the probability of i being assigned career k conditional on choosing major j. Once he realizes his draw on a career, the student makes no further decision 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.

4.1 Earnings and Consumption

We now lay out a set of assumptions that allow us to express a student's expected future streams of utility from consumption associated with alternative major-career pairs as a parsimonious function of the expected earnings for these pairs that we elicited in our data. Let Y_{ijkt} denote the earnings for individual i, with major j and career k, in future period t, where Y_{ijkt} is the following function of the individual's permanent premium for the major-career combination, μ_{ijk}, a growth rate which is major-specific but neither career or individual-specific, g_{jt},[13] and a mean-zero transitory error term, ϵ_{ijkt}:

$$Y_{ijkt} = \exp(\mu_{ijk} + g_{jt} + \epsilon_{ijkt}) \tag{2}$$

Individuals are assumed not to know ϵ_{ijkt} until after they choose their major, so that they only have expectations of the future ϵ's at the time they are making this decision.

We assume that the individual's utility in period t is proportional to the log of his consumption in that period, $\ln C_{ijkt}$, and that there is no savings so that individuals consume their earnings in each period, i.e., $C_{ijkt} = Y_{ijkt}$.[14] Normalizing the price of consumption to one, the expected present discounted value of the utility associated with consumption if individual i majors in major j, v_{ij}^C, is given by:

$$\begin{aligned} v_{ij}^C &\equiv \alpha \sum_{k=1}^{K} \sum_{t=1}^{T} \beta^t P_{ijk} E \ln(Y_{ijkt}) \\ &= \alpha \sum_{k=1}^{K} \sum_{t=1}^{T} \beta^t P_{ijk} \left(\mu_{ijk} + g_{jt}\right) \end{aligned} \tag{3}$$

where β is the rate of time preference and α is the (utility) value of log consumption.

It follows from (2) that a student's beliefs about the earnings associated with different major-career combinations 10 years after graduating from college, $\hat{Y}_{ijk10}$, is given by:

$$\hat{Y}_{ijk10} = E[\exp(\mu_{ijk} + g_{j10} + \epsilon_{ijk10})] \tag{4}$$

We assume that the ϵ's have the same moments across i and k, conditional on major j. It follows that $E[\exp(\epsilon_{ijk10})] = E[\exp(\epsilon_{ijk'10})]$ for all k, k', so that we can express v_{ij}^C as a function of $\hat{Y}_{ijk10}$ and a major-specific constant:

$$v_{ij}^C = \alpha^* \sum_{k=1}^{K} P_{ijk} \ln \hat{Y}_{ijk10} + \phi_j^* \tag{5}$$

where α^* and ϕ_j^* are given by:

$$\alpha^* = \frac{\alpha(\beta - \beta^T)}{1-\beta} \tag{6}$$

$$\phi_j^* = \sum_{t=1}^{T} \beta^t \left(g_{jt} - g_{j10} - \ln(E[\exp(\epsilon_{ijK10})])\right) \tag{7}$$

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

[14] 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.

where, since $E[\exp(\epsilon_{ijk10})] = E[\exp(\epsilon_{ijk'10})]$, we have expressed the last line relative to career K. Using the individual's subjective expectations of expected income by career and major, if follows that we can express v^C_{ij} as:

$$v^C_{ij} = \alpha^* \sum_{k=1}^{K} P_{ijk} \ln \hat{Y}_{ijk10} + \phi^*_j \tag{8}$$

In all of the empirical models of college choice that we estimate, the payoff associated with major j, v_{ij}, depends on expected future consumption via v^C_{ij} in (8). Our initial models assume that major payoffs are equal to v^C_{ij} plus an individual- and major-specific preference component, η_{ij}, that is unobserved by the econometrician, so that:

$$v_{ij} = \phi^*_j + \alpha^* \sum_{k=1}^{K} P_{ijk} \ln \hat{Y}_{ijk10} + \eta_{ij} \tag{9}$$

4.2 Utility while in College

Assuming that the payoffs from different majors depend only on expected lifetime consumption ignores the role that the coursework in a major may have on the choice of a major. Individuals may be selecting majors not because of the pay but because of the differences in the difficulty of coursework across majors and their abilities to do the coursework. These abilities to do the coursework then translate into higher expected earnings. 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:

$$v_{ij} = \gamma^*_j + A_{ij}\theta + \alpha^* \sum_{k=1}^{K} P_{ijk} \ln \hat{Y}_{ijk10} + \eta_{ij} \tag{10}$$

where $\gamma^*_j = \gamma_j + A_{ij}\theta$.

4.3 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:

$$v_{ij} = \gamma^*_j + A_{ij}\theta + \alpha^* \sum_{k=1}^{K} P_{ijk} \ln \hat{Y}_{ijk10} + \sum_{k=1}^{K-1} P_{ijk}\delta^*_k + \eta_{ij} \tag{11}$$

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:

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

4.4 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, the η_{ij}'s, follow a Type I extreme value distribution. Letting $\bar{v}_{ij}$ denote v_{ij} net of η_{ij}, the probability individual i chooses major j, p_{ij}, is:

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

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

$$L = \sum_i \sum_j 1[d_{ij} = 1] \log[p_{ij}] \tag{13}$$

where 1[ ] is the indicator function.

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. The details of the survey responses to this question are given in the Appendix. These data can be used to estimate the parameters of the alternative specifications of the payoff functions, v_{ij}, in (9), (10) and (11) via a rank-ordered, or exploded, logit model. Let $r_i = (r_{i1}, r_{i2}, ..., r_{im}, ..., r_{iJ})'$, where r_{im} denotes the major that student i ranked as the m^{th} highest of the J majors. Then it follows that the probability of observing student i's rankings of majors, r_i, is given by:

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

and the log likelihood for the data is:

$$L = \sum_i \log[p(r_i)]. \tag{15}$$

5 Results

Table 9 presents estimates for the three alternative specifications of a multinomial logit model of students' college major choices corresponding to the major-specific payoff functions in (9), (10) and (11), respectively. For all three specifications, we find that the coefficient on expected log earnings ten 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. For example, moving from a four to a five 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' choice of a major. 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.

As noted in Section 4.4, we also estimated an exploded logit model for the same specifications used in the multinomial logit model, using the data on the preference orderings over majors elicited from students. Results for alternative specifications of the latter model are presented in Table 14 of the Appendix. Many of the estimates for the exploded logit models are qualitative similar to those for the multinomial logit models in Table 9. For example, the coefficients on expected log earnings and on the ability measures have the same signs and patterns of statistical significance as those found in Table 9. At the same time, the magnitudes of the coefficient estimates on log earnings and the ability measures in the exploded logit models are substantially smaller in magnitude than those for the multinomial logit models. Furthermore, the effect of careers in government in the exploded logit model is no longer negative or statistically significant. These differences in estimates between the two models may result from the violations of the assumption made in both models that the errors in the payoffs to alternative majors are independent. As noted in Section 4.4, we also estimated an exploded logit model for the same specifications used in the multinomial logit model, using the data on the preference orderings over majors elicited from students. Results for alternative specifications of the latter model are presented in Table 14 of the Appendix. Many of the estimates for the exploded logit models are qualitative similar to those for the multinomial logit models in Table 9. For example, the coefficients on expected log earnings and on the ability measures have the same signs and patterns of statistical significance as those found in Table 9. At the same time, the magnitudes of the coefficient estimates on log earnings and the ability measures in the exploded logit models are substantially smaller in magnitude than those for the multinomial logit models. Furthermore, the effect of careers in government in the exploded logit model is no longer negative or statistically significant. These differences in estimates between the two models may result from the violations of the assumption made in both models that the errors in the payoffs to alternative majors are independent. As noted in Section 4.4, we also estimated an exploded logit model for the same specifications used in the multinomial logit model, using the data elicited from students on their preference orderings over majors. Results for alternative specifications of the latter model are presented in Table 14 of the Appendix. Many of the estimates for the exploded logit models are qualitative similar to those for the multinomial logit models in Table 9. For example, the coefficients on expected log earnings and on the ability measures have the same signs and patterns of statistical significance as those found in Table 9. At the same time, the magnitudes of the coefficient estimates on log earnings and the ability measures in the exploded logit models are substantially smaller in magnitude than those for the multinomial logit models. Furthermore, the effect of careers in government in the exploded logit model is no longer negative or statistically significant. These differences in estimates between the two models may result from the violations of the assumption made in both models that the errors in the payoffs to alternative majors are independent.

Using the multinomial logit estimates from the last column of Table 9, we examine the effect of expected log earnings and abilities on major choice. These results are presented in Table 10. 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 in part because earnings now plays a greater role in sorting and, in part, because students' beliefs about their ability to do well in Engineering are much lower than their beliefs about their abilities to perform in other majors. In contrast, when earnings are set equal, the share of individuals

Table 9: Multinomial Logit Estimates of Major Choice†

	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 Science	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)
Govt. Career					-4.225	(1.244)
Education Career					0.069	(1.284)
Log Likelihood	296.1		223.8		216.4	

† $N = 173$. The omitted major category is public policy. The omitted career category is law.

choosing Humanities and Social Science 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 10 show the effects of one standard deviation increases in the earnings of Science and Business careers, respectively. These standard deviation increases are calculated conditional on a major. 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. 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 10 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 11, 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 corresponding exploded logit model estimates are presented in Table 15 of the Appendix. The pattern of the coefficients is quite similar across the two groups of students. In both the multinomial logit and exploded logit estimates, the only significant difference is that under-classmen prefer Education careers relatively more than do upper-classmen. (Recall this pattern was found in Table 4 for the unadjusted differences between classes in expected earnings for different careers and majors.) Note that the coefficients on expected log earnings are not only statistically significant for both under- and upper-classmen but they also are virtually identical in magnitude. In his study of the choice of college majors by students at Northwestern

Table 10: The Effect of Expected Earnings and Abilities on Major Choice†

	Baseline	Equal Abilities	Equal Earnings	1 Std. Dev. Increase Science Career	1 Std. Dev. Increase Business Career	1 Std. Dev. Increase Major
Natural Science	17.9%	16.6%	17.8%	18.9%	16.2%	25.9%
Humanities	9.3%	5.9%	10.9%	8.6%	9.1%	15.0%
Engineering	19.1%	27.1%	19.0%	21.1%	18.6%	26.6%
Social Science	17.9%	12.2%	19.7%	17.4%	17.2%	26.8%
Economics	19.7%	23.8%	16.6%	18.6%	22.9%	29.3%
Public Policy	16.2%	14.4%	16.0%	15.4%	16.1%	23.2%

† Forecasts used the multinomial logit estimates from the last column in Table 9. 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.

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.

6 Forecast Errors and Choice of Major

As noted in Section 3.3, students differ in their forecasts not only because they differ in their abilities to succeed in different majors and careers, but also because they make errors in these forecasts. We provided some initial evidence for such errors, using data students provided about their forecasts of earnings for common person, namely the average Duke student. In what follows, we use the latter data, along with the model estimates presented above to address the following hypothetical question: How would the choice of college majors change, if at all, if student forecasts about future earnings in various majors and careers were not subject to idiosyncratic forecast errors? In what follows, we outline our strategy for purging students' forecasts of such errors and then present results on the extent to which such forecast errors may affect the college major choices of students.

6.1 Adjusting Expected Earnings for Student Forecast Errors

To characterize students' forecast errors for their future earnings associated with the alternative majors and careers, we proceed as follows. Let each student's earnings premium for career k and major j in period t, μ_{ijkt}, be written as

$$\mu_{ijkt} = \mu_{jkt} + \zeta_{ijkt} + \lambda_{ijk} \tag{16}$$

where μ_{jkt} is the average premium in the (student) population for the various major-career combinations, ζ_{ijkt} is student i's corresponding *forecast error* relative to this population average

Table 11: Multinomial Logit Estimates of Major Choice by Class[†]

	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 Science	-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)
Govt. 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	

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

premium and λ_{ijk} denotes the student's comparative advantage in earnings for the particular major-career combination. We also assume that ζ_{ijkt} has a median of zero. Finally, we assume that student responses to what they 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 sum of μ_{jkt} and ζ_{ijkt} as follows:

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

It follows that an estimate of μ_{jk10} is given by the sample median of the students' log expectations of the average Duke student's earnings:[15]

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

Then it follows that we can purge students' expectations about their own earnings in different majors and careers of their forecast errors, ζ_{ijk10}, as follows:

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

where Y^{*}_{ijk10} denotes student i's adjusted earnings for major j and career k as of $t = 10$.

6.2 Choices without Forecast Errors

We use the estimation results presented in Table 9 to examine how the students' choice of majors would have changed if their forecasts of the premiums for different major-career combinations had been purged of forecast errors, using the strategy outlined in the preceding section. To do this, we return to the model, focusing in particular on the case where we control for major-specific abilities and career preferences. In this case, student i chooses major j_1 when:

$$j_1 = \arg\max_j \gamma_j + A_{ij}\theta + \alpha^* \sum_{k=1}^{K} P_{ijk} \ln \hat{Y}_{ijk10} + \sum_{k=1}^{K-1} P_{ijk}\delta_k + \eta_{ij} \tag{20}$$

We can use this decision rule to generate η's consistent with their choice behavior. Once we have this set of η's we can then see how often decisions would change if we purged expected log earnings of measurement error. We first draw one hundred sets of η's for each individual such that their choice of major is consistent with the decision rule in (20). Consider an individual who chooses j_1. This individual would have chosen a different major when the combination of how expected earnings changed due to removing forecast error and the draw on the η's is such that it is no longer optimal to choose major j_1:

$$j_1 \neq \arg\max_j \gamma_j + A_{ij}\theta + \alpha^* \sum_{k=1}^{K} P_{ijk} \ln Y^{*}_{ijk10} + \sum_{k=1}^{K-1} P_{ijk}\delta_k + \eta_{ij}$$

We average over the implied switching behavior across individuals and draws on the η's for their initial choice. Average switching behavior is reported in the first row of Table 12. The

[15] We allow the estimates of μ_{jk10} to vary by whether the individual is an upperclassmen 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 12: Forecast Errors and Switching Behavior†

	Overall	$A_{ij} = 5$ in major	$A_{ij} < 5$ in major
Share switching if forecast error was removed	7.77%	4.32%	10.06%
Fraction of positive forecast errors	53.3%	54.1%	52.7%
Fraction of positive forecast errors in major	55.5%	58.0%	53.9%
Fraction of positive forecast error out of major	52.8%	53.3%	52.5%

† Forecasts used the multinomial logit estimates from the last column in Table 9. See text for details of the construction of the forecast errors.

average probability of switching due to the removal of the forecast error was a little over seven and a half percent. At a little over four percent, switch rates were significantly lower for the 40% of the sample who ranked themselves at the top of the self assessment scale in their major ($A_{ij} = 5$). For those who did not self report their ability as the highest category for their major, switch rates were much higher at ten percent. This latter group is more likely to be on the margin of switching majors and also may have chosen majors on the basis of bad information regarding their labor market prospects. We distinguish between these possibilities next.

To investigate how forecast errors may be affecting college major decisions we calculate the fraction of positive forecast errors both in and out of one's own major. The overall rate is above fifty percent. Since at the major-career level the rate would be at exactly fifty percent, this suggests forecast error is affecting the probabilities individuals will end up in particular careers. Namely, if individuals erroneously believe premiums are high in a particular career, they associate higher probabilities of being in the career. This suggests, in contrast to what we have estimated, that choice of career is endogenous even after controlling for major.[16]

The third and fourth rows of Table 12 suggest that individuals are more likely to have upward-biased estimates of earnings in their own major. This makes sense in a model where individuals are making their major decisions based upon signals of market rewards for particular major-career combinations. The forecast errors are actually smaller for those who report lower abilities in their major. Hence, the higher switching behavior observed for those with lower within-major ability occurs because these individuals are at the margin of switching, not because of higher forecast errors. In fact, the lower forecast errors for this group suggests that these individuals, because they were at the margin, invested more time in finding out the true market premiums when making their decisions.

7 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,

[16]In future work, we hope to model this endogeneity explicitly.

as well as conditional on majors they did not choose, 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 the 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 also use the data from this latter set of forecasts to purge students' forecasts about their own earnings prospects in different majors and careers and how their choices of a college major would differ from the choices of majors that they actually made. Our results indicate that correcting for these forecast errors with the estimates from our model of college major choice would lead to 7.5% of the students in our sample switching their majors.

The approach and findings of this paper about college major choice illustrates the potential for using counterfactual expectations in choice models. Furthermore, following the strategy for used in this paper to elicit student probabilities of being in (or choosing) particular careers, represents a potentially useful alternative to relying solely on data on *observed* discrete choices and earnings to estimate conditional choice probabilities (CCP), the fundamental building block of structural dynamic discrete choice models.[17] In future work, we plan to conduct a panel study to see how individuals update their expectations over time. Updating would occur on their abilities to do the coursework, the expected earnings in the various careers, and their preferences over working in different careers.

[17]See Manski (1993b), Hotz and Miller (1993), Hotz, Miller, Sanders and Smith (1994) and Arcidiacono and Miller (2009) for strategies for using observed choices and earnings to estimate conditional choice probabilities in dynamic discrete choice models.

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A Appendix

In the survey, we also elicited from all students their preference orderings over all majors. These orderings provide us with additional information with which to analyze how students determined their choice of major. We first examine the proportion of students who ranked their own major as most preferred. These results are given in Table 13. Here we see that, while there is clearly a strong positive correlation, many students do not rank their own major first. This suggests that some individuals are answering this question based upon what they enjoy outside of labor market considerations. This is confirmed in the next two tables where we estimate exploded logit models of major choice. While the income measures are still significant, they are about half the magnitude of the estimates when actual major choice is used.

Table 13: Proportion of Students that Rank Own Major First out of All Majors†

	Freshman & Sophomores	Juniors & Seniors	Overall
Science	0.857	0.824	0.839
Humanities	0.750	0.750	0.750
Engineering	0.833	0.619	0.697
Social Science	0.833	0.684	0.742
Economics	0.818	0.696	0.735
Public Policy	0.714	0.929	0.821

† Student respondents were asked: "Rank your preference for the following fields, from the most preferred to the least. To help you answer this question, we provide the list of majors and their respective fields below." and given a list of majors. Above, we report the proportion that ranked their own major first.

Table 14: Exploded Logit Estimates of Major Choice[†]

	Coeff.	St. Error	Coeff.	St. Error	Coeff.	St. Error
Natural Science	-0.047	(0.133)	-0.103	(0.140)	-0.392	(0.188)
Humanities	-0.018	(0.130)	-0.266	(0.138)	-0.367	(0.159)
Engineering	-0.789	(0.140)	-0.610	(0.150)	-0.828	(0.198)
Social Science	0.335	(0.126)	0.026	(0.134)	-0.045	(0.143)
Economics	0.038	(0.129)	0.123	(0.135)	0.062	(0.159)
Expected Ln Earnings	0.698	(0.185)	0.661	(0.197)	0.693	(0.221)
$A_{ij} = 3$			0.771	(0.132)	0.774	(0.133)
$A_{ij} = 4$			1.530	(0.147)	1.539	(0.148)
$A_{ij} = 5$			2.408	(0.182)	2.437	(0.183)
Science Career					0.587	(0.398)
Health Career					1.218	(0.411)
Business Career					0.518	(0.376)
Govt. Career					0.250	(0.450)
Education Career					0.799	(0.541)
Log Likelihood	1093.2		980.4		975.2	

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

Table 15: Exploded Logit Estimates of Major Choice by Class[†]

	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	-0.150	(0.208)	0.015	(0.173)	-0.391	(0.223)	0.076	(0.183)	-0.512	(0.284)	-0.396	(0.262)
Humanities	-0.101	(0.205)	0.041	(0.169)	-0.258	(0.219)	-0.259	(0.178)	-0.479	(0.253)	-0.253	(0.211)
Engineering	-0.916	(0.221)	-0.718	(0.182)	-0.910	(0.239)	-0.436	(0.196)	-1.083	(0.304)	-0.748	(0.272)
Social Science	0.447	(0.197)	0.258	(0.165)	0.194	(0.211)	-0.086	(0.175)	0.121	(0.217)	-0.139	(0.194)
Economics	0.048	(0.194)	0.009	(0.173)	0.074	(0.204)	0.151	(0.183)	-0.081	(0.233)	0.174	(0.223)
Expected Ln Earnings	0.526	(0.276)	0.851	(0.250)	0.665	(0.298)	0.690	(0.267)	0.914	(0.331)	0.719	(0.314)
$A_{ij} = 3$					0.601	(0.208)	0.870	(0.172)	0.576	(0.209)	0.864	(0.174)
$A_{ij} = 4$					1.342	(0.232)	1.671	(0.191)	1.352	(0.235)	1.678	(0.192)
$A_{ij} = 5$					2.696	(0.311)	2.351	(0.230)	2.748	(0.313)	2.392	(0.231)
Science Career									0.812	(0.551)	0.529	(0.609)
Health Career									0.678	(0.620)	1.624	(0.590)
Business Career									0.969	(0.573)	0.140	(0.511)
Govt. Career									0.648	(0.678)	-0.009	(0.620)
Education Career									1.992	(0.762)	0.065	(0.789)
Log Likelihood	443.9		647.4		396.1		578.2		392.4		572.3	

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