Gender Differences in Choice of Educational Field: Evidence from a Large-Scale Survey Experiment *

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Abstract

Gender differences in college major explain a large share of the gender gap in earnings. To examine potential reasons why men and women sort into different fields, we conduct a large-scale survey experiment among almost 20,000 college applicants that allows us to estimate their beliefs and preferences when choosing a college major. College applicants perceive significant tradeoffs associated with more heavily female majors, expecting lower earnings but increased likelihood of parenthood and partnership and higher work and educational satisfaction. Combining applicants' beliefs and preferences, our results suggest that the biggest deterrent to women entering male dominated fields is their perception that they will have lower educational satisfaction during college. Examining within-gender heterogeneity, we find substantial differences between applicants entering female vs. male-dominated majors, particularly the weight they put on parenthood when selecting a field. Finally, in contrast to outcomes among prior cohorts of college graduates, we find no evidence that women anticipate lower earnings associated with motherhood. Our findings inform policies aimed at shifting the gender composition of college majors and subsequent gender earnings gaps.

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1 Introduction

Despite decades of increasing gender equality, there remains a large gender gap in earnings (Blau and Kahn, 2017). A long line of literature demonstrates the importance of college major in explaining subsequent gender differences in labor market outcomes (Grogger and Eide, 1995; Brown and Corcoran, 1997; Gemici and Wiswall, 2014). Prior work estimates that gender differences in college major can explain slightly over half of the eventual gender wage gap in the U.S. (Black et al., 2008; Altonji et al., 2012). This is because more heavily female fields have lower wages (Sloane et al., 2021).

In this paper, we examine potential reasons why men and women sort into different fields. To do so, we conduct a large-scale survey experiment among college applicants that allows us to estimate their beliefs and preferences when choosing a college major. We conduct the survey among a national sample of almost 20,000 college applicants in Denmark. In Denmark, college applicants submit their rank ordered choices of college degree programs to a national clearinghouse that matches students to programs using a truncated serial dictatorship assignment mechanism based on high school GPA. We survey students about each of their top-ranked choices after they have submitted their applications but before they learn the results. We elicit beliefs about their labor market and family outcomes ten years after graduating from each of their top choices, as well as beliefs about their experience during their education. We then incorporate national administrative register data on realized labor market and family outcomes by degree program from over 189,000 college graduates.

We document that college applicants expect a strong role of field in explaining gender earnings differences and perceive significant tradeoffs associated with more heavily female majors. Both men and women expect lower earnings ten years after graduating from female dominated majors compared to male dominated majors. In contrast, they expect higher outcomes in non-earnings attributes of heavily female fields: parenthood, partnership (marriage/cohabitation), work satisfaction and satisfaction during studies. Applicant expectations qualitatively align with realized outcomes in the national population of college graduates for earnings and parenthood but not partnership (we do not have satisfaction data for the population).

Our estimates of applicant preferences find that women put more weight than men on non-earnings attributes when choosing an educational field. In particular, women are more likely than men to prefer a major they associate with having a higher probability of marriage and children but lower earnings. However, gender differences in preferences for earnings vs. non-earnings attributes of fields are not large enough to explain gender differences in educational choices. Combining applicants' expectations and preferences, our results suggest that the biggest deterrent to women entering male dominated fields is their perception that they will have lower satisfaction during college. Women and men put similar weight on educational satisfaction, but only women expect it to relate closely to their choice of field. These results point to potential policy interventions that could focus on understanding and improving the experience of women in male dominated college majors.

In addition to examining differences across gender, we take advantage of our large and diverse sample to examine heterogeneity *within* gender. We find that women selecting into more heavily male fields ("male majors") have substantially different expectations and preferences than women applying to more heavily female fields ("female majors"). Men selecting into different male and female majors are more similar to each other. Where both women and men differ most within gender is in their willingness to tradeoff earnings for parenthood.[1] Women applying to female majors have an estimated willingness to pay for parenthood that is over four times larger than that of women applying to male majors, with a similar ratio among men. By comparison, women on average are willing to pay about twice as much for parenthood compared to men. These results suggest that within-gender differences are critical for understanding college major choice, particularly in relation to parenthood considerations.

Finally, we examine the interaction of earnings with non-earnings outcomes. In the population data, we document a negative association between both partnership and parenthood

[1] We estimate compensating differentials in terms of percent of median income willing to pay for a one standard deviation increase in the probability of having children.

with women's earnings relative to men's, which aligns with prior literature on the male marriage premium and motherhood penalty (Ribar, 2004; Angelov et al., 2016; Kleven et al., 2018, 2019). Among survey applicants, we find evidence that women expect relatively lower earnings associated with marriage but no evidence that they expect a motherhood penalty. These results suggest that, while women care about the impact of their educational field on having children, they are not directly considering motherhood penalties when choosing a college major.

Related work has linked educational fields to the labor market, estimating the causal effects of college degree on earnings (Altonji et al., 2016, provide a review). These studies find substantial differences in earnings returns from different degrees. For example, Kirkeboen et al. (2016) estimate that, in Norway, differences across high earning fields (e.g., science) and low earnings fields (e.g., humanities) are similar in size to the college wage premium. More recent work finds evidence that college degree also causally affects marriage outcomes, with individuals more likely to marry someone at their same institution and in their same field (Kirkebøen et al., 2021).

Our paper contributes to a growing literature on the drivers of degree choice, and the extent to which expectations align with realized outcomes. Related to our focus on gender differences, Zafar (2013); Wiswall and Zafar (2018, 2021); Gong et al. (2020) conduct survey experiments similar to ours and examine gender differences in expectations and/or preferences. In line with our utility function estimates, Zafar (2013); Wiswall and Zafar (2018, 2021) find that women put higher weight than men on marriage, fertility, work flexibility, and reconciling work and family; whereas men put higher weight on earnings growth.

Related to our work on expectations about earnings-family tradeoffs across fields and the marriage and motherhood penalties, Wiswall and Zafar (2021) find that both men and women expect lower rates of fertility in science and business fields; and women (but not men) think that marriage will decrease their labor supply. Related to our work comparing expected and realized outcomes, they find that expected earnings are close to realized earnings six years later (at average age 25), but expectations about marriage are overly optimistic. Similarly, Gong et al. (2020) find in ten-year follow up (at age 28) that men and women are overly optimistic about marriage and fertility rates but correctly expect that women's labor supply will decline if they have young children. In contrast, using surveys from both the U.S. and UK, Kuziemko et al. (2018) argue that women do not anticipate the labor market participation and earnings declines associated with having children.

The prior experimental studies among college students each include several hundred undergraduates enrolled at a single four-year college or university. Our study includes thousands of applicants to hundreds of different fields spanning vocational, bachelor's and bachelor/master's degrees. This allows us to examine earnings and non-earnings differences across a wide range of educational fields among a heterogeneous national population of college applicants. To our knowledge, we are the first to examine within-gender differences for understanding college major choice. Related to our work on heterogeneity within gender, Boudreau and Kaushik (2022) find important within-gender differences in willingness to compete by field, comparing STEM and non-STEM fields.

In the remainder of the paper, Section 2 describes the institutional setting and the design and implementation of our experiment. Section 3 describes the data. Section 4 presents the reduced form results. Section 5 describes the probabilistic choice model and presents results from the model estimation and counterfactual simulations. Section 6 concludes.

2 Institutional setting and experimental design

2.1 Danish postsecondary education

There are three types of postsecondary degree programs in Denmark: Short degrees (SVU), Middle-long degrees (MVU) and Long degrees (LVU). Short degrees (2-2.5 years) are vocational degrees that include an apprenticeship, such as construction technician and dental hygienist. Middle-long degrees (3.5-4 years) are professional bachelor's degrees that include an internship, such as nursing, elementary school teacher and pharmacist. Long degrees (5-6 years) are theoretical/research degrees that include both a bachelor's and master's, such as art, biology, math, economics, law, and medicine. Some fields have degrees across types: for example, there are short, middle-long and long degrees in different areas of engineering and computer science/information technology. There are 8 colleges/universities for each degree type. In our analysis we pool fields across universities – e.g., economics at the University of Copenhagen and economics at the University of Aarhaus are pooled into the same field, Economics.

In order to enroll in post secondary education, all applicants enter a national clearinghouse, administered by the Ministry of Education. The Ministry also sets the number of slots available in each degree program (school and field). Applicants submit a rank ordered list of up to eight degree programs (school and field). Submissions begin as early as February and must be finalized and submitted by a deadline in early July (applicants may revise their list up until the deadline). After the submission deadline, the Ministry of Education matches applicants to degree programs using a truncated serial dictatorship based on grade point average (GPA). That is, the applicant with the highest GPA receives their top ranked choice.[2] The applicant with the second highest GPA receives their top ranked choice if there are slots available. If there are no slots available, they receive their next ranked choice, if they have one. If none of their choices have slots available, they do not match. The process continues through to the lowest ranked applicant or until all the slots are filled, whichever occurs first.[3] The results of the clearinghouse

Students either match to a single degree program or receive no match. Students who receive a match can choose to enroll in the matched program or not to enroll in post secondary education that year. Students who are are not matched or choose not to enroll in their

[2]If there are many students with the same GPA they make a draw to determine the order in which students are matched.

[3]Students have the option to supplement their GPA with additional materials, including job experience, performance in a prior degree program. The majority of applicants are assessed on solely their high school GPA. About a quarter of applicants are accepted based on both their GPA and these additional materials.

matched degree can reapply to the clearinghouse in future years. Students who enroll in a program and later decide to transfer to a different degree must also do so through the clearinghouse, using the same procedure. are announced at the end of July, students make their enrollment decisions in early August, and enrollment usually occurs by the end of August.

The results of the clearinghouse generate GPA cutoffs for each degree (i.e., the lowest GPA admitted to the degree). The GPA cutoffs for the specific degrees are formed every year and are, therefore, unknown to the applicants at the time they submit their application. However, previous years' cutoffs are publicly available at the Ministry of Education's website and the cutoffs for a given degree are similar from year to year.[4]

2.2 Experimental design and implementation

We conducted the experiment in the summer of 2018. Final application submissions to the national clearninghouse were due July 5th. On July 10th, we contacted every applicant using their official online mailbox. On July 16th, we sent a reminder for those who had not already answered the questionnaire. The invitation letter asked applicants to participate in a research project about educational choices by answering a survey about their application. The letter also informed applicants that participation was anonymous and voluntary, alongside informing them about their rights. As an incentive for answering the survey we included a lottery for five gift cards worth 1000 DKK (about 150 USD). The deadline for completing the study was July 27th to ensure that applicants completed the survey prior to learning the results of the clearinghouse, which were announced on July 28th.

In order to participate in the study, applicants clicked on a survey link that was prepopulated with the choices they had made in their application. For applicants who only listed one choice, we asked them about their first choice and also asked them to fill in a second choice for their next most preferred degree program in a different location from their

[4] For example, at the University of Copenhagen, psychology and political science varied by 0.3 grade-points, and medicine by 0.7 grade-points over the period 1996 to 2006.

first choice. For applicants who listed at least two choices, we asked them about their top two choices. If the top two choices were in the same location, we asked the applicant fill in a third choice for their next most preferred degree in a different location. If the top two choices were the same degree, we asked the applicant fill in a third choice for their next most preferred degree in a different field.

We elicited applicants' expectations about up to their top three choices, both actual and experimentally induced (i.e., the top two choices of applicants with only two choices and the top three choices of applicants with three or more choices). In this paper we use the following questions. For each choice we asked applicants about their experience *during their studies* if they were to enroll in the degree. We asked their expected satisfaction with their studies on a 1-10 scale. For each choice, we also asked applicants their expectations *ten years after graduating* if they were to graduate in the degree. We asked the probability of having a romantic partner, probability of having at least one child, pre-tax monthly earnings, and satisfaction with work on a 1-10 scale.[5]

Finally, we elicit time and risk preferences using hypothetical questions. For time preferences, we ask respondents to choose the number of weeks 1-26 they would be willing to wait for a payment that starts at 10,000 DKK and grows by 100 DKK per week up to 12,500 DKK. Larger values correspond to more patient choices. For risk preferences, we ask respondents to choose a number 0-10,000 DKK to invest in a stock that has a 50% chance of tripling and a 50% chance of losing all its value, where respondents keep what they do not invest (Gneezy and Potters, 1997). Larger values correspond to more risk-tolerant choices.

[5]The ministry of education hosts an informational site, UddannelsesZOOM, that provides information about students' experience in each degree program (based on student surveys) and employment rates and earnings of graduates in each degree program (based on administrative data from Statistics Denmark). Less than 5% of our respondents report using the site.

3 Data

3.1 National administrative data

We use national administrative register data from Statistics Denmark to generate a population of higher education graduates. We include cohorts of college graduates from 1998-2006 (the 2006 cohort is the most recent cohort that has ten-year post-graduation outcomes available). If an individual obtained more than one degree during the period, we consider the most recent.

From the registers we also obtain background characteristics for both the population of college graduations and the 2018 college applicant cohort. We merge information about high school grades, parental education, gender and ethnicity from the register data with the graduate population and college applicant samples. For the graduate population, we additionally use register data to provide earnings and parenthood outcomes ten years after graduation.

3.2 Measurement of field attributes

For the graduate population, we we use the labor force register to obtain information about yearly pre-tax earnings ten years after graduating from postsecondary education. We divide yearly earnings by 12 to estimate monthly earnings (because we ask about monthly earnings in the survey). For the college applicants, we use their survey responses for each of their top choices about their expected pre-tax monthly earnings ten years after graduation (fill-in-the-blank question). We winsorize the top 1 percent of responses for earnings in the survey, which censors responses at 244,620 DKK.[6] We then censor the population data at the same level, 244,620 DKK, which only applies to the top 61 earners in the data. We index all earnings to 2015 prices using the consumer price index. For graphical presentations, summary statistics tables and the structural model, earnings are presented in U.S. dollars.

[6]The reported level of censored earnings is calculated as an average of the five surrounding earnings, which is a data security requirement from Statistics Denmark.

For parenthood, in the graduate population we create an indicator for having at least one child ten years after graduation. Individuals who appear in the register as having a child are coded as parents; all others are coded as non-parents. For the college applicants, we use their survey responses for each of their top choices about their expected probability of having children ten years after graduation (on a 0-100 scale in 10 percentage point increments: 0, 10, 20 . . , 90, 100).

For partnership, in the population we consider an individual in a partnership if they are married or living with their partner. For college applicants, we ask the probability of marriage or cohabitation with a romantic partner ten years after graduation on the same scale that we use for parenthood.

For the the college applicants we also report educational satisfaction during one's studies and work satisfaction ten years after graduation, both on a 1-10 scale.

As noted in Section 2.1, we pool fields across institutions. For example, nursing counts as one field even though it can be studied at several institutions. If a field can be studied in different degree types, these count as separate fields. For example, a middle-long degree in engineering and a long degree in engineering are included as different fields.

3.3 Sample construction

We restrict the population sample to include graduates for whom we observe information about gender in the register data. The main population sample consists of 189,331 individuals from 790 degrees. As described in section 2.2, the survey was sent out to all 2018 college applicants. There were a total 77,701 applicants in the 2018 cohort. Of these, 19,778 applicants from 259 educations responded with at least one degree choice with non-missing values for expected earnings, parenthood, partnership, work satisfaction, or educational satisfaction, and could be identified as either a man or woman (an effective 25% response rate). There are 45,655 total degree choices in this sample (15.5% of which are experimentally induced hypothetical choices).[7]

The main sample is constructed so as to use as much data as possible; avoiding any decisions or restrictions that would lead us to drop observations. We also define "restricted" samples for both the population and survey which drop any degree choices which lack complete information over the attributes we study. For the population this means dropping any individual that is missing earnings, parenthood, or partnership, or with zero earnings. For the survey this means dropping any degree choice (not any individual) that is missing expected earnings, parenthood, partnership, work satisfaction, or educational satisfaction, or with zero expected earnings. The restricted sample remains constant across models that consider different attributes. This sample contains 173,585 individuals from 769 degrees for the population and 12,534 applicants from 258 degrees for the survey. Individuals may contribute one (N = 1,685), two (N = 6,181), or three (N = 4,668) degree choices, giving us a total of 28,051 degree choices (16.2% of the degree choices in this sample are hypothetical).

3.4 Sample characteristics

Table 1 presents demographic data for the population, the 2018 cohort who matched with a degree program, the full 2018 cohort and the survey sample.[8] We compare the population to the 2018 cohort who matched because this is the closest comparison of the 2018 cohort to the population of eventual college graduates. This allows us to examine the extent to which the characteristics of the college population have changed across cohorts (we report p-values in column 5). We compare the full 2018 cohort to the survey sample in order to examine selection into the survey (p-values in column 6). Finally, we compare the population to the survey sample, which is our primary focus for the remainder of the paper (p-values in column 7).

Compared to the population of college graduates, the 2018 cohort of matched applicants

[7] Graphical presentations only include fields with at least five males and five females: 182,908 individuals from 384 fields in the population and 44,523 degree choices from 225 fields in the survey.

[8] Appendix Table A.1 shows the same information for the restricted samples.

is less female, younger, has a higher average high school grade point average (GPA) is more likely to be of foreign origin and has more highly educated parents.

Comparing the survey respondents to the full 2018 cohort, respondents are more likely to be female and less likely to be of foreign origin. There are not statistically significant differences in median age or parental education. Survey respondents do not differ from the full applicant cohort on the number of degrees they rank on their application. However,

Table 1: College graduate population, applicants and survey respondents

Sample:	Graduates	College Applicants			Hypothesis tests (p-values)		
Subsample:	All	Matched	All	Survey	(1) = (2)	(3) = (4)	(1) = (4)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Individuals	189,331	54,531	77,701	19,778			
Demographics							
Female	0.62	0.57	0.58	0.65	0.000	0.000	0.000
Median age 10 years after graduation	38						
Median age at application	23	21	21	21	0.000	1	0.000
High school GPA	6.26	7.19	6.85	7.42	0.000	0.000	0.000
Foreign origin	0.05	0.13	0.16	0.14	0.000	0.000	0.000
Mother has less than high school education	0.27	0.11	0.12	0.12	0.000	0.688	0.000
Mother has completed high school	0.38	0.41	0.42	0.41	0.000	0.350	0.000
Mother has completed further education	0.34	0.47	0.46	0.46	0.000	0.234	0.000
Father has less than high school education	0.22	0.15	0.16	0.16	0.000	0.476	0.000
Father has completed high school	0.46	0.46	0.46	0.46	0.984	0.175	0.326
Father has completed further education	0.32	0.39	0.38	0.39	0.000	0.053	0.000
College application							
Ranked 1 degree program		0.36	0.37	0.36		0.000	
Ranked 2 degree programs		0.23	0.23	0.23		0.602	
Ranked 3 or more degree programs		0.40	0.40	0.41		0.000	
Ranked 8 degree programs		0.04	0.04	0.04		0.420	
Matched to a degree program		1	0.74	0.81		0.000	
Matched to 1st choice program		0.82	0.60	0.68		0.000	
Matched to 2nd choice program		0.10	0.09	0.08		0.004	
Matched to 3rd choice or lower program		0.08	0.06	0.06		0.016	

Notes: The graduate population (column (1)) includes the 1998-2006 graduation cohorts. The matched cohort (column (2)) includes 2018 college applicants who matched to a degree program. The survey cohort (column (4)) includes 2018 college applicants in our experimental survey. Columns (5)-(7) report p-values from t-tests of differences of means/proportions and quantile regressions for differences of medians.

survey respondents have higher average high school GPA and are more likely to match to a degree program, suggesting positive selection into the survey.

The survey sample differs significantly from the population on all demographics (except share of fathers who have completed high school). Compared to the population, survey respondents are more likely to be female, are younger, have a higher average high school GPA, are more likely to be of foreign origin and have more highly educated parents. However, the survey matches the population on share female more closely than the full or matched cohorts, with 62% female in the population and 65% female in the survey.

4 Reduced-form analysis

We start by describing the top-ranked fields and summary statistics of the outcomes we examine: earnings, parenthood, partnership, work satisfaction and educational satisfaction in Section 4.1. In Section 4.2, we estimate the gender earnings gap and demonstrate that gender differences in choice of field explain a large share of the gap. Given the importance of gender differences in field, we estimate the earnings and non-earnings tradeoffs associated with more heavily female fields in Section 4.3. We find that looking across applicants, the association between female share of field and the expected outcomes we examine is always stronger for women than for men. Finally, in Section 4.4, we explore whether these gender differences are due to differences in the perceived causal impacts of field selection, or whether they are more likely to reflect gender differences in self-selection.

4.1 Most popular fields by gender

Table 2 lists the top ten fields by gender in both our population and survey samples. We note the degree type –short, middle, or long– in parentheses. Half of the top ten fields are the same for men and women in both the college graduate population and survey of college applicants: elementary school teacher, pedagogy, economics and business administration, law and medicine. Physiotherapy is additionally a top field for both men and women in the survey. The remaining top fields for women are ergotherapy, midwifery, nursing, social work and psychology. For men, top fields additionally include computer science, finance economics, architecture and construction, building engineering, civil engineering and political science. Thus, while there is substantial overlap in the most popular field choices between men and women, the popular fields that are not shared are very different in nature. And notably, they differ by stereotypical gender roles both in the population sample of individuals graduating between 1998 and 2006, and in the survey sample of 2018 applicants.

Table 2: Most common fields by gender

Female (Population)	Male (Population)
Econ. and bus. administration (long)	Econ. and bus. administration (long)
Elementary school teacher (middle-long)	Elementary school teacher (middle-long)
Law (long)	Law (long)
Medicine (long)	Medicine (long)
Pedagogy (middle-long)	Pedagogy (middle-long)
Ergotherapy (middle-long)	Architecture & construction (middle-long)
Nursing (middle-long)	Building engineering (middle-long)
Physiotherapy(middle-long)	Civil engineering (long)
Social work (middle-long)	Computer science (short)
Textile design (middle-long)	Multimedia design (short)
Female (Survey)	**Male (Survey)**
Econ. and bus. administration (long)	Econ. and bus. administration (long)
Elementary school teacher (middle-long)	Elementary school teacher (middle-long)
Law (long)	Law (long)
Medicine (long)	Medicine (long)
Pedagogy (middle-long)	Pedagogy (middle-long)
Physiotherapy (middle-long)	Physiotherapy (middle-long)
Midwifery (middle-long)	Computer science (short)
Nursing (middle-long)	Computer science (long)
Social work (middle-long)	Finance economics (short)
Psychology (long)	Political science (long)

Notes: The table lists the top ten fields by gender in the population (top panel) and the survey (bottom panel). Fields are not listed in order of size. The degree type is reported in parentheses: short, middle-long or long. Fields in red are common across all samples. Fields in blue are common within the survey sample. The top 10 fields in the survey account for about 40% of the choices we consider (47% for women, 33% for men). 48% of the population sample graduated from one of the top 10 fields (58% for. women and 38% for men).

Table 3 summarizes our five field attributes –earnings, parenthood, partnership, work satisfaction, and educational satisfaction– in the population and survey samples.[9] Ten years after graduation, men earn more than women. College applicants expect higher earnings compared to the population but still expect a gender earnings gap. That is, female college applicants report lower expected earnings than male college applicants. The gender gap is lower among applicants than in the in the population because female college applicants expect more earnings growth compared to the population than do male applicants: female applicants expect to earn about 1,000 USD more on average compared to women in the population, a 22% difference; male applicants expect to earn about 650 USD more on average compared to men in the population, an 11% difference.

In both the population and survey there is a 73% (expected) probability of having at least one child ten years after graduation. Women are more likely to have children than men (because women have children at younger ages on average than men). Applicant expectations are similar to outcomes in the population, with male applicants expecting lower fertility compared to male graduates.

Partnership rates are also similar in the population and survey, 78% and 77% respectively. Men and women have similar rates of marriage and cohabitation, with male college applicants again expecting lower partnership rates compared to realized outcomes in the population.

College applicants expect slightly higher average work satisfaction (8.39 with a standard deviation of 1.63) than educational satisfaction (7.99 with a standard deviation of 1.89) with little gender difference in expectations (we do not have satisfaction data for the population).

[9] Appendix Table A.2 shows the same information for the restricted samples.

Table 3: Summary statistics of field attributes

Data:	Population			Survey		
Sample:	All	Men	Women	All	Men	Women
	(1)	(2)	(3)	(4)	(5)	(6)
Observations	189,331	71,580	117,751	45,655	15,797	29,858
Individuals	189,331	71,580	117,751	19,778	6,900	12,878
Degrees	790	682	719	259	257	258
Average monthly earnings	5,031	6,037	4,418	5,885	6,683	5,412
(2015 USD)	(2,843)	(3,478)	(2,154)	(4,102)	(4,790)	(3,548)
Median monthly earnings	4,897	5,752	4,512	5,091	5,818	5,091
Parenthood	0.73	0.68	0.76	0.73	0.65	0.76
(at least one child)	(0.44)	(0.47)	(0.43)	(0.31)	(0.32)	(0.29)
Partnership	0.78	0.79	0.78	0.77	0.74	0.79
	(0.41)	(0.41)	(0.41)	(0.24)	(0.25)	(0.24)
Work satisfaction				8.39	8.34	8.41
(1-10 scale)				(1.65)	(1.63)	(1.65)
Educational satisfaction				7.99	8.04	7.97
(1-10 scale)				(1.89)	(1.83)	(1.93)

Notes: The table reports summary statistics for our field attributes of interest both in the population data (corresponding to actual outcomes ten years after graduation) and in the survey data (corresponding to expected outcomes ten years after graduation). Observations are at the individual level in the population, and the individual degree-choice level in the survey. Earnings are pre-tax, and reported in USD using 2015 prices and exchange rates. Population earnings are yearly earnings divided by 12. Average earnings are winsorized at the top 1% of survey earnings with the same level applied then applied to population earnings. Standard deviations are reported in parentheses.

4.2 Gender earnings gap and role of educational field

In Table 4, we estimate the gender gap in log earnings, restricted to non-zero earnings. We estimate that among employed college graduates, women earn 29% less than men (column 1). Our estimates are very similar to the estimated gender earnings gap among full-time employed college graduates in the U.S. (Blau and Winkler, 2021, Figure 7-3). In column 2, we add field fixed effects and the estimated gender earnings gap declines by 39%, which aligns with estimates from the U.S. for the role of field in explaining the gender earnings gap.

As discussed in Section 4.1, college applicants expect a smaller gender earnings gap than in the population, an estimated 17% (column 3). However, the expect a strong role for gender differences in choice of major. Adding field fixed effects reduces the estimated gender earnings gap by 53%.[10]

Our main estimates drop observations with zero earnings, which excludes 6.2% of individuals in the population and 1.2% of degree choices in the survey. Appendix Table A.4 shows corresponding estimates including all observations to estimate the gender gap in the extensive margin of having non-zero earnings.

Table 4: Gender earnings gap

	DV: log earnings			
Data:	Population		Survey	
	(1)	(2)	(3)	(4)
Female	-0.289***	-0.177***	-0.171***	-0.080***
	(0.003)	(0.004)	(0.015)	(0.016)
Mean non-log DV	5,031		5,885	
Observations	175,011		34,428	
Individuals	175,011		15,044	
Field fixed effects	No	Yes	No	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All models are linear OLS regressions. The dependent variable is log earnings, and thus only non-zero earnings are in the sample. In columns (1) and (2), heteroskedasticity robust standard errors are in parentheses. In columns (3) and (4) standard errors clustered at the individual level are in parentheses. Columns (1) and (2) include graduation year fixed effects. Pre-tax monthly earnings measured in 2015 USD.

Figure 1 shows estimates of the gender earnings gap in a variety of sub-samples of the data, for both the population and survey. In essentially every cut of the data, we find significant gender earnings gaps, with the population estimate substantially exceeding the survey estimate. While we do not focus on the gap between the population and survey – these estimates are difficult to compare properly– there are a number of important instances where the population and survey estimates shows different patterns. While the population gender earnings gap is substantially larger in above-median earnings fields than below-median earnings fields, applicants do not expect differences in earnings gaps across these fields. Similarly, business and tech fields exhibit gender earnings gaps in the population that are

[10]Appendix Table A.3 shows the same estimates for the restricted samples. The results do not change.

about twice the size of the earnings gaps for graduates of science and health fields (our findings align with Goldin (2014) for business and science but not tech). In contrast, college applicants do not expect differential gaps across these fields. This pattern suggests it is unlikely that the lower share of women in high-earnings, business and tech fields is due to women's relative pessimism about gender gaps in those fields.

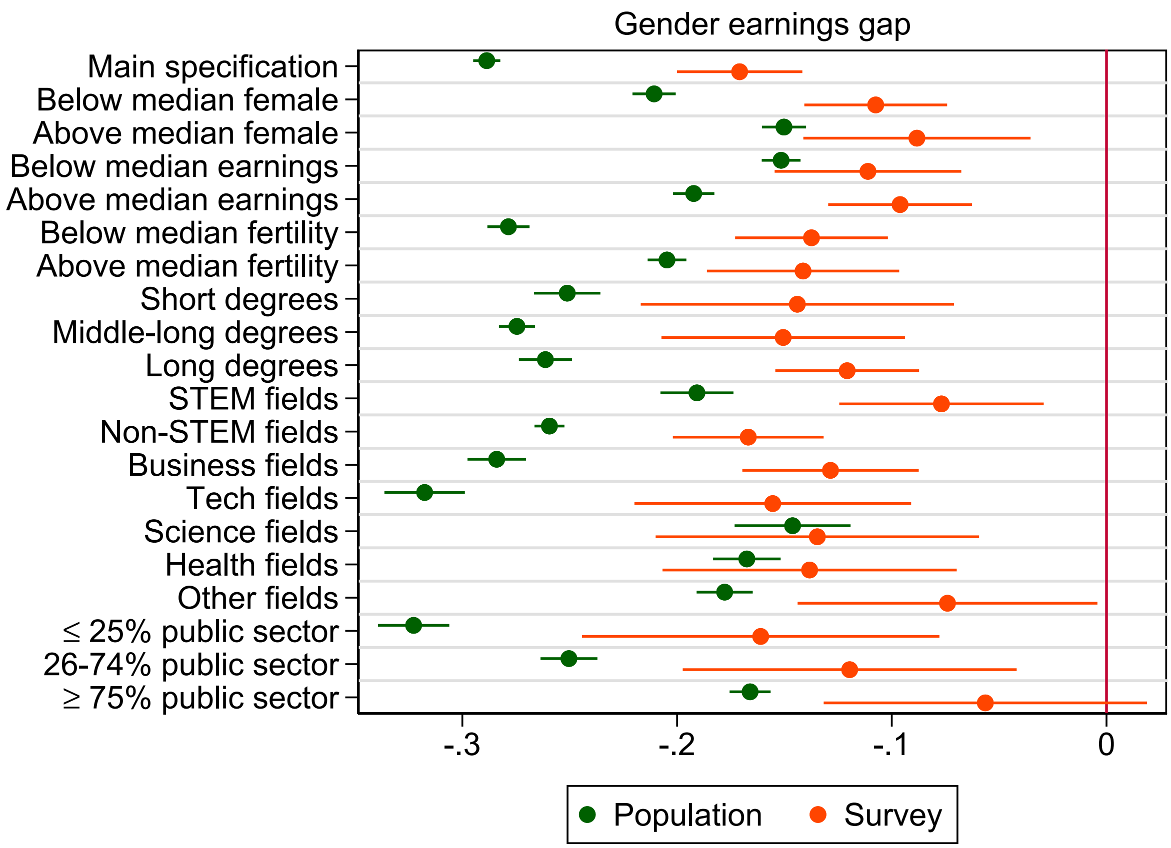

Figure 1: Gender earnings gap heterogeneity

Notes: Estimates correspond to the models in columns (1) and (3) of Table 4. Bars indicate 95% confidence intervals.

Interestingly, applicant's expectations align with heterogeneity in the population data for STEM vs. non-STEM fields, with STEM fields having smaller expected gaps among applicants and smaller realized gaps in the population. Similarly, applicants to degrees that feed into the public sector expect smaller gender gaps than applicants to degrees that feed into the private sector, which aligns with the pattern in the population data.

4.3 Earnings and non-earnings tradeoffs in more female fields

Having established a sizeable across-field gender gap and an important role for differences in field selection by gender, we explore how applicants beliefs about a field relate to how female or male that field is. First, we present our data at the field level. In Figure 2, we plot the attribute data against the female share of the field. We do this separately for men and women (i.e. every field with both men and women appears twice at the same position on the horizontal axis, but at potentially different positions on the vertical axis). Observations are weighted by within gender field size. We also include a fit line for men and women separately. For earnings, parenthood, and partnership, we plot both the population and survey sample relationships, while for work and educational satisfaction, we can only plot the survey relationships.

Panels A and B show how a field's monthly pre-tax average earnings ten years after graduating relates to field female share in the population and survey, respectively. For both men and women in both samples, the relationship is negative: more female fields are expected to feature lower earnings. This is not surprising given the substantial fraction of the gender earnings gap estimate in Table 4 explained by across-field variation. The negative relationship is stronger for women than men; women expect a larger premium (penalty) than men for going into less (more) female fields.

Panels C and D show how field average parenthood (probability of a child by ten years after graduating in the survey; an indicator for having at least one child by that time in the population) relates to field female share in the population and survey, respectively. The relationship is now positive: more female fields feature and are expected to feature a higher chance of becoming a parent within ten years of graduating. As with earnings, women both experience and expect a stronger tradeoff across fields of varying female share.

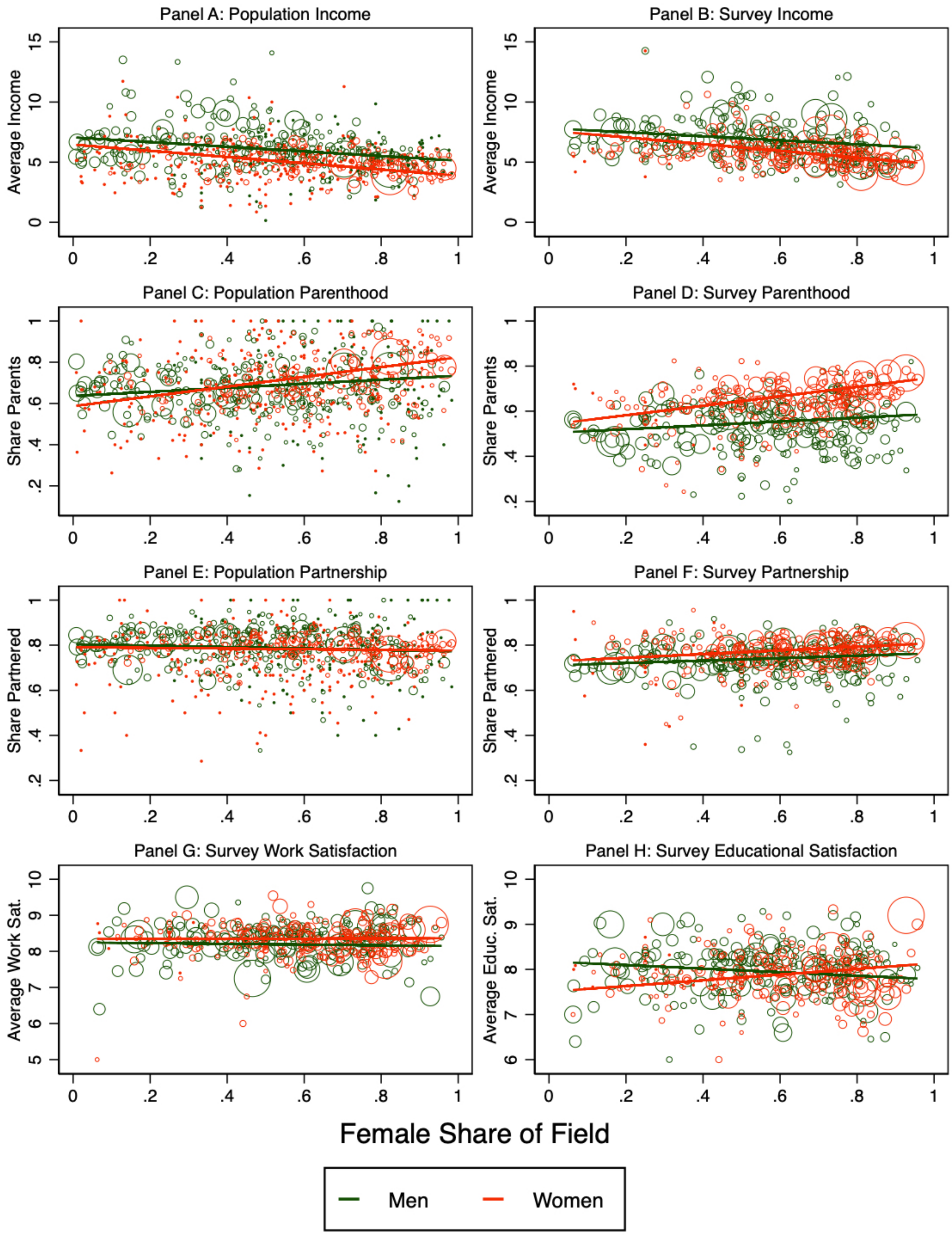

Figure 2: Attribute tradeoffs with female share of field by gender

Notes: Each observation represents a gender-field combination. Observations are weighted by size, within gender. Fields with fewer than 5 individuals are excluded from the figure due to privacy requirements. Fit lines are from gender-field weighted OLS regressions. Pre-tax monthly earnings measured in thousands of 2015 USD.

This same pattern holds for expected partnership in the survey (Panel F), work satisfaction (Panel G) and educational satisfaction (Panel H). When it comes to selecting a university field, women's outcomes and expected outcomes are generally more sensitive to the field's gender composition.

Table 5 shows estimates of the association between field female share and individual expectations/outcomes, separately for men and women.[11] In the survey data, we find that the tradeoff between non-pecuniary field attributes and female share always goes in the opposite direction to the tradeoff between income and female share: applicants expect that more female fields pay less, but compensate along the other dimensions of parenthood, partnership, work satisfaction, and educational satisfaction. We also corroborate that these tradeoffs are steeper for women than men; for every attribute except work satisfaction we reject that the male and female coefficients are equal ($p = 0.120$ for work satisfaction). For every 10 percentage points of female share, women (men) associate 5.5% (3.5%) less income, a 2ppt (0.8ppt) greater chance of becoming a parent, a 0.9ppt (0.5ppt) higher chance of having a partner, 0.03 points (< 0.01 points) more work satisfaction, and 0.05 points (0.01 points) more educational satisfaction. We consider similar tradeoffs in our population data for income, parenthood, and partnership. For income and parenthood, we get a qualitatively similar result: more female fields feature less pay and a higher chance of parenthood, more so for women than men. There is no partnership-female share tradeoff in the population data, nor is there a gender difference in this tradeoff.

[11]Estimates for the restricted sample are in Appendix Table A.5, and estimates for a sample limited to individuals providing a non-missing value of an attribute for at least two degree choices (in order to correspond exactly to the sample in Table 6) are in Appendix Table A.6.

Table 5: Association of female share of field with field attributes

Data:	Population		Survey	
Sample:	Male	Female	Male	Female
	(1)	(2)	(3)	(4)
Panel A - DV: log earnings				
Female share	-0.305***	-0.432***	-0.350**	-0.546***
	(0.094)	(0.111)	(0.137)	(0.173)
H_0: Male = Female	$p = 0.168$		$p = 0.062$	
Mean non-log DV	6,037	4,418	6,683	5,412
Observations	66,293	108,718	12,893	21,535
Individuals	66,293	108,718	5,666	9,378
Panel B - DV: Parenthood probability				
Female share	0.094**	0.240***	0.078**	0.195***
	(0.039)	(0.040)	(0.031)	(0.036)
H_0: Male = Female	$p = 0.003$		$p = 0.001$	
Mean DV	0.68	0.76	0.65	0.76
Observations	71,580	117,751	13,309	27,043
Individuals	71,580	117,751	5,855	11,709
Panel C - DV: Partnership probability				
Female share	-0.034	-0.008	0.047**	0.088***
	(0.037)	(0.031)	(0.021)	(0.022)
H_0: Male = Female	$p = 0.518$		$p = 0.088$	
Mean DV	0.79	0.78	0.74	0.79
Observations	70,563	117,035	13,145	26,203
Individuals	70,563	117,035	5,804	11,385
Panel D - DV: Work satisfaction				
Female share			0.033	0.309**
			(0.146)	(0.138)
H_0: Male = Female			$p = 0.120$	
Mean DV			8.34	8.41
Observations			13,797	26,413
Individuals			6,115	11,542
Panel E - DV: Educational satisfaction				
Female share			0.064	0.546***
			(0.167)	(0.173)
H_0: Male = Female			$p = 0.021$	
Mean DV			8.04	7.97
Observations			14,654	27,775
Individuals			6,492	12,169

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All models are linear OLS regressions. In columns (1) and (2) standard errors are clustered at the field level. In columns (3) and (4) standard errors clustered at both the individual and field level are in parentheses. Pre-tax monthly earnings measured in 2015 USD. Work and educational satisfaction are measured on a 1-10 scale.

4.4 Within-individual tradeoffs

Applicants anticipate both a gender wage gap within fields and gender differences in the way income and other field attributes trade off across fields of varying female share. Is this because, *across applicants*, individuals who select into different fields have different expectations; or because *within applicants*, individuals expect different outcomes if they select into different fields.

First we note that while the within-individual variation in female share across ranked fields is less than the overall variation in female share in the survey sample, there is still considerable within-individual variation that allows us to make comparisons between the two types of estimates. The full survey sample standard deviation is 22 percentage points, compared to nine percentage points for the individual mean-differenced female share, and the average within-individual range of female share is 12 percentage points. We show the full CDF of the within-individual female share range in Appendix Figure A.1. While roughly one-third of the individuals in the survey sample rank fields with essentially identical female share, the remaining two-thirds of the sample covers a wide range of the space. Over 10% of the data (roughly 1,400 respondents) features individuals with a female share range of more than 32 percentage points, and we observe non-trivial density up to a range of about 60 percentage points. Thus, while the individual fixed effects models will place more weight on associations with local variation in female share, there are plenty of individuals selecting between fields with very different gender compositions that will also inform these estimates.[12]

Individual fixed-effect model results are presented in Table 6. For earnings, parenthood and partnership, the fixed effects estimates are much smaller in magnitude for both men and women. This is evidence that the strong relationship between female share and field attributes has more to do with differences across individuals –selection– than perceived causal impacts of field selection. Those perceived causal impacts do exist, but they are relatively

[12]Given our linear model, in theory this difference in the within vs. overall variation in female share should have no impact. However, if the true relationship is non-linear this issue may be important. For this reason, we also present individual fixed effect effect estimate split by below- vs. above-mean female share top-ranked choices in Table 6 alongside the full (gender-specific) sample estimates.

small. Furthermore, the stronger relationships between female share out outcomes for women disappear. These results suggest that differences across women selecting into more or less female fields are stronger than differences across men selecting into more or less female fields.

Men –for whom we estimated no significant work and educational satisfaction gradients with respect to female share– also show no evidence of such gradients in the individual fixed-effect models, with the exception of men in above-median female share fields, who expect *lower* educational satisfaction as a field gets more female. Women on the other hand anticipate *larger* tradeoffs between both types of satisfaction and female share in the individual fixed effect models; women perceive that work and educational satisfaction are strongly impacted by their choice of field –even within the small set of their most preferred fields. This is important: it suggests that changes to expectations about work and educational satisfaction have the potential to actually change the choices people make, and to do so differently for men and women. We return to this by also considering the preference weight men and women put on these non-pecuniary attributes in Section 5.

Table 6: Within-individual association of female share of field with field attributes

Female share vs. mean:	All		Below		Above	
Sample:	Male	Female	Male	Female	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A - DV: log earnings						
Female share	-0.133***	-0.109***	-0.142***	-0.101**	-0.495*	-0.448***
	(0.037)	(0.026)	(0.052)	(0.041)	(0.270)	(0.152)
H_0: Male = Female	$p = 0.596$		$p = 0.536$		$p = 0.879$	
Observations	12,296	20,583	7,795	5,089	2,896	12,580
Individuals	5,069	8,426	3,337	2,239	1,285	5,382
Panel B - DV: Parenthood probability						
Female share	0.016*	0.023***	0.020*	0.020	-0.055	0.036*
	(0.009)	(0.006)	(0.011)	(0.015)	(0.067)	(0.019)
H_0: Male = Female	$p = 0.355$		$p = 1.000$		$p = 0.191$	
Observations	12,661	25,862	7,987	6,287	3,011	15,915
Individuals	5,207	10,528	3,422	2,759	1,333	6,779
Panel C - DV: Partnership probability						
Female share	0.028**	0.034***	0.032**	0.046**	-0.038	0.056***
	(0.011)	(0.009)	(0.013)	(0.022)	(0.059)	(0.021)
H_0: Male = Female	$p = 0.673$		$p = 0.584$		$p = 0.133$	
Observations	12,476	25,014	7,876	6,077	2,973	15,428
Individuals	5,135	10,196	3,379	2,665	1,317	6,579
Panel D - DV: Work satisfaction						
Female share	0.005	0.687***	-0.112	0.376	-0.928	0.138
	(0.147)	(0.176)	(0.209)	(0.279)	(0.740)	(0.479)
H_0: Male = Female	$p = 0.003$		$p = 0.162$		$p = 0.227$	
Observations	13,065	25,133	8,183	6,186	3,157	15,404
Individuals	5,383	10,262	3,507	2,773	6,581	8,517
Panel E - DV: Educational satisfaction						
Female share	-0.142	1.061***	-0.250	0.464	-1.986**	0.882*
	(0.167)	(0.183)	(0.273)	(0.349)	(0.952)	(0.479)
H_0: Male = Female	$p < 0.001$		$p = 0.107$		$p = 0.007$	
Observations	13,869	26,366	8,730	6,469	3,310	16,191
Individuals	5,707	10,760	3,739	2,841	1,463	6,914

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All models are individual fixed-effect linear regressions. Standard errors clustered at both the individual and field level are in parentheses. The mean female share of applicants' top choices is 0.65. Pre-tax monthly earnings measured in 2015 USD. Work and educational satisfaction are measured on a 1-10 scale.

5 Structural Model

To better understand how gender differences in preferences and gender differences in beliefs about school and work attributes contribute to gender differences to educational choices, we estimate a structural model of survey respondents' degree rankings. We use the model to compare men's and women's compensating differentials for education and work attributes, decompose the sources of gender differences in field selection, and consider the relative magnitude of within-gender versus across-gender heterogeneity in preferences.

5.1 General Formulation

Survey respondents are denoted by $i = 1 \dots I$. Their ordinally-ranked degree options are $j = 1 \dots J$. Individual utility, u_{ij}, is given by the equation

$$U_{ij} = X^1_{ij} + \delta_i X^2_{ij} + \epsilon_{ij} \quad , \tag{1}$$

where X^1_{ij} and X^2_{ij} are the individual-degree option specific attributes during and ten years after the degree, respectively. We specify those attributes in the following section. δ_i is the individual-specific discount factor between those periods, and ϵ_{ij} is the idiosyncratic error term, distributed independently according to a type-1 extreme value (T1EV) distribution.

We take a logistic choice model approach to estimating the parameters of the model. Call Z_i an individual's selected degree option from $j = 1 \dots J$. Using the softmax representation, this means that the probability of observing individual i ranking degree k first is

$$Pr(Z_i = k) = \frac{exp(U_{ik})}{\sum_{j=1}^{J} exp(U_{ij})} \quad . \tag{2}$$

Individuals in our survey may supply data for two or three degree choice options. For individuals with only two, the log of equation 2 fully describes their contribution to the likelihood function we maximize. For individuals with three, we exploit the additional piece of information that the second-ranked option is preferred to the third-ranked option. Assume that an individual ranks degree k first, ahead of degree m, ahead of the rest. Call Y_i an individual's second-ranked degree option from $j = 1 \dots k-1, k+1 \dots J$. Using the same model, the probability of observing individual i making this ranking is

$$Pr(Z_i = k, Y_i = m) = \frac{exp(U_{ik})}{\sum_{j=1}^{J} exp(U_{ij})} \cdot \frac{exp(U_{im})}{\sum_{j=1}^{k-1} exp(U_{ij}) + \sum_{j=k+1}^{J} exp(U_{ij})} \quad . \tag{3}$$

Thus, the structure of an individual's contribution to the log-likelihood function depends on whether they ranked two or three degree options. Call $R_i \in \{2, 3\}$ the number of degree options listed by individual i, and assume as above that an individual's top choice is degree k, second choice is degree m and third choice (if it exists) is degree n. The log-likelihood function is thus

$$\begin{aligned} \ell = \sum_{i=1}^{I} \mathbb{1}(R_i = 3) \cdot ln\left(\frac{exp(U_{ik})}{exp(U_{ik}) + exp(U_{im}) + exp(U_{in})} \cdot \frac{exp(U_{im})}{exp(U_{im}) + exp(U_{in})}\right) + \\ \mathbb{1}(R_i = 2) \cdot ln\left(\frac{exp(U_{ik})}{exp(U_{ik}) + exp(U_{im})}\right) \quad . \end{aligned} \tag{4}$$

We estimate the model using a maximum likelihood routine in Stata.[13]

5.2 Attributes in the utility function

We select the attributes of an education option that enter the utility function in order to focus on fertility and income, while controlling for key factors that may be related to those attributes. Work utility, X_{ij}^2, consists of income, the probability of having children, the probability of being married/having a long-term partner, and work satisfaction ten years after graduation. School utility, X_{ij}^1 consists only of educational satisfaction as a blanket control for aspects of an education experience itself that may correlated with future income and fertility.

[13] Maximization is performed using the "ml maximize" command in Stata Version 16.1. All parameters are initialized at zero, and we use the "difficult" option.

While we allow for diminishing marginal utility over income using a CRRA utility function, we assume linear utility over the probabilities and satisfaction ratings. This means that income utility and other aspects of utility are additively separable, which reduces the complexity of the maximization process. Work utility is thus given by

$$X_{ij}^2 = \frac{y_{ij}^{1-\sigma_i}}{1-\sigma_i} + \beta_1 f_{ij} + \beta_2 p_{ij} + \beta_3 s_{ij}^w \quad , \tag{5}$$

where y_{ij} is individual i's expected monthly pre-tax income (in 1000s of 2015 U.S. dollars) ten years after graduating from degree j, p_{ij} is individual i's percentage chance of being married ten years after graduating from degree j (0-100), f_{ij} is individual i's percentage chance of being having children ten years after graduating from degree j (0-100), and s_{ij}^e is individual i's expected satisfaction with their job ten years after graduating from degree j (1-10 scale).[14] σ_i is an individual-specific CRRA parameter, with

$$\sigma_i = \sigma_0 + \sigma_1 r_i \quad , \tag{6}$$

where r_i is an individual's standardized response to a Gneezy and Potters (1997) style risk preference question in our survey.[15] Larger values of r_i correspond to more risk-tolerant choices.

Work utility is discounted by factor

$$\delta_i = \bar{\delta}_{10} + \delta t_i \quad , \tag{7}$$

where $\bar{\delta}_{10}$ is the 10-year discount factor extrapolated from the main estimate of Andersen et al. (2014) for the average Dane, and t_i is individual i's standardized choice from a time-

[14]We ask respondents to assume there is no inflation when predicting their future earnings.

[15]We ask subjects, "Imagine that you have up to 10,000 krone that you can invest in a stock for one day. With a 50% chance, the stock will triple in value today, and any money you invest will be tripled. With a 50% chance, the stock will become worthless today, and any money you invest will be lost. Any money that you do not invest in the stock will be yours to keep. How much would you invest?.

preference question embedded in our survey module.[16] Larger values of t_i correspond to more patient choices.[17]

School utility is not discounted, and given by

$$X_{ij}^1 = \alpha s_{ij}^e \quad , \tag{8}$$

where s_{ij}^e is individual i's expected satisfaction with their educational experience during degree j (1-10 scale).

Our identification of the α and β parameters –which weight the option-specific attributes– comes exclusively from within-subject variation because if each option featured the same exact attributes, the probabilistic choice model would predict random choice between those options. The σ_0, σ_1 and δ parameters are identified based on across-subject relationships between income differentials and choice, how that relationship correlates with r_i and how t_i correlates with the ratio of present and future utility in determining choices, respectively.

5.3 Results

The results of our model estimation are presented in Table 7. Column (1) shows the results for the entire sample, and columns (2) and 3 show the results for the male and female samples, respectively.[18] We start by discussing the risk and time preference parameters, and then move to the degree attribute preference parameters.

[16] Assuming exponential discounting, Andersen et al. (2014) estimates an average annual discount rate of 0.09 in a nationally representative danish sample. Thus $\bar{\delta}_{10} = (\frac{1}{1+0.09})^{10} = 0.42$. t_i comes from the response to, "Imagine that you win a lottery prize of 10000 krone. You can choose to receive the prize in a week, or choose to wait and receive an even larger amount. For every extra week you wait, the prize grows by 100 krone, up to a maximum of 12500 krone in 26 weeks from now. How many extra weeks would you wait to receive your prize?"

[17] Unlike the CRRA parameter, the discount factor multiplies all work utility terms. Thus, the average discount factor is highly co-linear with the attribute parameters. For that reason, we specify the sample average while allowing for individual heterogeneity around that average.

[18] We re-standardize r_i within each of the samples so that σ_0 retains its interpretation at the average CRRA parameter within the estimation sample.

Table 7: Structural model estimates

Sample:	All	Male	Female
	(1)	(2)	(3)
CRRA parameter (σ_0, sample average level)	0.820***	0.760***	0.862***
	(0.026)	(0.060)	(0.025)
Parenthood (β_1, 0-100 percent)	0.031***	0.022*	0.037***
	(0.007)	(0.012)	(0.010)
Partnership (β_2, 0-100 percent)	0.087***	0.074***	0.094***
	(0.005)	(0.009)	(0.007)
Work satisfaction (β_3, 1-10 scale)	0.558***	0.603***	0.551***
	(0.041)	(0.070)	(0.051)
Educational satisfaction (α, 1-10 scale)	0.573***	0.596***	0.563***
	(0.016)	(0.026)	(0.019)
Discount factor heterogeneity (δ, SD patience)	0.046***	0.078***	0.022
	(0.015)	(0.022)	(0.020)
CRRA heterogeneity (σ_1, SD risk tolerance)	0.012	0.106*	-0.042
	(0.029)	(0.064)	(0.032)
Observations	26,690	9,595	17,095
Individuals	10,551	3,866	6,685

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Data enter the model at the individual level, and standard errors are shown in parentheses. The σ_0 estimates represent the estimation sample average CRRA utility parameter. The σ_1 estimates represent how an individual's σ_i varies with their standardized response on the risk preference elicitation, r_i. The standardization is estimation-sample specific. The β_1 and β_2 estimates are measured per percentage point. The β_3 and α estimates are measured per Likert scale point. The δ estimates represent how an individual's δ_i varies with their standardized response on the time preference elicitation. The standardization is done once in the full sample.

5.3.1 Risk & time preferences

Subjects exhibit substantial diminishing marginal utility in earnings, with a notable gender gap in magnitude. We estimate slightly more utility curvature in our sample of university applicants than Andersen et al. (2014) obtain from a representative sample of Danes, but the parameters are quite close. This is reassuring given that parameter identification comes from entirely different sources of variation. Women's utility diminishes faster, although the difference is not statistically significant ($p = 0.117$). Under an expected utility assumption, this is consistent with a considerable literature showing gender differences in risk preferences (see Charness and Gneezy (2012) for a discussion). Indeed we find that on average, men are willing to invest 22% more of their endowment than women in a risky asset in the hypothetical Gneezy and Potters (1997) task ($p < 0.001$). However, we do not find evidence of important individual heterogeneity in utility curvature predicted by our risk measure, as we cannot reject that $\sigma_1 = 0$. Within the male sample, more risk tolerant individuals actually exhibit *more* utility curvature, suggesting that risk preference may not have an important bearing on expected earnings curvature in this setting (i.e. an expected utility failure similar to that observed in Andreoni and Sprenger (2012)), although this relationship is only marginally statistically significant ($p = 0.098$). Altogether, these estimates suggest that while gender differences in utility curvature may be important for evaluating education choices, the role of idiosyncratic individual risk preference is less clear.

On the other hand, we find strong evidence of individual heterogeneity in discounting: our estimate of δ_1 suggests that subjects making more patient choices in our time task are more willing to trade present utility for future utility ($p = 0.002$). This relationship is driven entirely by men. While we estimate that women are more patient than men (on average women wait 6% longer than men in our hypothetical time preference task, $p < 0.001$), impatient men are making very different tradeoffs than patient men, whereas our measure of patience doesn't relate to the educational tradeoffs of women.

5.3.2 Field attribute preferences

We start by making across-parameter, within-sample comparisons, before using compensating differentials to compare the male and female sample estimates. First, we note that the value of finding a partner is substantially higher than the value of fertility ($p < 0.001$), and that work and educational satisfaction have roughly similar weights *within their respective time periods* ($p = 0.733$). Given that work satisfaction is discounted, as is earnings utility, this means that the compensating differential for educational satisfaction will be substantially higher than for work satisfaction. Indeed, our preferred metric for considering these utility attributes is using a compensating differential for earnings. We calculate these at the full sample median earnings level of the highest-ranked option, and present the results –scaled to a standard deviation of each attribute– in Table 8.

Table 8: Monthly pre-tax earnings compensating differentials (1000s 2015 USD)

Sample:	All	Male	Female
	(1)	(2)	(3)
Parenthood (per SD, SD = 31 ppt)	3.65	2.35	4.66
% of Median income:	71.7%	46.1%	91.6%
Partnership (per SD, SD = 24 ppt)	7.93	6.12	9.17
% of Median income:	155.8%	120.2%	180.2%
Work sat. (per SD, SD = 1.65 points)	3.50	3.43	3.70
% of Median income:	68.7%	67.3%	72.6%
Educational sat. (per SD, SD = 1.89 points)	9.74	9.35	10.21
% of Median income:	191.3%	183.7%	200.6%

Notes: Each compensating differential is evaluated at survey median earnings of $5091 per month. All differentials are per standard deviation (SD) of the corresponding field attribute, using the full-sample SD of that attribute.

Overall, we find that there is a substantial willingness to trade earnings for non-pecuniary aspects of an education. For all attributes, that willingness is higher for women than men. In fact, because we use full-sample median earnings in order to focus on gender differences solely due to the estimated utility parameters, the gender gap in the compensating differentials as a percent of median income actually understates the gap between the median man and woman. Fertility features the biggest relative gender disparity: women's willingness to trade earnings for fertility probability is nearly double (98% higher than) men's. Specifically, women are willing to trade $150 (2.9% of median income) per month in per-tax earnings for a one percentage point increase in the chance of having children, compared to $76 for men (1.5% of median income). Both men and women are more responsive to the probability of being married or partnered ($255 and $382 per month, respectively, per percentage point), with a smaller relative gender disparity in the rate of willingness to trade (women's is 50% higher). The gender disparities are much smaller for both work satisfaction and educational satisfaction, with women 7% and 9% more willing to trade, respectively. Table 8 measures these changes in terms of standard deviations in order to facilitate across-attribute comparisons, but the magnitudes are overstated as they neglect diminishing marginal utility. Relative to partnership and educational satisfaction, parenthood and work satisfaction are considerably less important for both men and women.

5.4 Explaining gender differences in selection

Having identified substantial gender differences in preferences for parenthood and partnership, we now consider whether those differences are capable of explaining gender differences in field selection. We apply our estimated utility parameters to a choice between two hypothetical fields. Field A features the gender-specific average expected attributes of all degree choices in the survey (see Table 3). Field B is constructed using the gender-specific estimates of the within-individual tradeoff between field and female share in Table 6. We use the individual fixed-effect estimates of these tradeoffs, which correspond naturally to our model of ranking fields within an applicant's consideration set. All expected attributes of Field B are what we would predict using those coefficients if Field B were 10 percentage points more female than Field A.[19] Using the two-option logistic choice model functional form in equation 2, we predict men's and women's probabilities of selecting Field B. Assuming an equal number of men and women characterized by those choice probabilities, we then calculate the predicted female share of each field. The difference in predicted female share between fields is the benchmark against which we evaluate counterfactuals; either changing only one field attribute at a time, or limiting gender differences to either preferences or field attributes (or both).

We attribute essentially all of the gender difference in field selection to gender differences in the work and educational satisfaction expectations across fields. This is for two reasons.

[19] The magnitude of the difference between fields A and B does not affect these results (e.g. 10 ppt, as we use here). The gender differences in coefficients are all that matter for determining the share of the predicted shift that each attribute explains.

First, Table 6 showed that with individual fixed effects, men and women perceive very similar tradeoffs between female share and income, parenthood, and partnership within their considerations sets. On the other hand, men and women perceive very different tradeoffs between female share and satisfaction within their consideration sets. Women anticipate a substantial causal effect of their field choice on both educational and work satisfaction. Men anticipate no effect. Second, Table 8 shows that men and women are both highly responsive to differences in educational satisfaction in particular.

Figure 3 illustrates the consequences of these two findings on the prediction exercise. Of the overall predicted difference in female share between fields A and B, 72% is explained by educational satisfaction, and 17% is explained by work satisfaction. All of that is due to gender differences in expectations from Table 6, rather than gender difference in preferences over these attributes from Table 8. An important detail about this exercise is that despite work satisfaction having the smallest standardized compensating differential in the pooled sample ($3500 per SD), the gender difference in the expected work satisfaction tradeoff is large enough for it to explain a non-trivial fraction of the female share difference between Fields A and B. This suggests that the similar magnitudes of the gender differences in preferences for parenthood (women willing to give up an extra $2310 per SD) and partnership (women willing to give up an extra $3050 per SD) could have explained gender differences in field selection if the magnitude of the expected partnership or parenthood tradeoffs had been larger.

Overall, the results of this decomposition exercise suggest that while we estimate gender differences in preferences that qualitatively appear consistent with gender differences in field selection, they are substantially less important quantitatively than gender differences in education and work satisfaction tradeoffs that men and women expect across fields. Overall preferences explain only an estimated 3.2% of the difference in female share of field in our decomposition exercise.

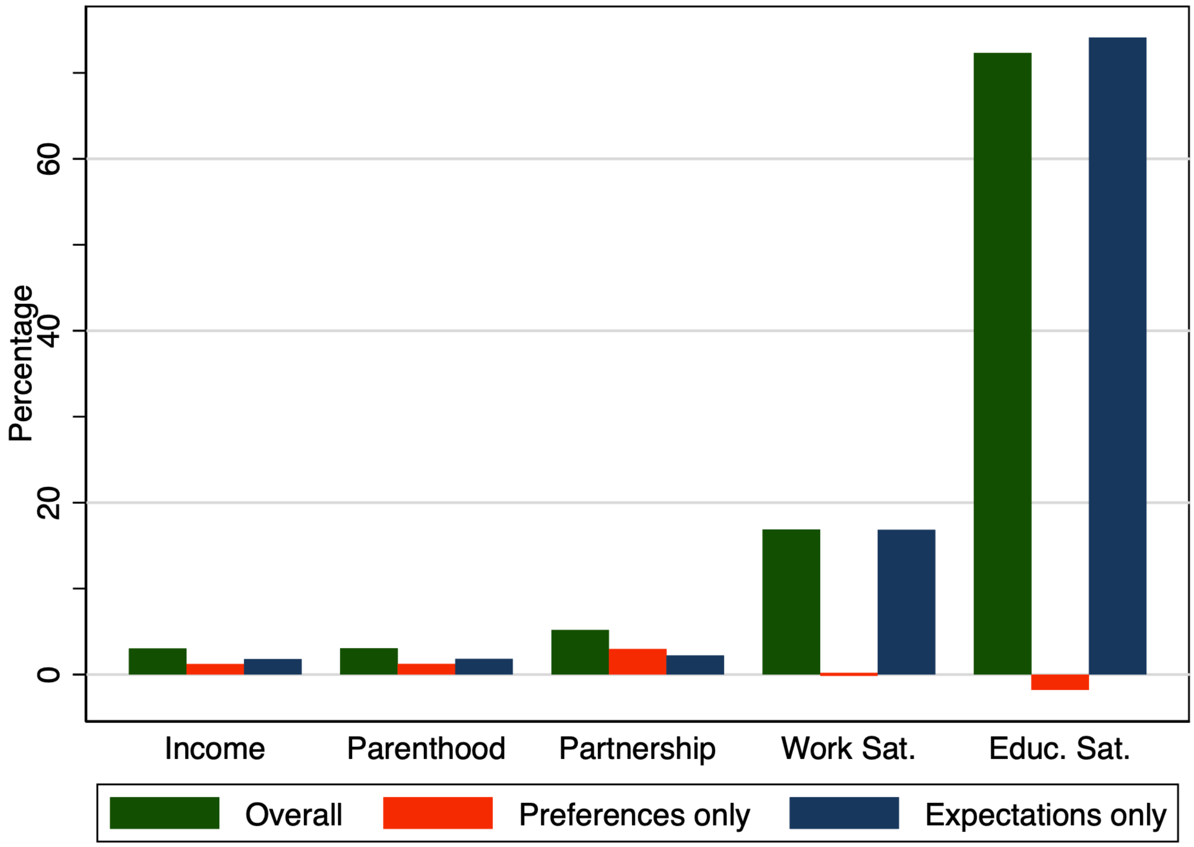

Figure 3: Percentage of hypothetical field female share difference explained by field attributes

Notes: Positive values imply that a gender difference in preferences, expectations, or both over an attribute explains some of the predicted overall difference in female share between Fields A and B. Negative values imply that a gender difference in preferences, expectations, or both over an attribute predicts the opposite of the predicted overall difference in female share between Fields A and B. The preferences only and expectations only bars show the mean of the high and low predictions.

5.5 Within- vs. between-gender preference heterogeneity

One reason why gender differences in preferences do not appear to explain a large portion of gender differences in field selection could be because gender –while clearly correlated with preference heterogeneity– is not a powerful predictor of preference heterogeneity over the attributes of fields that we consider. To evaluate this, we split each of our male and female samples by median female share and estimate four sets of preference parameters. If non-gender preference heterogeneity matters for field selection we should see that conditioning on a measure of field selection reveals large within-gender preference differentials. Estimates are presented in Table 9, and the corresponding compensating differentials are in Table 10.

Table 9: Structural model estimate by female share of top-choice field

Sample:	Male		Female	
Female share of field vs. median:	Below	Above	Below	Above
	(1)	(2)	(3)	(4)
CRRA parameter (σ_0, sample average)	0.753***	0.757***	0.855***	0.867***
	(0.105)	(0.071)	(0.062)	(0.029)
Parenthood (β_1, 0-100 percent)	0.009	0.035**	0.017	0.074***
	(0.017)	(0.017)	(0.013)	(0.016)
Partnership (β_2, 0-100 percent)	0.073***	0.075***	0.111***	0.078***
	(0.012)	(0.012)	(0.010)	(0.009)
Work satisfaction (β_3, 1-10 scale)	0.604***	0.610***	0.633***	0.439***
	(0.099)	(0.098)	(0.071)	(0.075)
Educational satisfaction (α, 1-10 scale)	0.621***	0.567***	0.591***	0.540***
	(0.036)	(0.038)	(0.027)	(0.028)
Discount factor heterogeneity (δ, SD patience)	0.078**	0.084***	0.045*	0.029
	(0.035)	(0.028)	(0.027)	(0.029)
CRRA heterogeneity (σ_1, SD risk tolerance)	0.101	0.109	-0.092	-0.019
	(0.086)	(0.094)	(0.068)	(0.035)
Observations	4,992	4,603	9,211	7,884
Individuals	2,026	1,840	3,493	3,068

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Data enter the model at the individual level, and standard errors are shown in parentheses. Median female share for men's top-choice field is 0.56. Median female share for women's top-choice field is 0.76. The σ_0 estimates represent the estimation sample average CRRA utility parameter. The σ_1 estimates represent how an individual's σ_i varies with their standardized response on the risk preference elicitation, r_i. The standardization is estimation-sample specific. The β_1 and β_2 estimates are measured per percentage point. The β_3 and α estimates are measured per Likert scale point. The δ estimates represent how an individual's δ_i varies with their standardized response on the time preference elicitation. The standardization is done once in the full sample. For the female below median sample, we have to loosen the second-order condition tolerance criteria in order to achieve convergence.

The structural estimates reveal that utility curvature varies by gender in the expected direction, but there is almost no within-gender variation. Thus, gender differences in preferences in theory would be able to explain gender differences in field selection; however the within-individual income-female share relationship is about an order of magnitude too weak

Table 10: Monthly pre-tax earnings compensating differentials (1000s 2015 USD) by female share of top-choice field

Sample:	Male		Female	
Female share of field vs. median:	Below	Above	Below	Above
	(1)	(2)	(3)	(4)
Parenthood (per SD, SD = 31 ppt)	0.95	3.72	2.12	9.41
% of Median income:	18.7%	73.1%	41.6%	184.8%
Partnership (per SD, SD = 24 ppt)	5.97	6.17	10.71	7.68
% of Median income:	117.2%	121.2%	210.4%	150.8%
Work sat. (per SD, SD = 1.64 points)	3.37	3.43	4.17	2.95
% of Median income:	66.3%	67.4%	82.0%	58.0%
Educational sat. (per SD, SD = 1.89 points)	9.59	8.87	10.51	9.92
% of Median income:	188.3%	174.3%	206.4%	194.8%

Notes: Each compensating differential is evaluated at survey median earnings of $5091 per month. All differentials are per standard deviation (SD) of corresponding field attribute, using the full-sample SD of that attribute for the first-ranked choice. Median female share for men's top-choice field is 0.56. Median female share for women's top-choice field is 0.76.

for income to be as important as educational satisfaction in explaining the predicted gender gap in field selection.

On the other hand, the compensating differentials suggest that there are very large within-gender differences in preferences, especially when it comes to parenthood. Women who pursue more male-dominated fields and women who do not are *very* different from each other. Women in above-median female share fields are willing to trade nearly 4.5 times as much income for parenthood than women in below-median female share fields. We see a similar pattern for men, where men in above-median female share fields are nearly four times as willing to trade income for parenthood than men in below-median female share fields, although the levels of the compensating differentials are lower.

Besides parenthood, we find very limited differences in preferences within the men in our sample. Women in below-median female share fields place *higher* weight on partnership, work satisfaction, and educational satisfaction than women in above-median female share fields, who have compensating differentials closer to those of men. Overall, this exercise shows that the modest gender differences in preferences we estimate in Table 7 mask larger within-gender differences in preferences for non-pecuniary attributes, especially when it comes to parenthood.

6 Earnings penalties

Finally, we consider the interaction of non-earnings attributes with earnings to examine the gender earnings gap within fields. Table 4 showed that field fixed effects explained 39% of the earnings gap in the population, and 53% of the gap amongst applicants in the survey. Table 11 shows how the remaining earnings gap changes as the non-pecuniary attributes and their interaction with gender are added to the model.[20]

Column (1) replicates the baseline field fixed effect earnings gap estimates of 18% in the population and 8% in the survey. We add parenthood and its interaction with gender in column (2). In the population, we find a positive association between earnings and fatherhood. Relative to fathers, mothers have significantly lower earnings. These findings are in line with prior work on the fatherhood premium and motherhood penalty. Both male and female college applicants expect a parenthood premium. We find no evidence that women expect a motherhood penalty – if anything, directionally women expect relatively higher earnings associated with motherhood relative to the earnings premium for fathers.

In column (3), we add partnership and its interaction with gender. Partnership plays a similar role to parenthood in the population –there is a premium for men but not women, in line with work on the male marriage premium. Male college applicants expect a positive association between partnership and earnings. Women directionally expect a lower partnership premium than men, though it is not statistically significant. College applicants also expect a positive association between earnings and both work and educational satisfaction with no significant gender differences.

[20]Corresponding estimates without field fixed effects are in Appendix Table A.8 and estimates using the restricted sample are in Appendix Table A.9.

Table 11: Gender differences in within-field earnings penalties

	DV: log earnings						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Population (Mean non-log DV = 5,031)							
Female	-0.177***	-0.112***	-0.044***			-0.028***	
	(0.004)	(0.006)	(0.007)			(0.008)	
Parenthood		0.094***				0.032***	
		(0.005)				(0.005)	
Fem. X Parent		-0.092***				-0.039***	
		(0.007)				(0.007)	
Partnership			0.175***			0.162***	
			(0.006)			(0.006)	
Fem. X Partner			-0.170***			-0.155***	
			(0.007)			(0.008)	
Observations	175,011	175,011	173,585			173,585	
Panel B: Survey (Mean non-log DV = 5,885)							
Female	-0.080***	-0.118***	-0.033	0.034	-0.048	-0.056	0.075
	(0.016)	(0.042)	(0.058)	(0.096)	(0.075)	(0.061)	(0.127)
Parenthood		0.077**				-0.029	-0.045
		(0.036)				(0.041)	(0.045)
Fem. X Parent		0.025				0.081	0.084
		(0.051)				(0.059)	(0.063)
Partnership			0.188***			0.224***	0.181**
			(0.057)			(0.067)	(0.071)
Fem. X Partner			-0.073			-0.131	-0.141*
			(0.068)			(0.081)	(0.085)
Work satisfaction				0.052***			0.047***
				(0.009)			(0.010)
Fem. X Work sat.				-0.014			-0.023*
				(0.011)			(0.012)
Educational sat.					0.032***		0.003
					(0.007)		(0.008)
Fem. X Educ. sat.					-0.004		0.010
					(0.009).		(0.010)
Observations	34,428	31,827	31,153	32,777	32,243	30,315	28,051
Individuals	15,044	13,971	13,725	14,492	14,271	13,356	12,534

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All are linear OLS regressions. Panel A shows robust standard errors in parentheses, and Panel B shows standard errors clustered at the individual level. Pre-tax monthly earnings measured in 2015 USD. Work and educational satisfaction are measured on a 1-10 scale.

Our results suggest that women may expect an earnings penalty associated with partnership (relative to men), but do not expect a motherhood penalty or earnings penalties associated with selecting a field with higher levels of educational and work satisfaction. Given applicants' expectations it is not likely that college applicants are directly considering motherhood penalties across fields when choosing a college major.

7 Conclusion

We conduct a large-scale survey experiment among a national cohort of college applicants in Denmark who submit their rank ordered choices for degree programs to a national clearinghouse. We elicit their beliefs about labor market and family outcomes ten years after graduating from their top choice college degrees, as well as satisfaction during their studies. We examine applicants' expectations and preferences in order to understand how attributes of programs shape gender differences in choice of educational field.

Several findings emerge from our study. First, women, but not men, expect that they will have significantly lower educational satisfaction in more heavily male fields, which deters them from entering male dominated majors. Prior interventions aimed at increasing female entry into these fields have informed women about earnings returns to male majors (e.g., Ding et al., 2021). Our findings suggest that interventions targeting women's (perceived) experience during their studies could be more effective.

Second, there is substantial heterogeneity within gender, particularly for women and particularly related to the weight put on parenthood considerations when choosing an educational field. A better understanding of within-gender heterogeneity can help inform policies aimed not only at shifting more women into traditionally male occupations, but also shifting more men into traditionally female occupations, with the increase of "pink collar" jobs (see e.g., Delfino, 2021, for discussion)

Finally, our results suggest that when women are choosing a college major they are not directly considering subsequent motherhood penalties, though they care about the impact of their choice on both earnings and parenthood. If college applicants are not considering motherhood penalties, they may not be making optimal choices given their preferences. Additionally, they may not be responsive to policies aimed at reducing motherhood penalties, particularly in male dominated fields.

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A Appendix

A.1 Supplementary Tables and Figures

Table A.1: College graduate population, applicants and survey respondents - Restricted sample

Sample:	Graduates	College Applicants			Hypothesis tests (p-values)		
Subsample:	All	Matched	All	Survey	(1) = (2)	(3) = (4)	(1) = (4)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Individuals	185,152	54,531	77,701	12,668			
Demographics							
Female	0.62	0.57	0.58	0.64	0.000	0.000	0.000
Median age 10 years after graduation	38						
Median age at application	23	21	21	21			
High school GPA	6.26	7.19	6.85	7.47	0.000	0.000	0.000
Foreign origin	0.048	0.13	0.16	0.14	0.000	0.000	0.000
Mother has less than high school education	0.28	0.11	0.12	0.12	0.000	0.897	0.000
Mother has completed high school	0.38	0.41	0.42	0.41	0.000	0.558	0.000
Mother has completed further education	0.34	0.47	0.46	0.46	0.000	0.622	0.000
Father has less than high school education	0.22	0.15	0.16	0.16	0.000	0.502	0.000
Father has completed high school	0.46	0.46	0.46	0.46	0.789	0.916	0.925
Father has completed further education	0.32	0.39	0.38	0.38	0.000	0.539	0.000
College application							
Ranked 1 degree program		0.36	0.37	0.36		0.012	
Ranked 2 degree programs		0.23	0.23	0.22		0.327	
Ranked 3 or more degree program		0.40	0.40	0.41		0.001	
Ranked 8 degree programs		0.04	0.04	0.04		0.749	
Matched to a degree program		1	0.74	0.81		0.000	
Matched to 1st choice degree program		0.82	0.60	0.68		0.000	
Matched to 2nd choice degree program		0.10	0.09	0.08		0.174	
Matched to 3rd choice or lower degree program		0.075	0.062	0.055		0.005	

Notes: The graduate population (column (1)) includes the 1998-2006 graduation cohorts. The matched cohort (column (2)) includes 2018 college applicants who matched to a degree program. The survey cohort (column (4)) includes 2018 college applicants in our experimental survey. Columns (5)-(7) report p-values from t-tests of differences of means/proportions and quantile regressions for differences of medians.

Table A.2: Summary statistics of field attributes - Restricted sample

Data:	Population			Survey		
Sample:	All	Men	Women	All	Men	Women
	(1)	(2)	(3)	(4)	(5)	(6)
Observations	173,585	65,430	108,155	28,051	10,140	17,911
Individuals	173,585	65,430	108,155	12,534	4,548	7,986
Degrees	769	663	695	258	253	256
Average monthly earnings	5,377	6,462	4,721	6,026	6,859	5,554
(2015 USD)	(2,600)	(3,196)	(1,878)	(4,063)	(4,809)	(3,485)
Median monthly earnings	5,025	5,917	4,613	5,091	5,818	5,091
Parenthood	0.74	0.69	0.76	0.74	0.67	0.78
(at least one child)	(0.44)	(0.46)	(0.42)	(0.30)	(0.31)	(0.28)
Partnership	0.79	0.80	0.79	0.78	0.75	0.80
	(0.40)	(0.40)	(0.41)	(0.24)	(0.25)	(0.23)
Work satisfaction				8.42	8.39	8.44
(1-10 scale)				(1.62)	(1.61)	(1.63)
Educational satisfaction				8.05	8.09	8.03
(1-10 scale)				(1.84)	(1.77)	(1.87)

Notes: The table reports summary statistics for our field attributes of interest both in the population data (corresponding to actual outcomes ten years after graduation) and in the survey data (corresponding to expected outcomes ten years after graduation). Observations are at the individual level in the population, and the individual degree-choice level in the survey. Earnings are pre-tax, and reported in USD using 2015 prices and exchange rates. Population earnings are yearly earnings divided by 12. Average earnings are winsorized at the top 1% of survey earnings with the same level applied then applied to population earnings. Standard deviations are reported in parentheses.

Table A.3: Gender earnings gap - Restricted sample

	DV: log earnings			
Data:	Population		Survey	
	(1)	(2)	(3)	(4)
Female	-0.293***	-0.180***	-0.179***	-0.087***
	(0.003)	(0.004)	(0.016)	(0.017)
Mean non-log DV	5,377		6,026	
Observations	173,585		28,051	
Individuals	173,585		12,53	
Field fixed effects	No	Yes	No	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All models are linear OLS regressions. The dependent variable is log earnings, and thus only non-zero earnings are in the sample. In columns (1) and (2), heteroskedasticity robust standard errors are in parentheses. In columns (3) and (4) standard errors clustered at the individual level are in parentheses. Columns (1) and (2) include graduation year fixed effects. Pre-tax monthly earnings measured in 2015 USD.

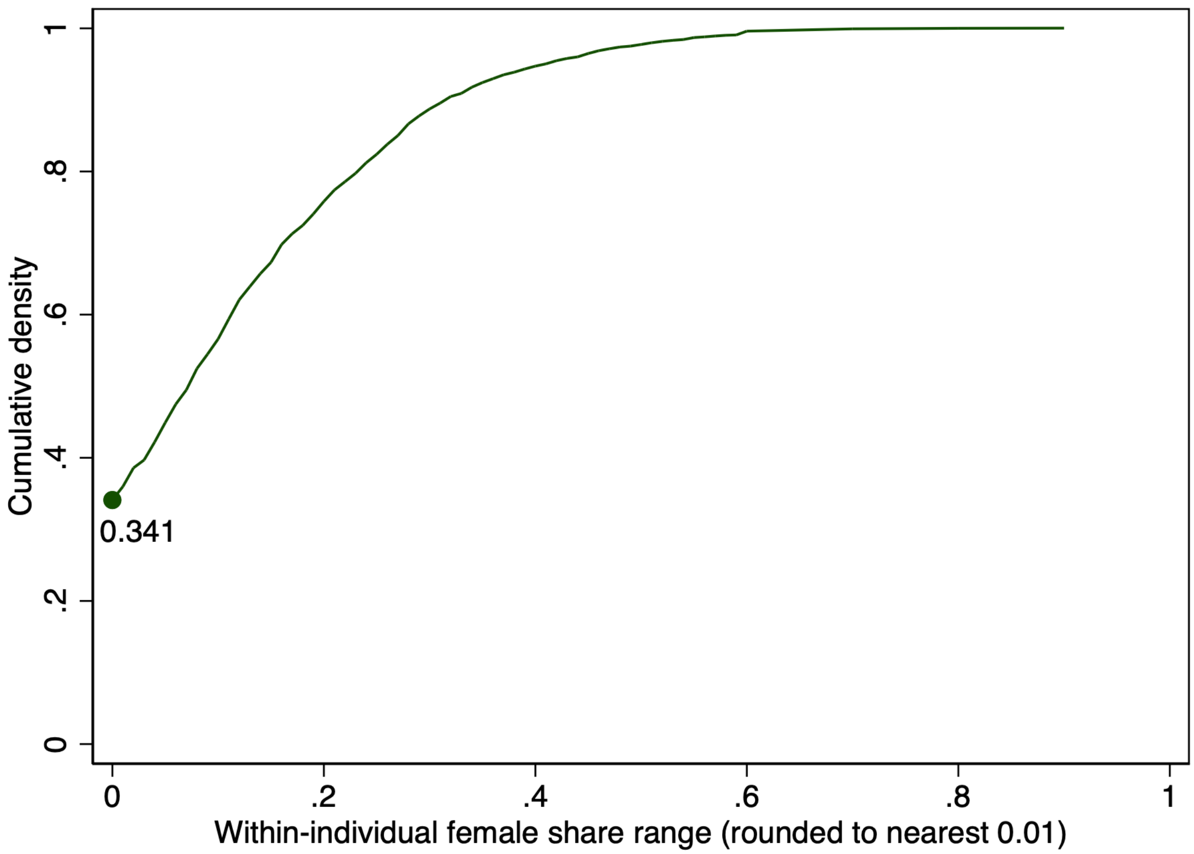

Figure A.1: Empirical CDF of within choice-set female share variation

Notes: We round female share to the nearest percentage point in order to create a discrete mass that represents individuals with effectively no variation. Female share range is defined as the distance between the maximum and minimum female share of field for an individual.

Table A.4: Gender earnings gap, extensive margin

	DV: $1(earnings > 0)$			
Data:	Population		Survey	
	(1)	(2)	(3)	(4)
Female	0.035	0.677***	-0.865***	-0.909***
	(0.116)	(0.139)	(0.187)	(0.200)
Mean DV	93.696		98.408	
Observations	186,762		34,983	
Individuals	186,762		15,244	
Field fixed effects	No	Yes	No	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All models are linear OLS regressions. The dependent variable is an indicator for strictly positive earnings conditional on non-missing earnings. In columns (1) and (2), heteroskedasticity robust standard errors are in parentheses. In columns (3) and (4) standard errors clustered at the individual level are in parentheses. Columns (1) and (2) include graduation year fixed effects. Pre-tax monthly earnings measured in 2015 USD.

Table A.5: Association of female share of field with field attributes - Restricted sample

Data:	Population		Survey	
Sample:	Male	Female	Male	Female
	(1)	(2)	(3)	(4)
Panel A - DV: log earnings				
Female share	-0.310***	-0.436***	-0.335**	-0.543***
	(0.096)	(0.114)	(0.137)	(0.120)
H_0: Male = Female	$p = 0.179$		$p = 0.084$	
Mean non-log DV	6,462	4,721	6,859	5,554
Panel B - DV: Parenthood probability				
Female share	0.095**	0.235***	0.069**	0.192***
	(0.038)	(0.041)	(0.030)	(0.034)
H_0: Male = Female	$p = 0.005$		$p < 0.001$	
Mean DV	0.69	0.76	0.67	0.78
Panel C - DV: Partnership probability				
Female share	-0.030	-0.006	0.047**	0.094***
	(0.033)	(0.027)	(0.019)	(0.023)
H_0: Male = Female	$p = 0.521$		$p = 0.032$	
Mean DV	0.80	0.79	0.75	0.80
Panel D - DV: Work satisfaction				
Female share			0.107	0.298**
			(0.143)	(0.144)
H_0: Male = Female			$p = 0.325$	
Mean DV			8.39	8.44
Panel E - DV: Educational satisfaction				
Female share			0.206	0.634***
			(0.168)	(0.182)
H_0: Male = Female			$p = 0.069$	
Mean DV			8.09	8.03
Observations	65,430	108,155	10,140	17,911
Individuals	65,430	108,155	4,548	7,986

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All models are linear OLS regressions. In columns (1) and (2) standard errors are clustered at the field level. In columns (3) and (4) standard errors clustered at both the individual and field level are in parentheses. Pre-tax monthly earnings measured in 2015 USD. Work and educational satisfaction are measured on a 1-10 scale.

Table A.6: Association of female share of field with field attributes, individuals with multiple non-missing degree choices only (separately by attribute)

Sample:	Male	Female
	(1)	(2)
Panel A - DV: log earnings		
Female share	-0.323**	-0.571***
	(0.137)	(0.122)
H_0: Male = Female	$p = 0.030$	
Observations	12,296	20,583
Individuals	5,069	8,426
Panel B - DV: Parenthood probability		
Female share	0.080**	0.198***
	(0.032)	(0.036)
H_0: Male = Female	$p = 0.001$	
Observations	12,661	25,862
Individuals	5,207	10,528
Panel C - DV: Partnership probability		
Female share	0.049**	0.087***
	(0.022)	(0.022)
H_0: Male = Female	$p = 0.106$	
Observations	12,476	25,014
Individuals	5,135	10,196
Panel D - DV: Work satisfaction		
Female share	0.058	0.322**
	(0.151)	(0.142)
H_0: Male = Female	$p = 0.148$	
Observations	13,065	25,133
Individuals	5,383	10,262
Panel E - DV: Educational satisfaction		
Female share	0.093	0.529***
	(0.169)	(0.172)
H_0: Male = Female	$p = 0.027$	
Observations	13,869	26,366
Individuals	5,707	10,760

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All models are linear OLS regressions. Standard errors clustered at both the individual and field level are in parentheses. Pre-tax monthly earnings measured in 2015 USD. Work and educational satisfaction are measured on a 1-10 scale.

Table A.7: Within-individual association of female share of field with field attributes - Restricted samples

Female share vs. mean:	All		Below		Above	
Sample:	Male	Female	Male	Female	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A - DV: log earnings						
Female share	-0.111***	-0.110***	-0.149**	-0.107**	-0.658***	-0.470***
	(0.039)	(0.030)	(0.058)	(0.045)	(0.214)	(0.159)
H_0: Male = Female	$p = 0.984$		$p = 0.567$		$p = 0.481$	
Panel B - DV: Parenthood probability						
Female share	0.016	0.017***	0.010	0.016	-0.053	0.039*
	(0.011)	(0.007)	(0.012)	(0.019)	(0.082)	(0.021)
H_0: Male = Female	$p = 0.939$		$p = 0.789$		$p = 0.277$	
Panel C - DV: Partnership probability						
Female share	0.039***	0.033***	0.038**	0.068**	-0.091	0.023
	(0.014)	(0.010)	(0.016)	(0.027)	(0.076)	(0.021)
H_0: Male = Female	$p = 0.728$		$p = 0.339$		$p = 0.148$	
Panel D - DV: Work satisfaction						
Female share	0.042	0.488**	0.031	0.314	-1.925**	-0.254
	(0.162)	(0.206)	(0.240)	(0.354)	(0.901)	(0.573)
H_0: Male = Female	$p = 0.089$		$p = 0.508$		$p = 0.118$	
Panel E - DV: Educational satisfaction						
Female share	0.003	0.864***	0.183	0.223	-2.380**	0.665
	(0.179)	(0.209)	(0.293)	(0.422)	(0.990)	(0.571)
H_0: Male = Female	$p = 0.002$		$p = 0.938$		$p = 0.008$	
Observations	9,524	16,842	6,007	4,051	2,260	10,434
Individuals	3,932	6,917	2,579	1,789	1,001	4,474

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All models are individual fixed-effect linear regressions. Standard errors clustered at both the individual and field level are in parentheses. The mean female share of applicants' top choices is 0.65. Pre-tax monthly earnings measured in 2015 USD. Work and educational satisfaction are measured on a 1-10 scale.

Table A.8: Gender differences in earnings penalties

	DV: log earnings						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Population (mean non-log DV = 5,031)							
Female	-0.289***	-0.208***	-0.135***			-0.107***	
	(0.003)	(0.006)	(0.007)			(0.008)	
Parenthood		0.078***				-0.004	
		(0.002)				(0.006)	
Fem. X Parent		-0.113***				-0.046***	
		(0.007)				(0.007)	
Partnership			0.227***			0.228***	
			(0.006)			(0.007)	
Fem. X Partner			-0.196***			-0.187***	
			(0.008)			(0.008)	
Observations	175,011	175,011	173,585			173,585	
Panel B: Survey (mean non-log DV = 5,885)							
Female	-0.171***	-0.185***	-0.116*	-0.058	-0.125	-0.126	0.010
	(0.015)	(0.044)	(0.060)	(0.010)	(0.078)	(0.064)	(0.132)
Parenthood		0.068*				-0.037	-0.053
		(0.039)				(0.044)	(0.047)
Fem. X Parent		-0.012				0.048	0.049
		(0.053)				(0.062)	(0.065)
Partnership			0.173***			0.214***	0.159**
			(0.060)			(0.071)	(0.074)
Fem. X Partner			-0.090			-0.131	-0.143
			(0.072)			(0.085)	(0.088)
Work satisfaction				0.060***			0.051***
				(0.009)			(0.011)
Fem. X Work sat.				-0.014			-0.019
				(0.011)			(0.013)
Educational sat.					0.040***		0.011
					(0.008)		(0.009)
Fem. X Educ. sat.					-0.005		0.005
					(0.009).		(0.010)
Observations	34,428	31,827	31,153	32,777	32,243	30,315	28,051
Individuals	15,044	13,971	13,725	14,492	14,271	13,356	12,534

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All are linear OLS regressions. Panel A shows robust standard errors in parentheses, and Panel B shows standard errors clustered at the individual level. Pre-tax monthly earnings measured in 2015 USD. Work and educational satisfaction are measured on a 1-10 scale.

Table A.9: Gender differences in earnings penalties - Restricted sample

	DV: log earnings						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Population (Mean non-log DV = 5,377)							
Female	-0.293***	-0.215***	-0.135***			-0.107***	
	(0.003)	(0.006)	(0.007)			(0.008)	
Parenthood		0.067***				-0.004	
		(0.005)				(0.006)	
Fem. X Parent		-0.108***				-0.046***	
		(0.007)				(0.007)	
Partnership			0.227***			0.228***	
			(0.006)			(0.007)	
Fem. X Partner			-0.196***			-0.187***	
			(0.008)			(0.008)	
Observations	173,585	173,385	173,585			173,585	
Panel B: Survey (Mean non-log DV = 6,026)							
Female	-0.179***	-0.156***	-0.080	-0.027	-0.120	-0.087	0.010
	(0.016)	(0.047)	(0.066)	(0.011)	(0.084)	(0.068)	(0.132)
Parenthood		0.077*				-0.039	-0.053
		(0.044)				(0.047)	(0.047)
Fem. X Parent		-0.040				0.050	0.049
		(0.058)				(0.065)	(0.065)
Partnership			0.209***			0.239***	0.159**
			(0.067)			(0.077)	(0.074)
Fem. X Partner			-0.137*			-0.174*	-0.143
			(0.078)			(0.091)	(0.088)
Work satisfaction				0.062***			0.051***
				(0.011)			(0.011)
Fem. X Work sat.				-0.018			-0.019
				(0.012)			(0.013)
Educational sat.					0.039***		0.011
					(0.008)		(0.009)
Fem. X Educ. sat.					-0.007		0.005
					(0.010).		(0.010)
Observations	28,051	28,051	28,051	28,051	28,051	28,051	28,051
Individuals	12,534	12,534	12,534	12,534	12,534	12,534	12,534

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All are linear OLS regressions. Panel A shows robust standard errors in parentheses, and Panel B shows standard errors clustered at the individual level. Pre-tax monthly earnings measured in 2015 USD. Work and educational satisfaction are measured on a 1-10 scale.