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

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April 2, 2024

Abstract

Gender differences in college major explain a large share of the gender gap in earnings. To study why men and women sort into different fields, we conduct a large-scale survey experiment among almost 20,000 college applicants in Denmark. We estimate the expected tradeoffs associated with the gender composition of a major within each applicant's set of rank-ordered most-preferred fields. Both men and women expect that if they major in more female fields, they will have lower earnings and a higher probability of partnership and parenthood. In contrast, only women expect higher educational and work satisfaction in female fields; while men do not expect a significant relationship between the gender composition of a field and their satisfaction with it. We structurally estimate preferences over earnings, family outcomes, and educational/work satisfaction and find that women put more weight on family outcomes than men. However, these gender differences in preferences do little to explain differences in choice of major. Instead, of the factors we consider, 73% (17%) of the gender difference in major choice is driven by women expecting a larger tradeoff than men between how female a major is and educational (work) satisfaction. Our results suggest that women are deterred from male dominated fields largely due to expectations about poor classroom and workplace experiences. Our findings inform policies aimed at shifting the gender composition of college majors and subsequent gender earnings gaps.

JEL Classification: I23, I26, J24
Keywords: college major, gender wage gap

*We thank conference participants at the 2019 CEN meeting at The Rockwool Foundation, as well as seminar participants at University of Copenhagen, Center for Economic Behavior and Inequality, UC San Diego, New York University, The Ohio State University, Queen's University, and VIVE- The Danish Center for Social Science Research. Furthermore, we thank Gordon Dahl, Julie Cullen, Claus Thustrup Kreiner, Mette Gørtz, Mette Ejrnæs, and Marco Piovesan for valuable inputs.
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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).

In the U.S., prior work estimates that gender differences in college major can explain slightly over half of the gender wage gap (Black et al., 2008; Altonji et al., 2012).

This is because more female fields by composition have lower wages (Sloane et al., 2021).

In this paper, we examine potential reasons why men and women sort into different fields. 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 (major-institution pairs) 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 also incorporate national administrative register data on realized labor market and family outcomes by degree program from over 189,000 college graduates.

To understand why certain fields attract more women, we use these data to separately estimate applicants' expectations and preferences. First, for expectations, we examine the extent to which applicants believe their outcomes will differ across majors that attract more women, as measured by the *female share* of the major within their application cohort.[1] We pay particular attention to differences across majors *within* an applicant's list of most-preferred fields. Second, for preferences, we use a structural model to estimate the weights

[1] We use information about gender from the Danish administrative registers, which registers the sex of individuals given at birth as binary (male/female). Individuals can change their legal gender and we use registered gender at the time of the college application. Due to the binary categories, we are not able to identify the approximately 1-2% of the Danish youth cohort that define themselves as non-binary or transsexual.

applicants put on different outcomes when choosing which major to rank first versus second or third. Finally, we conduct two simulations to understand the relative importance of expectations and preferences in explaining gender differences in choice of major. In our first simulation, we use our model to identify the contribution of gender differences in both expectations and preferences to the predicted difference in female share across two composite fields. In our second simulation, we focus on applicants who ranked a female dominated field above a male dominated field and estimate the extent to which changing women's expectations or preferences would shift them to preferring the male-dominated major.

We examine three broad attributes of degrees that could potentially drive gender differences in educational choices: earnings, family considerations, and satisfaction with the field itself. For these attributes to explain gender differences in majors, there must either be gender differences in expectations about the outcomes in more heavily female (vs. more heavily male) fields; or there must be gender differences in the weight applicants put on a given attribute when choosing a major.

Regarding earnings, we explore two hypotheses for why women do not enter male dominated fields. First, relative to men, women may underestimate the earnings returns to male fields. Second, women may put less weight on future earnings than men. We find no evidence that women underestimate the returns to male fields. This result suggests that policy interventions focused on providing information about earnings across majors may have little impact on closing gender gaps. In line with prior work, we find that women do place less weight than men on future earnings when choosing a college major. However, the gender differences in preferences are not large enough to explain a significant share of the gender differences in educational choices in our simulations.

For family considerations, we explore three hypotheses that have gained increased attention from researchers and policymakers. First, women may expect that entering more heavily male fields will lower their chances of getting married and having children while men do not. Second, women may place more weight than men on family considerations when choosing a major. Third, women may believe that male dominated fields have larger motherhood penalties – i.e., lower earnings associated with having children. We find that all applicants expect lower probabilities of having a partner and children within ten years of graduation in more heavily male fields, with men and women holding similar beliefs. Because there is little gender difference in expected tradeoffs across fields, there is little scope for expectations about family outcomes to drive gender differences in choice of major. In line with prior work, women place more weight than men on family outcomes when choosing a major. However, similar to the results for earnings, the gender differences in family expectations and preferences do little to explain the magnitude of gender differences in simulated choices of college major. Finally, while estimates from the population suggest that motherhood penalties are larger in male-dominated majors, we find no evidence that college applicants perceive a relationship between motherhood penalties and the female share of a field. These results suggest it is unlikely that motherhood penalties are driving applicants' decisions. And so, policies aimed at reducing motherhood penalties may have limited impact on bringing women into male dominated fields early in the pipeline.

Turning to satisfaction with the field itself, we focus on both educational satisfaction during college and work satisfaction ten years after graduation. Here, we find stark differences between male and female college applicants. Women expect significantly higher educational and work satisfaction if they enter more female fields, whereas men expect no relationship between the gender composition of a field and their satisfaction with it. Men and women have similar preferences for work and educational satisfaction when choosing a major and so preferences explain little of the gender difference in choices. Instead, of the factors we consider, gender differences in expected educational satisfaction explain the largest share of gender differences in choices. In our simulated choice between two hypothetical fields that differ in female share by ten percentage points, 73% of the gender gap in major choice is explained by gender differences in expected educational satisfaction, and 17% by gender differences in expected work satisfaction. When we simulate choices of women who we directly observe ranking a female-dominated field over a male-dominated field, we find that women would be indifferent between the two fields if their educational satisfaction in the male-dominated field were increased by about 1.1 standard deviations, all else equal. These results suggest that policy interventions that improve the experience of women in male dominated college majors could have a meaningful impact on closing gender gaps in these fields, but that there is a long way to go.

Related work has linked educational fields to the labor market, estimating the causal effects of college degrees 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 a 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. Zafar (2013),Wiswall and Zafar (2018), Wiswall and Zafar (2021), and Gong et al. (2020) conduct survey experiments similar to ours and examine gender differences in expectations and/or preferences. Our study makes several methodological contributions to this line of work. First, we use revealed-preference rankings of applicants' most preferred majors. By estimating expectations and preferences for majors that are within an applicant's consideration set, we focus on marginal choices – i.e., across major shifts that applicants are most likely to make. These are also the majors for which applicants are likely to be most informed. A second innovation of our approach is the scope of our sample. Prior survey experiments 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. In particular, we can directly estimate applicants' expectations about the tradeoffs associated with the female share of a field. The sample also allows us to hone in on applicants who are choosing between a male-dominated major and a female-dominated major – and investigate if changes in preferences or expectations could make this group of influenceable women enter male-dominated fields.

In line with our 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 results on expectations about earnings-family tradeoffs across fields and 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. Gong et al. (2020) finds that women believe they are less likely to work when they have young children, moreso than men. In contrast, Kuziemko et al. (2018) argue that women do not anticipate the labor market participation and earnings declines associated with having children based on survey data in the U.S. and U.K. Our study highlights that both men and women perceive systematic tradeoffs between earnings and family if they enter more male or female dominated fields. And, these tradeoffs do matter for their choice of major. However, because men and women expect similar tradeoffs, earnings and family considerations do little to explain gender differences in choice of educational field. Instead, expectations about educational and work satisfaction are the leading driver, explaining an estimated 89% of gender differences in college major.

These results suggest that policies aiming to attract women to male dominated fields should focus on improving women's experience in them. Prior work finds that exposing women to more female peers can increase the likelihood of entering and persisting in male dominated fields (Schneeweis and Zweimüller, 2012; Booth et al., 2018; Borges and Estevan, 2023; Shan, 2022), as can providing women with female mentors, such as professors (Carrell et al., 2010) or alumni(Porter and Serra, 2020). This may occur in part because it increases the perceived female share of a field, which in itself can attract more women to enter (Carlana and Corno, 2021). These interventions may also improve women's satisfaction. For example, recent work shows that higher representation of women increases their influence, leadership opportunities (Stoddard et al., 2020), and willingness to lead (Born et al., 2022; Chen and Houser, 2019) . Our findings highlight the need to understand not only what shapes women's experience in male-dominated fields but also their expectations about them.

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 our model of major choice 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 a 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 Aarhus 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. 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]

[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, and 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.

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 not matched or choose not to enroll in their 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. The results of the clearinghouse 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 clearinghouse were due July 5th. On July 10th, we contacted every applicant using their official online mailbox. On July 16th, we sent a reminder to 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 Danish Krone (DKK), equivalent to about 150 U.S. Dollars (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 pre-populated with the choices they had made in their application. For applicants who only

[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.

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 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 to 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 to 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 from our survey for each choice: we asked applicants about their expected satisfaction with their studies *during their studies* if they were to enroll in the degree, and, their expected probability of having a romantic partner, probability of having at least one child, pre-tax monthly earnings, and satisfaction with work *ten years after graduating* if they were to graduate from the degree.

[5]

Finally, we elicited 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.

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, as of writing). 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 graduates 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 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.

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

[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.

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 surveyed college applicants we report educational satisfaction during one's studies and work satisfaction ten years after graduation, both on a 1-10 scale. We also asked applicants about other types of satisfaction during these periods–personal life satisfaction, physical and mental health satisfaction, financial satisfaction, as well as overall life satisfaction. All these measures appear closely related to one another. Given our focus on educational choices and how they translate into the labor market, we use the specific "educational" and "work" satisfaction measures throughout the paper to avoid both over-specification and over-testing. Results that consider other dimensions of satisfaction are left to the Appendix, and tell a similar story.

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 of 77,701 applicants in the 2018 cohort. Of these, 19,778 applicants from 259 fields 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. This sample includes 189,331 individuals from 790 degrees for the population and 19,778 applicants from 259 degrees for the survey. Individuals in the survey may contribute one (N = 1,892), two (N = 9,895), or three (N = 7,991) degree choices, giving us a total of 45,655 degree choices (20.1% of the degree choices in this sample are hypothetical). We note that the size of the main sample varies across models that consider different attributes due to different rates of missing observations (e.g., a degree choice on the survey could include expected parenthood but not expected work satisfaction).

We also construct a restricted sample that only includes degree choices with non-missing and non-zero data. 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 earnings, parenthood, or partnership, work satisfaction, educational satisfaction or with zero earnings. The restricted sample contains 173,585 individuals from 769 degrees for the population and 12,534 applicants from 258 degrees for the survey. Individuals in the survey 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 (19.5% of the degree choices in this sample are hypothetical). By construction, the restricted sample remains constant across models that consider different attributes.

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

[7]Due to data security requirements, 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.

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.

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 is less female, younger, has a higher average high school 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, 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 the 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 the choice of field explain a large share of the gap. Given the importance of gender differences in the 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 the female share of field and the expected outcomes we examine is always stronger for women than for men, but that the picture changes dramatically when we restrict our identifying variation to be exclusively within-applicant.

4.1 Summary of gender differences in fields and attributes

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 gender both in the population sample of individuals graduating between 1998 and 2006, and in the survey sample of 2018 applicants.

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

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

Table 2: Most common fields by gender

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

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).

Table 3: Summary statistics of field attributes and preference data

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	5,033	6,041	4,418	5,965	6,800	5,470
(2015 USD)	(2,865)	(3,517)	(2,160)	(4,720)	(5,546)	(4,072)
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)
Risk tolerance				4,371	4,940	4,042
(0-10,000 DKK invested)				(2,914)	(3,211)	(2,674)
Patience				21.83	21.09	22.25
(0-25 weeks waited)				(8.65)	(9.35)	(8.19)

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 then applied to population earnings. Standard deviations are reported in parentheses. Risk tolerance is measured using hypothetical responses to a risky investment decision described in Section 5.2. Patience is measured using hypothetical responses to an asset redemption decision described in Section 5.2. Risk tolerance and patience data are only reported for the 10,551 subjects in the structural estimation sample we use in Section 5 because missing values of these variables are the limiting factor in determining that sample.

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.[10] 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 (Black et al., 2008; Altonji et al., 2012). As discussed in Section 4.1, college applicants expect a smaller gender earnings gap than in the population, an estimated 17% (column 3). However, they expect a strong role for gender differences in choice of major. Adding field fixed effects reduces the estimated gender earnings gap by 53%.[11]

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. In many cases, applicants' expectations about the relative size of the gender earnings gap does not align with the patterns of realized outcomes in the population. For example, the population gender earnings gap is substantially larger in higher earning, lower fertility, and more heavily male fields. However, applicants do not expect significant differences in earnings gaps across these fields. Similarly, business and technology (tech) fields exhibit gender earnings gaps in the population that are 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.

In other cases, applicants' expectations align with the patterns in the population data.

[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.3 shows corresponding estimates including all observations to estimate the gender gap in the extensive margin of having non-zero earnings.

[11] Appendix Table A.4 shows the same estimates for the restricted sample, and Appendix Table A.5 shows versions of the survey estimates weighted to look like the entire pool of applicants or the population of graduates. The results are almost identical.

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.

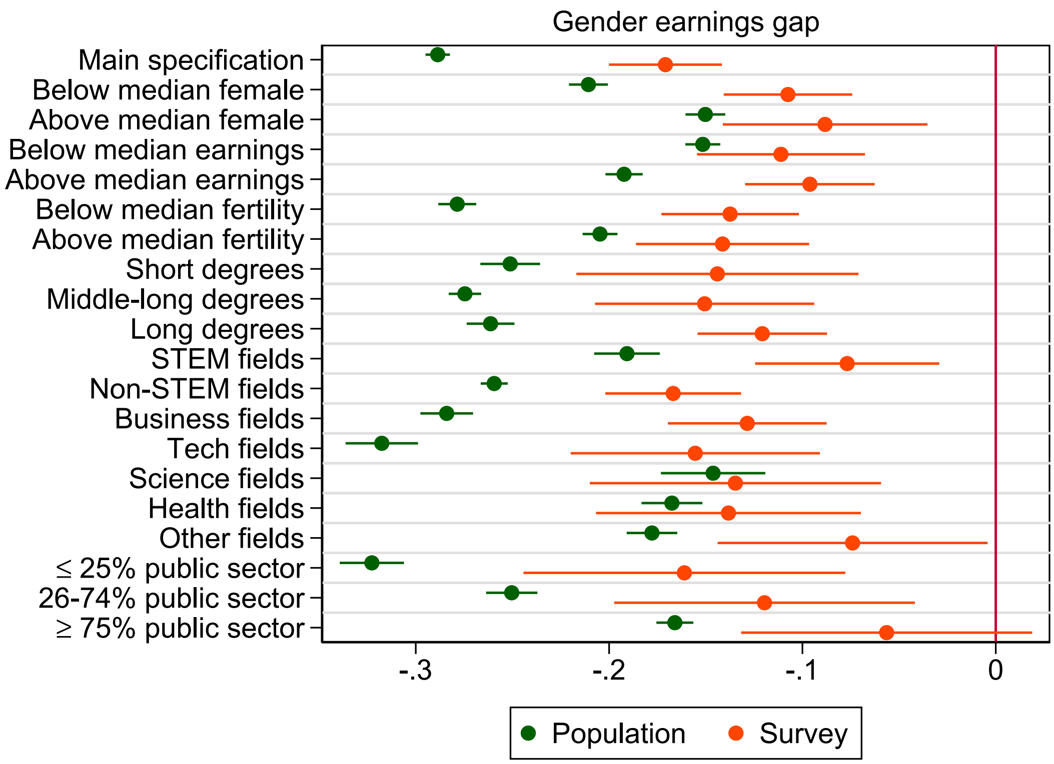

Figure 1: Gender earnings gap heterogeneity

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

For example, aligned with realized outcomes, applicants expect significantly lower gender earnings gaps in STEM fields (compared to non-STEM fields) and larger earnings gaps in majors that feed into the private sector (compared to the public sector). This pattern suggests that informing women about earnings (gaps) in STEM fields may have little impact on their choices since they already anticipate high returns to these majors. Finally, the large differences in the gender earnings gap across the private and public sectors may be a driver of women's educational fields and career paths. This finding adds to prior work suggesting that, after entering the labor market, women sort into the public sector because there are lower penalties for child-related leave Nielsen et al. (2004).

4.3 Earnings and non-earnings tradeoffs with field female share

Having established a sizeable and anticipated across-field gender earnings gap, as well as an important role for differences in field selection by gender, we explore how applicants' beliefs about a field relate to the share of women it attracts, as measured by its female share. First, we present our data at the field level. In Figure 2, we plot each outcome against the female share of the field 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 gender-specific field size. We also include fit lines from weighted-OLS regressions at the field level.[12] 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. At the field level, this negative relationship is stronger for women than men; women expect a larger penalty (premium) than men for going into more (less) female fields.

[12]Each field is weighted by its gender-specific population. Coefficients from these regressions are in Appendix Table A.6.

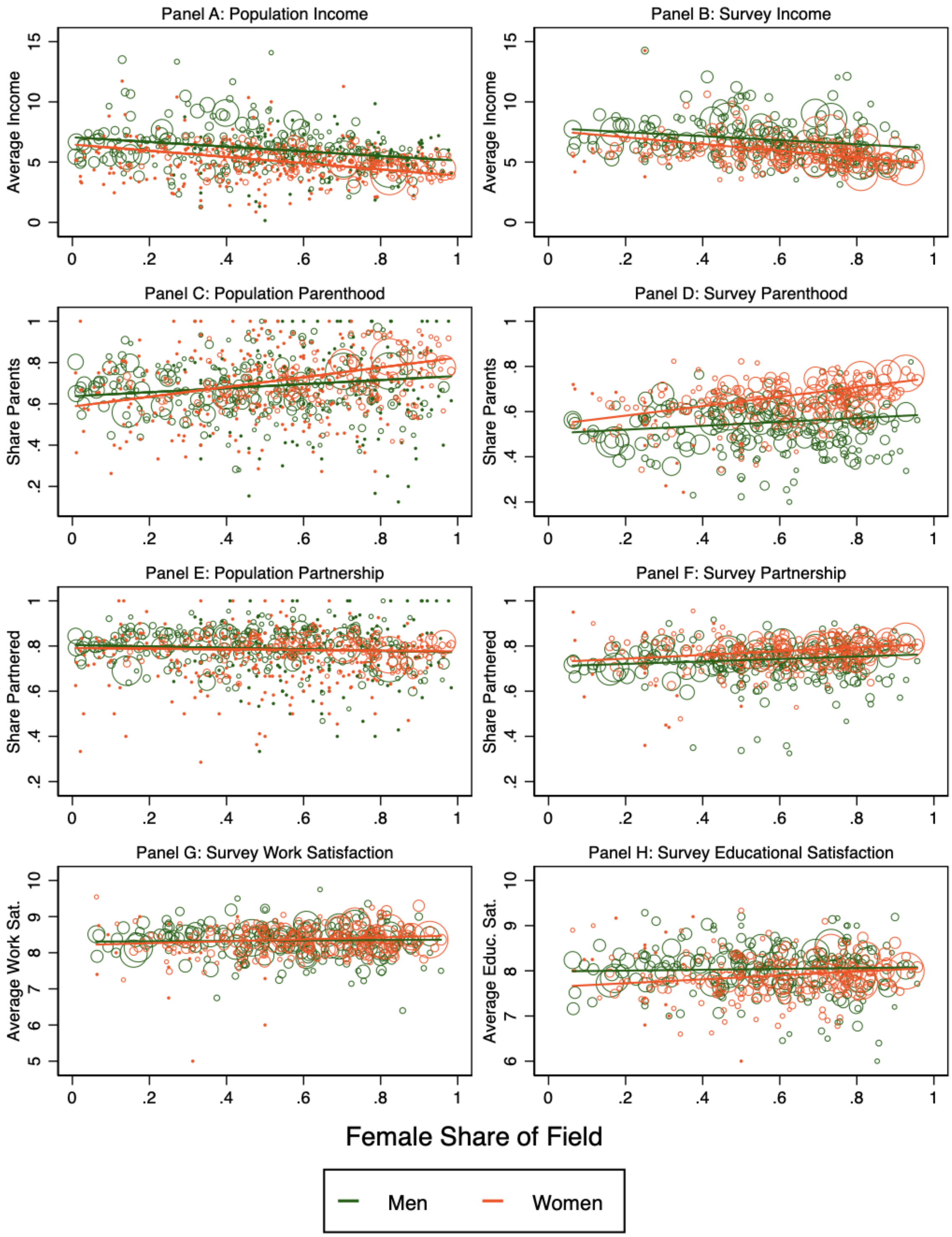

Figure 2: Attribute tradeoffs with female share of field by gender

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 are measured in thousands of 2015 USD.

Panels C and D show how field average parenthood relates to field female share in the population and survey, respectively. The relationship is 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, at the field level, women both experience and expect a stronger tradeoff across fields of varying female share. While there is not a relationship between partnership and female share of field in the population (Panel E), applicants expect higher partnership probability in more female fields. As with earnings and parenthood, the expected relationship is stronger for women (Panel F). This same pattern holds for expected work satisfaction (Panel G) and educational satisfaction (Panel H). Across all fields, women on average expect lower earnings and educational satisfaction and higher rates of parenthood and partnership than men. The gender gaps in expected earnings, parenthood and partnership are lowest in male dominated fields; but, for educational satisfaction, are largest in male dominated fields.

Table 5 shows estimates of the association between field female share and individual expectations/outcomes at the degree-choice level, separately for men and women.[13] Columns (1) and (2) show the population estimates, where we find that both men and women have lower earnings but are more likely to have children in more female fields. Women experience a steeper parenthood tradeoff than men ($p < 0.001$). We do not find that the likelihood of partnership is sensitive to field female share. For the survey data, we start by discussing the models without individual fixed effects (pooled OLS), shown in columns (3) and (4). 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. 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 5.7% (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

[13]Estimates for the restricted sample are in Appendix Table A.7. Appendix Table A.8 presents 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 individual fixed-effect sample in columns (5) and (6) of Table 5. Estimates where the survey data are weighted to look like the entire pool of applicants are in Appendix Table A.9. The results are almost identical.

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

Data:	Population		Survey			
Sample:	Male	Female	Male	Female	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A - DV: log earnings						
Female share	-0.305***	-0.432***	-0.350**	-0.566***	-0.133***	-0.109***
	(0.094)	(0.111)	(0.137)	(0.117)	(0.037)	(0.026)
H_0: Male = Female	$p = 0.132$		$p = 0.062$		$p = 0.596$	
Mean non-log DV	6,037	4,418	6,683	5,412	6,683	5,412
Observations	66,293	108,718	12,893	21,535	12,296	20,583
Individuals	66,293	108,718	5,666	9,378	5,069	8,426
Panel B - DV: Parenthood probability						
Female share	0.094**	0.240***	0.074**	0.195***	0.016*	0.023***
	(0.039)	(0.040)	(0.031)	(0.036)	(0.009)	(0.006)
H_0: Male = Female	$p = 0.003$		$p = 0.001$		$p = 0.355$	
Mean DV	0.68	0.76	0.65	0.76	0.65	0.76
Observations	71,580	117,751	15,797	27,043	12,661	25,862
Individuals	71,580	117,751	6,900	11,709	5,207	10,528
Panel C - DV: Partnership probability						
Female share	-0.034	-0.008	0.047**	0.088***	0.028**	0.034***
	(0.037)	(0.031)	(0.021)	(0.022)	(0.011)	(0.009)
H_0: Male = Female	$p = 0.518$		$p = 0.088$		$p = 0.673$	
Mean DV	0.79	0.78	0.74	0.79	0.74	0.79
Observations	70,563	117,035	13,145	26,203	12,476	25,014
Individuals	70,563	117,035	5,804	11,385	5,135	10,196
Panel D - DV: Work satisfaction						
Female share			0.033	0.309**	0.005	0.687***
			(0.146)	(0.138)	(0.147)	(0.176)
H_0: Male = Female			$p = 0.120$		$p = 0.003$	
Mean DV			8.34	8.41	8.34	8.41
Observations			13,797	26,413	13,065	25,133
Individuals			6,115	11,542	5,383	10,262
Panel E - DV: Educational satisfaction						
Female share			0.064	0.546***	-0.142	1.061***
			(0.167)	(0.173)	(0.167)	(0.183)
H_0: Male = Female			$p = 0.021$		$p < 0.001$	
Mean DV			8.04	7.97	8.04	7.97
Observations			14,654	27,775	13,869	26,366
Individuals			6,492	12,169	5,707	10,760
Individual FE	N	N	N	N	Y	Y

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Models in columns (1)-(4) are linear OLS regressions. Models in columns (5) and (6) are linear fixed-effect regressions. In columns (1) and (2) standard errors clustered at the field level are in parentheses. In columns (3)-(6) standard errors clustered at both the individual and field level are in parentheses. Pre-tax monthly earnings are measured in 2015 USD. Work and educational satisfaction are measured on a 1-10 scale.

points (0.003 points) more work satisfaction, and 0.05 points (0.006 points) more educational satisfaction.

Our results show that 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? To answer this question, we estimate individual fixed-effect models of the relationship between female share of field and our set of field attributes. We interpret these estimates as measuring whether an applicant's perceived causal impact of field on an attribute is related to the female share of that field.

First we note that while the within-individual variation in female share across ranked fields is smaller 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 standard deviation of female share in the full survey sample (at the degree-choice level) is 22 percentage points, compared to nine percentage points for the individual mean-differenced female share (i.e., the difference in female share between an individual's most female and least female field). 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. The average within-individual difference in female share is 12 percentage points. 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. Individual fixed-effect model results are presented in columns (5) and (6) of Table 5. For earnings, parenthood and partnership, the fixed effects estimates are significant but much smaller in magnitude than the pooled-OLS estimates for both men and women. And, the gender differences in tradeoffs disappear. This is evidence that applicants do perceive a causal impact of field selection on these outcomes, but a large share of the differences in outcomes across majors is also due to differences across applicants to those majors. Our findings that there are gender differences when looking across applicants but not within applicants 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. Finally, because men and women do not have significantly different expectations about the causal impact of more female fields on earnings and family outcomes, there is little scope for beliefs about these attributes to explain gender differences in choice of field.

We find a very different pattern for the expected impact of major on educational and work satisfaction. 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. Women, on the other hand, anticipate *larger* tradeoffs between both types of satisfaction and female share in the individual fixed effect models than in the pooled OLS estimates. 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 suggests that changes to expectations about work and educational satisfaction have the potential to change the choices people make about fields within their final consideration set, 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.

One restrictive feature of the individual fixed effect models is that we enforce the same female share gradient for every individual, regardless of where their consideration set sits within the female share range or by how much their choices differ in female share. Non-linearity in either the overall gradient, or due to scaling issues from narrow to broad consideration sets could complicate the comparison between the within- and between-individual models. To address this concern, we also take a less parametric approach to estimating the within-individual female share gradients by calculating the implied gradient by an individual's top two choices and constructing a distribution of individual gradients by gender. Consistent with the estimates in columns (5) and (6) of Table 5, we reject equality of the male and female distributions only for work and educational satisfaction ($p = 0.008$ and $p = 0.045$, respectively), in the direction of larger tradeoffs for women. We find no significant gender differences in the distributions of log-earnings, parenthood, or partnership ($p = 0.370$, $p = 0.977$, and $p = 0.856$, respectively).

In Appendix Tables A.10 and A.11, we examine additional measures of satisfaction that could be related to educational and work satisfaction, including satisfaction with one's personal life, physical and mental health, and financial security, as well as overall life satisfaction.[14] We ask expectations about these measures both during college and 10 years after graduating. During school, women expect that entering a more female field will significantly improve their overall life satisfaction, as well as satisfaction with their personal life and their physical and mental health, whereas men do not. We do not observe a significant gender difference in their expected financial security. Ten years after graduating, both men and women expect higher satisfaction with their personal life and health, but lower financial security in more female fields. Only women expect that female fields will improve their overall life satisfaction.

4.4 Child earnings penalties

Table 5 considers the female share gradient of each of our five attributes separately, but in the literature the value of non-pecuniary outcomes is often assessed in terms of earnings. For example, researchers may consider the compensating differentials associated with working conditions (Maestas et al., 2023) or the earnings impacts of fertility (Kleven et al., 2019). Recent work highlights parenthood in particular. According to Kleven et al. (2023), in developed economies, "child penalties [are] the dominant driver of gender inequality." Our data allow us to ask whether male and female applicants to university degree programs anticipate different relationships between income and parenthood –we call these the "motherhood" and "fatherhood" penalties, respectively– and whether any gender difference in the expected penalties depends on field gender composition in a way that could help explain field selection.

Table 6 extends Panel A of Table 5 with earnings as the dependent variable and controls for field female share (as in Table 5) as well as parenthood and its interaction with field female share. The coefficient on parenthood is our estimate of the child earnings penalty in

[14] We focus on the fixed effects analysis in columns 3 and 4, which correspond to to columns (5) and (6) of Table 5.

Table 6: Log-earnings penalties for parenthood

Sample:	Male	Female	Male	Female	Male	Female	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A - Population								
Parenthood	0.076***	-0.015***	0.002	-0.029***				
	(0.009)	(0.005)	(0.009)	(0.005)				
H_0: Male = Female	$p < 0.001$		$p = 0.003$					
Female share	-0.327***	-0.425***	-0.319***	-0.451***				
	(0.010)	(0.012)	(0.010)	(0.012)				
H_0: Male = Female	$p < 0.001$		$p < 0.001$					
Parenthood X Female share	-0.046**	0.011	-0.029	0.044*				
	(0.021)	(0.024)	(0.022)	(0.024)				
H_0: Male = Female	$p = 0.0756$		$p = 0.025$					
Mean non-log DV	6,037	4,418	6,037	4,418				
Observations	66,293	108,718	65,430	108,155				
Panel B - Survey								
Parenthood	0.054	0.095***	-0.067	0.035	0.300***	0.033	0.125	-0.105***
	(0.048)	(0.036)	(0.057)	(0.046)	(0.112)	(0.029)	(0.118)	(0.035)
H_0: Male = Female	$p = 0.495$		$p = 0.155$		$p = 0.021$		$p = 0.062$	
Female share	-0.367***	-0.591***	-0.368***	-0.605***	-0.115***	-0.111***	-0.095***	-0.140***
	(0.050)	(0.039)	(0.057)	(0.046)	(0.026)	(0.022)	(0.028)	(0.026)
H_0: Male = Female	$p < 0.001$		$p = 0.001$		$p = 0.907$		$p = 0.239$	
Parenthood X Female share	-0.157	-0.076	-0.152	-0.175	0.074	0.022	0.094	-0.000
	(0.139)	(0.138)	(0.177)	(0.157)	(0.147)	(0.082)	(0.129)	(0.083)
H_0: Male = Female	$p = 0.678$		$p = 0.921$		$p = 0.757$		$p = 0.540$	
Mean non-log DV	6,683	5,412	6,683	5,412	6,683	5,412	6,683	5,412
Observations	11,453	20,374	10,140	17,911	10,869	19,412	9,524	16,842
Individuals	5,061	8,910	4,548	7,986	4,477	7,948	3,932	6,917
Controls	N	N	Y	Y	N	N	Y	Y
Individual FE	N	N	N	N	Y	Y	Y	Y

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All explanatory variables are measured as differences from their median value. Models in columns (1), (2), (5), and (6) are linear OLS regressions. Models in columns (3), (4), (7), and (8) are linear fixed-effect regressions. In Panel A, standard errors clustered at the field level are in parentheses. In Panel B, standard errors clustered at both the individual and field level are in parentheses. Pre-tax monthly earnings measured in 2015 USD. Controls include our partnership, work satisfaction, and educational satisfaction measures, as well as the interactions between those and female share (only partnership in the population data). Full results are reported in Appendix Table A.12.

a field of median female share using the full sample. The coefficient on the interaction term is our estimate of the how the child earnings penalty varies with the gender composition of a college major. Panel A shows the population data, both with and without additional control variables for our other attributes of interest and their interactions with female share of field. Panel B shows the survey data, also varying whether we include individual fixed effects. All explanatory variables are median-differenced such that the un-interacted parenthood coefficient shows the child-earnings penalty in a field of median female share, and the un-interacted female share coefficient shows the earnings gradient for fields with median parenthood, roughly corresponding the the coefficients in Panel A of Table 5.

In the population, we find a robust motherhood penalty that is statistically different than the corresponding estimate for men, which if anything shows a fatherhood premium. While this is a cross-sectional correlation, it is qualitatively consistent with causal evidence in the literature. We also find evidence that the difference between the motherhood and fatherhood penalties is smaller in more female fields – with fathers earning relatively less and mothers earning relatively more compared to those in male dominated fields.

Our estimates of applicants' beliefs using the survey data do not align with the population. In the pooled OLS estimates, if anything, women expect a motherhood premium that is directionally *smaller* in more female fields. When we include individual fixed effects, we find that women expect parenthood penalties relative to men (i.e., smaller premiums or larger penalties). However, we find no evidence that women expect these penalties to differ across male and female dominated majors. None of the interaction coefficient estimates are statistically significant, and we cannot reject the equality of any of the sets of male and female coefficients. This makes it unlikely that concerns about motherhood penalties are deterring women from male dominated majors or attracting them to more female fields.

Overall, our reduced-form analysis finds that a substantial fraction of the extant gender earnings gap in the labor market is expected by college applicants, but that men and women have similar expectations about how their wages depend on the gender composition of their field of study within their choice set. They also have similar expectations about how their choices will affect their parenthood and partnership probabilities, and while there are gender differences in expected child-earnings penalties, these differences are invariant to field female share. These results suggest that expectations about earnings and family outcomes are not primary drivers of gender differences in choice of major. The key gender difference that we identify is that women expect to be more satisfied with their education and resulting career in more female fields, and men do not. Barring gender differences in preferences –which we investigate in the next section– these gendered satisfaction gradients are our best candidates for explaining gender differences in field selection.

5 Structural Model of Field Choice

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 estimates to compare men's and women's compensating differentials for education and work attributes and to decompose the sources of gender differences in field selection.

5.1 General Formulation

Survey respondents are denoted by $i = 1 \dots I$. Their ordinally-ranked degree choices are $j = 1 \dots J$. Individual-degree 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 choice 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 choices, the log of equation 2 fully describes their contribution to the log-likelihood function we maximize. For individuals with three choices, 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

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

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

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

We estimate the model using a maximum likelihood routine in Stata.[15]

5.2 Attributes in the utility function

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. To match our reduced-form specification, school utility, X_{ij}^1 consists only of educational satisfaction.

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

[15] 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.

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

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

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 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).[16] σ_i is an individual-specific CRRA parameter, with

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

where r_i is an individual's standardized response to a Gneezy and Potters (1997) style risk preference question in our survey.[17] Larger values of r_i correspond to more risk-tolerant choices.

Work utility is discounted by factor

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

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-preference question embedded in our survey module.[18] Larger values of t_i correspond to more

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

[17] 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?.

[18] 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?"

patient choices.[19]

School utility is not discounted, and given by

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

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. If each option featured the same 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.[20] We start by discussing the risk and time preference parameters, and then move to the degree attribute preference parameters.

5.3.1 Risk & time preferences

Subjects exhibit substantial diminishing marginal utility in earnings ($\sigma_0 = 0.83 > 0$). This is slightly more utility curvature in our sample of university applicants than Andersen et al. (2014) obtained from a representative sample of Danes (0.65), and quite close to, also representative, estimates from Andersen et al. (2008) of 0.74. 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 ($p = 0.140$). Under an

[19]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.

[20]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)	0.830***	0.781***	0.868***
	(0.024)	(0.054)	(0.023)
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)	0.559***	0.606***	0.552***
	(0.041)	(0.070)	(0.051)
Educational satisfaction (α, 1-10 scale)	0.574***	0.596***	0.563***
	(0.016)	(0.026)	(0.019)
Discount factor heterogeneity (δ, per SD patience)	0.046***	0.078***	0.021
	(0.015)	(0.022)	(0.020)
CRRA heterogeneity (σ_1, per SD risk tolerance)	0.015	0.108*	-0.037
	(0.027)	(0.060)	(0.030)
Observations	25,638	9,361	16,277
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.

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 ($p < 0.001$, see summary statistics in Table 3). Much of this is due to the fact that 17% of men are willing to invest their entire endowment, compared to 6% of women. However, we do not find evidence of important within-gender 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 ($p = 0.072$). 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, $p < 0.001$, see summary statistics in Table 3), 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. Our preferred metric for considering these utility attributes is in terms of 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.

Overall, we find that there is a substantial willingness to trade earnings for non-pecuniary aspects of an education. For all attributes, this willingness is higher for women than men. We note that we calculate the compensating differentials in terms of the median income in the full sample (pooling men and women). If we were to use gender specific earnings, the compensating differentials would be higher for women (because they have lower median earnings) and lower for men. Parenthood features the biggest relative gender disparity: women's willingness to trade earnings for fertility probability is nearly double (94% higher

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

Sample:	All	Male	Female
	(1)	(2)	(3)
Parenthood (per SD, SD = 31 ppt)	3,710	2,431	4,711
% of Median income:	72.9%	47.8%	92.5%
Partnership (per SD, SD = 24 ppt)	8,061	6,331	9,265
% of Median income:	158.3%	124.4%	182.0%
Work sat. (per SD, SD = 1.65 points)	3,561	3,564	3,740
% of Median income:	69.9%	70.0%	73.5%
Educational sat. (per SD, SD = 1.89 points)	9,915	9,678	10,314
% of Median income:	194.8%	190.1%	202.6%

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.

than) men's. Specifically, women are willing to trade an estimated $152 per month in pre-tax earnings (3% of median income) for a one percentage point increase in the chance of having children, compared to $78 for men (1.5% of median income). Compared to parenthood, both men and women put more weight on increasing the probability of having a partner ($264 and $386 per month, respectively, per percentage point), with a smaller relative gender disparity (46% higher for women than men). The gender disparities are much smaller for both work satisfaction and educational satisfaction, with women 5% and 7% more willing to trade earnings for improved satisfaction, respectively. Both men and women put less weight on satisfaction with the field than on family outcomes.[21]

6 Counterfactual simulations

Our results so far have shown that both men and women expect higher rates of partnership and parenthood in more female fields, but women place more weight than men on these family outcomes. Additionally, women expect higher work and educational satisfaction in

[21] 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. The disparity in compensating differentials between educational and work satisfaction in Table 8, despite the similar model coefficient estimates in Table 7, is due mostly to discounting, but also to the larger variance in educational satisfaction.

more female fields while men do not; and, both men and women highly value these attributes, educational satisfaction in particular. These findings suggest that the most likely drivers of gender differences in choice of major are gender differences in preferences over family outcomes or gender differences in expectations about satisfaction with the educational field – i.e., the ways in which men and women most differ. In this section we evaluate these two candidate explanations for gender differences in major choice by putting preferences and expectations together in a simulation exercise. From the perspective of a policy maker with the goal of reducing female share disparities, this exercise informs whether fixing certain incorrect beliefs or reducing gender differences in outcomes could attract women to male dominated majors; or, if instead, gender differences in preferences make this infeasible.

We first point out that correcting beliefs does not appear to be an effective strategy. Women already expect high earnings returns to male dominated fields that are as large as men's returns and similar to the returns estimated in the population. Similarly, women's and men's beliefs about the parenthood tradeoffs associated with entering heavily male majors largely align with estimates from the population. To the extent that applicants' expectations about motherhood penalties do not align with the population outcomes, informing them that relative motherhood penalties are larger in male-dominated fields would if anything reduce entry into these majors. The disagreement between survey expectations and population outcomes is most notable for partnership, where both men and women expect higher partnership rates in more female fields despite no such relationship in the population for either group. Correcting these beliefs could draw more female applicants into heavily male majors but would simultaneously draw males away from female fields, and so is unlikely to significantly shift the female share of these fields.

Next, we conduct two simulations. In our first simulation, we use our model to identify the contribution of gender differences in both expectations and preferences to the predicted difference in female share across fields. In our second simulation, we estimate the extent to which changing women's expectations or preferences would shift them to preferring a male-dominated major over a female-dominated one.

To conduct our first simulation, we construct two hypothetical fields: A and B. Field A features the gender-specific average expected attributes of all degree choices in the survey (see

Table 3, columns 5 and 6). For women (men), Field A has average earnings of 5470 (6800), fertility of 0.76 (0.65), partnership probability of 0.79 (0.74), work satisfaction of 8.41 (8.34), and educational satisfaction of 7.97 (8.04). We construct Field B to have the expected attributes of a field that has a 10 percentage point higher female share than Field A. To do so, we use the female share gradients estimated using individual fixed effects (Table 5, columns 5 and 6), which correspond naturally to our structural model of ranking fields within an applicant's consideration set. For example, we calculate the expected female parenthood in Field B as Field A female parenthood plus 0.023*10%, where 0.023 is is the coefficient on female share in Table 5, panel B, column 6. For men, it would be Field A male parenthood plus 0.016*10% (Table 5, panel B, column 5).

We then calculate the difference in female share between the two fields that would be predicted by our model. To do so, we first calculate the utility of Field A and Field B for women and men using equation 1, plugging in the expected attribute values discussed above and the gender-specific utility function parameters from Table 7 (column 2 for men, column 3 for women). We then use the two-option logistic choice model functional form in equation 2 to predict men's and women's probabilities of selecting Field B over Field A and the resulting female share of each field.[22] Our simulation predicts that Field B would be 2.34 percentage points more female than Field A. That is, our choice model explains almost a quarter (23.4%) of the expected difference in field female share based on observed attribute differences (i.e., the differences in attributes associated with a 10 percentage point increase in female share from the average field).[23]

Next, we decompose how much of the predicted overall difference in female share between Field A and B is due to each attribute. To do so, we modify Field B to have Field A's gender-specific expected values for all attributes except the focal attribute. For example, to estimate the role of educational satisfaction, we set Field B to have Field A's expected values for income, parenthood, partnership, and work satisfaction. We then estimate the predicted difference in female share between the two fields as discussed above. If we allow

[22]To translate the gender-specific choice probabilities into a female share of each field, we assume an equal number of women and men making this choice.

[23]The magnitude of the difference in female share between Fields A and B does not affect the analysis, we choose 10pp just for the example.

only expectations about educational satisfaction to differ between Field A and Field B, our simulation predicts their female share would differ by 1.7 percentage points, which is equivalent to 73% of the total predicted difference of 2.5 percentage points between the two fields. This exercise gives us the "overall" percentage of the difference in female share due to each attribute.

We further decompose the "overall" female share difference due to an attribute into the share due to gender differences in expectations and the share due to gender differences in preferences. For example, the 1.7 percentage point overall difference due to educational satisfaction is theoretically due both to gender differences in expected educational satisfaction across the two fields and to gender differences in the utility weight placed on educational satisfaction. To estimate the share due to expectations alone, we give women and men the same preferences and predict the female share difference between the two fields if only expectations differed.[24] To estimate the share due to preferences, we set women and men to have the same expectations and again predict the female share difference between the two fields if only preferences differ.[25] These exercises give us the percentage of the female share differences due to "preferences only" and "expectations only."

Figure 3 shows the results of this exercise. The "overall" shares for each attribute sum to one (i.e., the green bars add up to 100%). Within each attribute, the share due to "preferences only" and the share due to "attributes only" sums to the overall share for the attribute (i.e., for a given attribute, the blue and orange bars add up to the green bar). 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.

As noted above, of the total predicted difference in female share between Fields A and B, 73% is explained by educational satisfaction. An additional 17% is explained by work sat-

[24] We calculate this two ways: by using men's preferences for both women and men, and by using women's preferences for both women and men. We then average the predicted female share difference from the two approaches.

[25] As with expectations, we calculate this two ways: by using men's expectations for both women and men; and by using women's expectations for both women and men. We then average the predicted female share difference from the two approaches.

isfaction. Income, parenthood and partnership each explain less than 6% percent of the difference in female share. The contributions of work and educational satisfaction are entirely due to gender differences in expectations from Table 5, rather than gender difference in preferences over these attributes from Table 8. This is for two reasons: first, Table 5 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 effect of their field choice on both educational and work satisfaction. Men anticipate no effect. Second, Table 8 shows that applicants are highly responsive to differences in educational satisfaction in particular, which makes it an important driver of major choice. However, men and women place similar weight on both work and educational satisfaction and so there is little scope for gender differences in preferences for these attributes to explain gender differences in choice of field. Across all attributes, gender differences in expectations explain 96.9% of the predicted difference in female share of field between Fields A and B, with preferences explaining only 3.1%.

The hypothetical fields in our first simulation represent our best overall picture of how men and women expect different outcomes to correlate with the female share of their chosen degree. In our second simulation, we focus on a specific subset of women: those who rank female-dominated field (female share $>$ 50%) over a male-dominated field (female share $<$ 50%). 862 women (10.7% of the restricted sample) rank a female-dominated field first, but include a male-dominated field in the second or third rank. Because these applicants have included a male dominated field in their consideration set, their expectations may most closely reflect those who are deciding between entering and male vs. female dominated field.

Within this group of "influenceable" women, what would have to be different about their expectations or preferences to move the male-dominated field into the top rank? As shown in Table 9, within this group, the female-dominated first choice is 70% female on average, and about half (52%) of the fields are in business, science, or technology. By comparison, the male-dominated second or third choice is 39% female on average, and about three-quarters (74%) of the fields are in business, science, or technology. We apply the two-option logistic

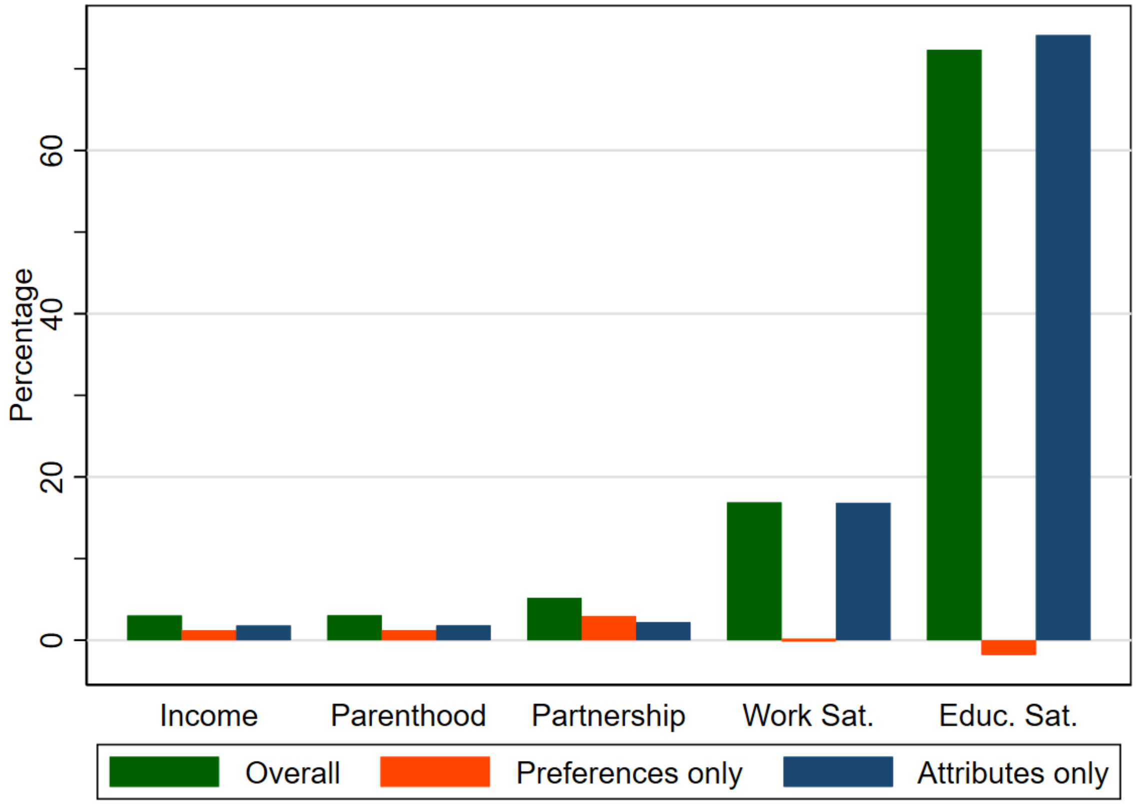

Figure 3: Percentage of hypothetical field female share difference explained by field attributes

Notes: The "overall" shares for each attribute sum to one (i.e., the green bars add up to 100%). Within each attribute, the share due to "preferences only" and the share due to "attributes only" sums to the overall share for the attribute (i.e., for a given attribute, the blue and orange bars add up to the green bar). 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.

choice formula (equation 2) to the average expectations of this group (columns 1 and 2), along with our estimates of women's preferences from Table 7. As shown in column 3, the model predicts only a 23% chance that these applicants would rank the male dominated field first (i.e., we predict a 77% probability that the top-ranked female dominated major is indeed selected first).

In Simulation A, we repeat the prediction exercise, replacing the expectations for the male-dominated major with the expectations for the female dominated major, one attribute at a time. Similar to our first simulation, we again find that differences in expected educational

Table 9: Simulated choices of women choosing a female field over a male field

	Choice 1: Female-dominated	Choice 2 or 3: Male-dominated	Probability of choosing a male-dominated field
	(1)	(2)	(3)
Sample characteristics			
Female share	0.70	0.39	0
Business, science, & tech share	0.522	0.737	
Model fit using observed expectations			
Average monthly earnings	5,765	5,572	
Parenthood	0.76	0.75	
Partnership	0.81	0.77	0.23
Work satisfaction	8.86	7.86	
Educational satisfaction	8.6	7.25	
Simulation A: survey attributes in (1) replace (2) in model			
Average monthly earnings			0.24
Parenthood			0.24
Partnership			0.26
Work satisfaction			0.28
Educational satisfaction			0.40
All			0.50
Simulation B: men's preferences replace women's preferences in model			
CRRA parameter (σ_0)			0.23
Parenthood (β_1)			0.24
Partnership (β_2)			0.24
Work satisfaction (β_3)			0.23
Educational satisfaction (α)			0.23
Discounting (δ, t)			0.24
All			0.23

Notes: Choice probabilities in column (3) are obtained by using the expectations of the 862 women in the restricted sample of our survey that ranked a field with female share greater than 0.5 (calculated using the top choices of all applicants) first, and a field with female share less than 0.5 second or third. Column (1) shows their average expectations about their first choice and column (2) shows their average expectations about their second choice if its female share is less than 0.5 and their third choice if not. Column (3) uses the two-option logistic choice probability formula and our estimated utility parameters from Table 7 to compute the probability of not choosing their first choice. We first use the attributes as observed (with women's preference parameters), then replace each attribute of the choice in column (2) with the value from (1) one at a time (except for the "all" row), then we replace women's preference parameters with men's (leaving attributes as observed) one at a time (except for the 'all' row).

satisfaction are the primary determinant of why the female-dominated field is ranked higher. Replacing educational satisfaction in the lower-ranked male dominated major (7.25/10) with its value from the higher-ranked female dominated major (8.6/10) increases the chance it is ranked first to 40%. We estimate would take an educational satisfaction value of 9.36 in male-dominated majors (a roughly 1.1 standard deviation increase) to equate the utilities of each field – i.e., a 50% chance of choosing the male dominated major first. Equating the other attributes across fields has much smaller impacts, although work satisfaction remains the most important other factor. As shown in Simulation B, applying men's preference estimates has essentially no impact on the model's predicted choice probabilities.

We entered our simulation exercises with two leading candidates for explaining the gender difference in choice of major: gender differences in preferences over family outcomes and gender differences in expectations about satisfaction with the educational field. In both of our simulations, we find a strong role for gender differences in expectations, particularly educational satisfaction with the field; and, little role for gender differences in preferences, including over family outcomes. Why do we find a strong role for expectations but a negligible role for preferences? For preferences over an attribute to matter, it must be the case that: (1) applicants care about the attribute when choosing a major; (2) there are substantial gender differences in preferences over the attribute; and (3) candidates expect that their choice of major will have a significant impact on the attribute (i.e., the attribute varies with female share of the field).

We examine each of the above conditions in turn. First, applicants care about family outcomes. In terms of compensating differentials (per standard deviation), applicants place more weight on parenthood than on work satisfaction, and nearly as much weight on partnership as they do on educational satisfaction (Table 8). Our first simulation finds important roles for both work and educational satisfaction in explaining gender differences in choice of major (Figure 3). This suggests we could potentially also find an important role family outcomes, which have similar utility weights.

Second, there are substantial gender differences in preferences over family outcomes. As shown in Table 8, female applicants place almost twice as much weight on parenthood compared to male applicants, and about 1.5 times more weight on parenthood. The gender differences in compensating differentials for parenthood and partnership are equivalent to about 44% and 57% of expected income, respectively. The magnitudes of these differences are close to the overall weight placed on work satisfaction (about 70% of income), again suggesting that gender differences in preferences have the potential to play a non-negligible role in explaining gender differences in choice of major.

Third, the reason preferences over family outcomes do not end up mattering is because candidates do not expect a large impact of their major choice on these outcomes. As shown in Table 5, applicants do expect a significant relationship between female share of a field and family outcomes. However, the magnitudes of these relationships are not large enough for these attributes to explain a meaningful share of gender differences in choice of field. The expected association of a 10 percentage point increase in female share of field with the probability of motherhood is equivalent to a 0.074 standard deviation (SD) increase. For the probability of finding a partner, it is associated with a 0.14 SD increase. By comparison, the expected associations with work and educational satisfaction respectively are 0.42 SD and 0.56 SD, respectively, over three times the magnitude in standard deviation terms.[26]

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. A number of our key findings are only possible because our unique data allow us to estimate the within-individual expected effect of field of study on life outcomes, within revealed-preference, rank-ordered lists of each applicant's consideration set.

Several findings emerge from our study. First, aside from the main focus of the paper on major choice, it is notable that college applicants have internalized so much of the gender

[26] We use the fixed effects estimates from Table 5 column 6. We report the standard deviations for each attribute in Table 8.

wage gap. The survey estimate of the gap is about 60% of the extant gap in our comparison population sample, entirely based on individuals' expectations *about themselves.*Nothing about the survey mentioned or primed respondents to consider the role of gender. We note that we cannot distinguish accurate beliefs about a smaller future gap from less-than-full internalization of the gap. Second, we find that men and women have indistinguishable expectations about how the gender composition of a field relates to earnings, parenthood, and partnership outcomes resulting from that field. On the other hand, women, but not men, expect that they will have significantly lower educational and work satisfaction in more heavily male fields, which we argue explains gender differences in field selection. Third, we find that while women expect a motherhood penalty relative to men, the expected size of the penalty appears be invariant to the gender composition of field. Finally, we find that women are generally more willing to trade income for non-pecuniary attributes of a field, especially parenthood and partnership–but that these differences are quantitatively too small to explain gender differences in field selection. This is not because the preference differences themselves are small, but rather because women (and men) do not expect a strong relationship between their choice of field and their parenthood and partnership outcomes.

Prior interventions aimed at increasing female entry into male dominated fields have informed women about earnings returns to male majors (e.g., Ding et al., 2021). Our findings suggest that interventions targeting women's actual and perceived experiences during their studies could be more effective than focusing on earnings. In this vein, recent work tests interventions that inform college students not only about earnings but also students' classroom experience in different majors Cao et al. (2023). The positive impacts of women's representation demonstrated in the literature – both as faculty (Carrell et al., 2010; Bettinger and Long, 2005) and, more recently, among the student body (Huntington-Klein and Rose, 2018; Booth et al., 2018; Porter and Serra, 2020; Shan, 2022) – could also operate partially through this channel of improving women's educational experience. More broadly, for a policy-maker looking to increase women's selection into male-dominated fields–such as those in business, science, and technology–a good place to start would be determining why women expect lower educational satisfaction in those fields and then taking steps to improve conditions for women.

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A Appendix

A.1 Additional Figures and Tables

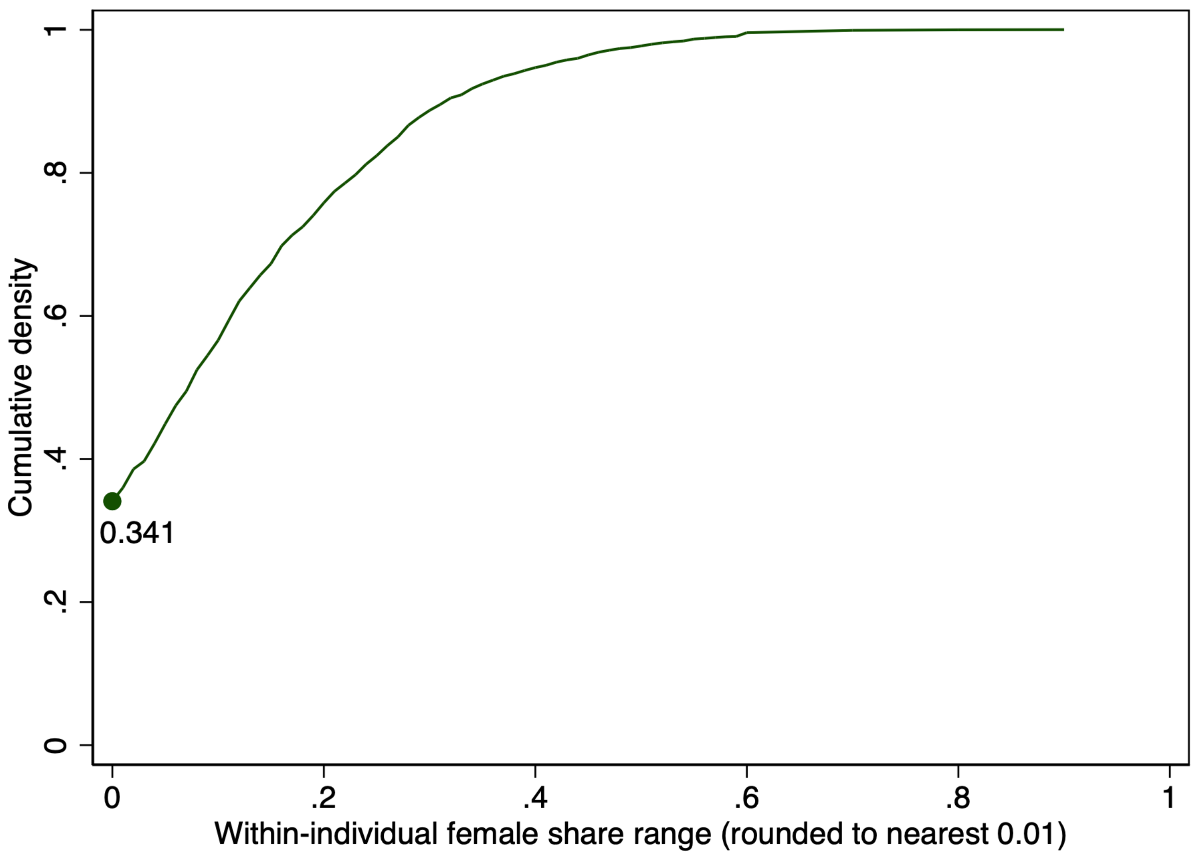

Figure A.1: Empirical CDF of within choice-set female share variation

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.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	173,585	54,531	77,701	12,534			
Demographics							
Female	0.62	0.57	0.58	0.64	0.000	0.000	0.002
Median age 10 years after graduation	38						
Median age at application	23	21	21	21			
High school GPA	6.25	7.19	6.85	7.47	0.000	0.000	0.000
Foreign origin	0.045	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	0.13	0.000	0.868	0.000
Mother has completed high school	0.38	0.41	0.42	0.41	0.000	0.536	0.000
Mother has completed further education	0.35	0.47	0.46	0.46	0.000	0.615	0.000
Father has less than high school education	0.22	0.15	0.16	0.16	0.000	0.437	0.000
Father has completed high school	0.46	0.46	0.46	0.46	0.622	0.849	0.904
Father has completed further education	0.32	0.39	0.38	0.38	0.000	0.435	0.000
College application							
Ranked 1 degree program		0.36	0.37	0.36		0.011	
Ranked 2 degree programs		0.23	0.23	0.22		0.302	
Ranked 3 or more degree program		0.40	0.40	0.41		0.011	
Ranked 8 degree programs		0.04	0.04	0.04		0.740	
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		0.157	
Matched to 3rd choice or lower degree program		0.075	0.062	0.055		0.006	

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	5,379	6,466	4,721	6,108	6,982	5,612
(2015 USD)	(2,625)	(3,240)	(1,887)	(4,698)	(5,591)	(4,023)
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)
Risk tolerance				4,371	4,940	4,042
(0-10,000 DKK invested)				(2,914)	(3,211)	(2,674)
Patience				21.83	21.09	22.25
(0-25 weeks waited)				(8.65)	(9.35)	(8.19)

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. Risk tolerance and patience data are only reported for the 10,551 subjects in the structural estimation sample we use in Section 5 because missing values of these variables are the limiting factor in determining that sample.

Table A.3: 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.4: 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.

Table A.5: Gender earnings gap - Survey data with weights

	DV: log earnings			
Weights:	Applicants		Population	
	(1)	(2)	(3)	(4)
Female	-0.156***	-0.077***	-0.154***	-0.074***
	(0.017)	(0.018)	(0.021)	(0.022)
Observations	29,176			
Individuals	12,566			
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. Standard errors clustered at the individual level are in parentheses. Pre-tax monthly earnings measured in 2015 USD. Our respondents are weighted to look like the pool of all applicants in columns (1) and (2) using gender, foreign born status, and high-school GPA. Our respondents are weighted to look like the population data in columns (3) and (4) using age, gender, high school GPA, mother's education, and father's education.

Table A.6: Association of female share of field with field attributes - Weighted field-level models

Data:	Population		Survey	
Sample:	Male	Female	Male	Female
	(1)	(2)	(3)	(4)
Panel A - DV: earnings (1000s 2015 USD)				
Female share	-1.941***	-2.586***	-1.684**	-2.788***
	(0.695)	(0.608)	(0.743)	(0.626)
H_0: Male = Female	$p = 0.301$		$p = 0.105$	
Observations	384	384	224	224
Panel B - DV: Parenthood probability				
Female share	0.098**	0.237***	0.085**	0.210***
	(0.042)	(0.044)	(0.034)	(0.040)
H_0: Male = Female	$p = 0.014$		$p = 0.012$	
Observations	384	384	224	224
Panel C - DV: Partnership probability				
Female share	-0.032	-0.015	0.054***	0.082***
	(0.040)	(0.034)	(0.020)	(0.021)
H_0: Male = Female	$p = 0.685$		$p = 0.283$	
Observations	384	384	224	224
Panel D - DV: Work satisfaction				
Female share			-0.103	0.020
			(0.300)	(0.365)
H_0: Male = Female			$p = 0.838$	
Observations			224	224
Panel E - DV: Educational satisfaction				
Female share			-0.394	0.634
			(0.315)	(0.842)
H_0: Male = Female			$p = 0.348$	
Observations			224	224

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All models are weighted OLS regressions, using gender-specific field size to weight each field. Heteroskedasticity-robust standard errors in parentheses. Pre-tax monthly earnings measured in 2015 USD. Work and educational satisfaction are measured on a 1-10 scale.

Table A.7: Association of female share of field with field attributes - Restricted sample

Data:	Population		Survey			
Sample:	Male	Female	Male	Female	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A - DV: log earnings						
Female share	-0.310***	-0.436***	-0.335**	-0.543***	-0.111***	-0.110***
	(0.096)	(0.114)	(0.137)	(0.120)	(0.039)	(0.030)
H_0: Male = Female	$p = 0.179$		$p = 0.084$		$p = 0.984$	
Mean non-log DV	6,462	4,721	6,859	5,554	6,859	5,554
Panel B - DV: Parenthood probability						
Female share	0.095**	0.235***	0.069**	0.192***	0.016	0.033***
	(0.038)	(0.041)	(0.030)	(0.034)	(0.011)	(0.007)
H_0: Male = Female	$p = 0.005$		$p < 0.001$		$p = 0.939$	
Mean DV	0.69	0.76	0.67	0.78	0.67	0.78
Panel C - DV: Partnership probability						
Female share	-0.030	-0.006	0.047**	0.094***	0.039***	0.033***
	(0.033)	(0.027)	(0.019)	(0.023)	(0.014)	(0.010)
H_0: Male = Female	$p = 0.521$		$p = 0.032$		$p = 0.728$	
Mean DV	0.80	0.79	0.75	0.80	0.75	0.80
Panel D - DV: Work satisfaction						
Female share			0.107	0.298**	0.042	0.488**
			(0.143)	(0.144)	(0.162)	(0.206)
H_0: Male = Female			$p = 0.325$		$p = 0.089$	
Mean DV			8.39	8.44	8.39	8.44
Panel E - DV: Educational satisfaction						
Female share			0.206	0.634***	0.003	0.864***
			(0.168)	(0.182)	(0.179)	(0.209)
H_0: Male = Female			$p = 0.069$		$p = 0.002$	
Mean DV			8.09	8.03	8.09	8.03
Observations	65,430	108,155	10,140	17,911	9,524	16,842
Individuals	65,430	108,155	4,548	7,986	3,932	6,917
Individual FE	N	N	N	N	Y	Y

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.8: 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.9: Association of female share of field with field attributes - Survey data with applicant weights

Sample:	Male	Female	Male	Female
	(1)	(2)	(3)	(4)
Panel A - DV: log earnings				
Female share	-0.335***	-0.547***	-0.139***	-0.104***
	(0.133)	(0.107)	(0.044)	(0.029)
H_0: Male = Female	$p = 0.079$		$p = 0.507$	
Observations	11,117	18,059	10,680	17,356
Individuals	4,804	7,762	4,367	7,059
Panel B - DV: Parenthood probability				
Female share	0.092***	0.206***	0.012	0.021**
	(0.033)	(0.043)	(0.011)	(0.008)
H_0: Male = Female	$p = 0.013$		$p = 0.508$	
Observations	13,655	25,214	13,136	24,311
Individuals	5,877	10,744	5,358	9,841
Panel C - DV: Partnership probability				
Female share	0.054**	0.085***	0.023*	0.026***
	(0.022)	(0.021)	(0.012)	(0.010)
H_0: Male = Female	$p = 0.185$		$p = 0.848$	
Observations	11,311	22,145	10,818	21,251
Individuals	4,910	9,503	4,417	8,609
Panel D - DV: Work satisfaction				
Female share	-0.007	0.249*	-0.065	0.658***
	(0.173)	(0.145)	(0.156)	(0.181)
H_0: Male = Female	$p = 0.173$		$p = 0.002$	
Observations	11,934	22,376	11,380	21,429
Individuals	5,207	9,644	4,653	8,697
Panel E - DV: Educational satisfaction				
Female share	0.017	0.560***	-0.176	1.032***
	(0.188)	(0.187)	(0.183)	(0.196)
H_0: Male = Female	$p = 0.018$		$p < 0.001$	
Observations	12,706	23,587	12,110	22,532
Individuals	5,543	10,190	4,947	9,135
Individual FE	N	N	Y	Y

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Models in columns (1)-(2) are linear OLS regressions. Models in columns (3) and (4) are linear fixed-effect 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. Our respondents are weighted to look like the pool of all applicants using gender, foreign born status, and high-school GPA.

Table A.10: Association of female share of field with additional satisfaction measures during school

Sample:	Male	Female	Male	Female
	(1)	(2)	(3)	(4)
Panel A - DV: Overall life satisfaction				
Female share	0.165	0.440***	-0.076	1.099***
	(0.151)	(0.140)	(0.184)	(0.183)
H_0: Male = Female	$p = 0.139$		$p < 0.001$	
Mean non-log DV	7.668	7.623	7.668	7.623
Observations	15,074	28,825	14,248	27,377
Individuals	6,699	12,617	5,873	11,169
Panel B - DV: Personal life satisfaction				
Female share	0.404***	0.562***	0.155	0.680***
	(0.155)	(0.118)	(0.153)	(0.137)
H_0: Male = Female	$p = 0.393$		$p = 0.011$	
Mean non-log DV	7.618	7.730	7.618	7.730
Observations	14,743	28,398	13,953	26,986
Individuals	6,542	12,424	5,752	11,012
Panel C - DV: Physical & mental health satisfaction				
Female share	0.132	0.465***	0.061	0.909***
	(0.160)	(0.131)	(0.131)	(0.132)
H_0: Male = Female	$p = 0.069$		$p < 0.001$	
Mean non-log DV	7.893	7.729	7.893	7.729
Observations	15,075	28,634	14,275	27,208
Individuals	6,680	12,533	5,880	11,107
Panel D - DV: Financial security satisfaction				
Female share	0.082	-0.452***	-0.079	0.165*
	(0.202)	(0.170)	(0.137)	(0.099)
H_0: Male = Female	$p = 0.002$		$p = 0.149$	
Mean non-log DV	6.647	6.388	6.647	6.388
Observations	14,988	28,652	14,196	27,255
Individuals	6,644	12,516	5,852	11,119
Individual FE	N	N	Y	Y

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Models in columns (1) and (2) are linear OLS regressions. Models in columns (3) and (4) are linear fixed-effect regressions. Standard errors clustered at both the individual and field level are in parentheses. Satisfaction is measured on a 1-10 scale.

Table A.11: Association of female share of field with additional satisfaction measures ten years after graduating

Sample:	Male	Female	Male	Female
	(1)	(2)	(3)	(4)
Panel A - DV: Overall life satisfaction				
Female share	0.066	0.372***	-0.062	0.685***
	(0.111)	(0.090)	(0.129)	(0.166)
H_0: Male = Female	$p = 0.019$		$p < 0.001$	
Mean DV	8.354	8.436	8.354	8.436
Observations	13,943	26,553	13,205	25,252
Individuals	6,175	11,614	5,437	10,313
Panel B - DV: Personal life satisfaction				
Female share	0.320**	0.482***	0.296***	0.498***
	(0.129)	(0.085)	(0.095)	(0.104)
H_0: Male = Female	$p = 0.223$		$p = 0.152$	
Mean DV	8.279	8.552	8.279	8.552
Observations	13,360	25,765	12,660	24,542
Individuals	5,909	11,242	5,209	10,019
Panel C - DV: Physical & mental health satisfaction				
Female share	0.166	0.177*	0.107	0.284**
	(0.131)	(0.106)	(0.102)	(0.142)
H_0: Male = Female	$p = 0.931$		$p = 0.311$	
Mean non-log DV	8.323	8.386	8.323	8.386
Observations	13,862	26,234	13,150	25,003
Individuals	6,122	11,433	5,410	10,202
Panel D - DV: Financial security satisfaction				
Female share	-0.497*	-0.810***	-0.440***	-0.316*
	(0.255)	(0.262)	(0.143)	(0.172)
H_0: Male = Female	$p = 0.298$		$p = 0.579$	
Mean non-log DV	8.248	8.179	8.248	8.179
Observations	13,798	26,145	13,076	24,877
Individuals	6,109	11,436	5,387	10,168
Individual FE	N	N	Y	Y

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Models in columns (1) and (2) are linear OLS regressions. Models in columns (3) and (4) are linear fixed-effect regressions. Standard errors clustered at both the individual and field level are in parentheses. Satisfaction is measured on a 1-10 scale.

Table A.12: Log-earnings penalties for parenthood - full results

Data:	Population		Survey							
Sample:	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Parenthood	0.002	-0.029***	-0.049	0.050	-0.067	0.035	0.194*	-0.051	0.125	-0.105***
	(0.009)	(0.005)	(0.054)	(0.043)	(0.057)	(0.046)	(0.111)	(0.034)	(0.118)	(0.035)
Female share (FS)	-0.319***	-0.451***	-0.367***	-0.583***	-0.368***	-0.605***	-0.112***	-0.114***	-0.095***	-0.140***
	(0.010)	(0.012)	(0.052)	(0.040)	(0.057)	(0.046)	(0.025)	(0.023)	(0.028)	(0.026)
Parenthood X FS	-0.029	0.044*	-0.134	-0.166	-0.152	-0.175	0.086	0.023	0.094	-0.000
	(0.022)	(0.024)	(0.165)	(0.155)	(0.177)	(0.157)	(0.115)	(0.080)	(0.129)	(0.083)
Partnership			0.220**	0.085*	0.181*	0.023	0.085*	0.099***	-0.016	0.009
			(0.093)	(0.046)	(0.097)	(0.047)	(0.045)	(0.024)	(0.048)	(0.025)
Partnership X FS			0.017	0.119	0.107	-0.029	-0.018	-0.069	-0.098	-0.039
			(0.256)	(0.171)	(0.278)	(0.170)	(0.177)	(0.090)	(0.191)	(0.094)
Work sat.					0.049***	0.034***			0.034***	0.029***
					(0.013)	(0.007)			(0.005)	(0.003)
Work sat. X FS					-0.009	-0.043			0.015	-0.009
					(0.046)	(0.030)			(0.018)	(0.013)
Educ. sat.					0.008	0.016***			0.010***	0.008***
					(0.009)	(0.005)			(0.004)	(0.003)
Educ. sat. X FS					-0.021	0.078***			-0.007	-0.009
					(0.040)	(0.025)			(0.015)	(0.012)
Mean non-log DV	6,037	4,418	6,683	5,412	6,683	5,412	6,683	5,412	6,683	5,412
Observations	66,293	108,718	10,140	17,911	10,140	17,911	9,524	16,842	9,524	16,842
Individuals	66,293	108,718	4,548	7,986	4,548	7,986	3,932	6,917	3,932	6,917
Individual FE	N	N	N	N	N	N	Y	Y	Y	Y

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All explanatory variables are measured as differences from their median value. Models in columns (1)-(6) are linear OLS regressions. Models in columns (7) and (8) are linear fixed-effect regressions. For the population data in columns (1) and (2), standard errors clustered at the field level are in parentheses. For the survey data in columns (3)-(8), standard errors clustered at both the individual and field level are in parentheses. Pre-tax monthly earnings measured in 2015 USD.