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Planting the Seeds for Success: Why Women in STEM Don't Stick in The Field*†

Gabi Xuan Jiang‡

Purdue University

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Abstract

Women are underrepresented in both STEM college degrees and STEM jobs. Even with a STEM college degree, women are significantly less likely to work in a STEM occupation than their male counterparts. This paper investigates whether men and women possess different ability distributions and examines how much the gender gap in major choice and job choice can be explained by gender differences in sorting on abilities. I use Purdue University's administrative data that contains every Purdue student's academic records linked to their first job information. I apply an extended Roy model of unobserved heterogeneity allowing for endogenous choice with two sequential optimizing decisions: the choice between a STEM and non-STEM major and the choice between a STEM and non-STEM job. I find that both abilities are significantly weaker determinants of major choice for women than for men. High-ability women give up $13,000–$20,000 in annual salary by choosing non-STEM majors. Those non-STEM high-ability women only make up 5.6% of the female sample, but their total gains—had they made the same decision as men—explain about 9.4% of the gender wage gap. Furthermore, the fact that female STEM graduates are less likely to stay in STEM is unrelated to the differences in ability sorting. Instead, home region may be important in women's job decisions; female STEM graduates who return to their home state are more likely to opt out of STEM.

Keywords: Women, STEM, Major, Job, Gender Differences
JEL Classification: I20, I23, J16, J24, J31

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†Click here or go to https://sites.google.com/site/gabixuanjiang/research for the latest version.

‡403 West State Street, KRAN 332, West Lafayette, IN 47907; email: gabijiang@purdue.edu
The author does not have access to any information leading to the identification of individuals in the data. All data analysis was carried out in a secure server.

1 Introduction

Women are underrepresented in Science, Technology, Engineering and Mathematics (STEM) college majors and occupations. There are about 2.5 million women and 6.7 million men in the labor force holding a STEM college degree, although women today receive the majority of college degrees in the US. Even among those women who hold a STEM college degree, it is likely that they are not working in a STEM occupation. About 40 percent of men with STEM college degrees work in STEM jobs, whereas only 26 percent of women with STEM degrees work in STEM jobs (Beede et al., 2011).

Why is the lack of women in the STEM field a concern? First of all, we face a scarcity of STEM workers in many industries, even though STEM jobs are among the best-paying jobs (Xue and Larson, 2015). Attracting and retaining more women in STEM will help with unfilled positions. Second, stereotyping women threatens our educational system. When women are not seen as equals to men in STEM, girls don't have role models to motivate them and help them envision themselves in those positions. They are deterred by the idea that STEM is a "man's field" where girls don't belong (Shapiro and Williams, 2012). Lastly, when women are not involved in STEM, products, services and solutions are mostly designed by men and according to their user experiences. Therefore, the needs and desires that are unique to women may be overlooked (Fisher and Margolis, 2002; Clayton et al., 2014).

This paper focuses on how much of the gender gap in major choice and job choice can be explained by gender differences in sorting on abilities. I apply an extended Roy model of unobserved heterogeneity to explore the endogenous choices of major and job and, more importantly, the gender differences in these choices. The model involves two sequential optimizing decisions: the choice between a STEM and non-STEM major and the choice between a STEM and non-STEM job. There is abundant literature that covers the issue of ability sorting in major choices and that of gender differences in college major, but the two elements—gender differences and ability sorting in major choice—have rarely been linked.

I use Purdue University's administrative data that contains every Purdue undergraduate student's academic records merged with the first destination survey conducted by the Purdue Center for Career Opportunities. I focus on the sample of college graduates from 2005-–2014. The data set provides rich information on individuals' high school GPA, standardized test scores—ACT English, ACT Reading, ACT Math and ACT Science—and entire college course histories. With these test scores and grades, I estimate distributions of two latent abilities—general intelligence and mathematical ability—for women and men separately.

My model relies on the identification of these two latent abilities to deal with sequential selection of major and job. Most of the literature[1] uses standardized test scores, such as SAT scores, as measures of ability. Those test scores, however, should only be considered as proxies or functions of true abilities (Carneiro et al., 2003; Heckman et al., 2006; Sarzosa and Urzúa, 2015; Prada et al., 2017). Moreover, the identification strategy here assumes a mixture of normals for the distributions of both latent abilities, avoiding the restriction for them being normal and guaranteeing the flexibility of the functional forms the latent abilities could take.

I find the distributions of abilities at the start of college are very different across gender; however, gender differences in abilities cannot explain the huge gender gap in major and job choices. Abilities are significantly weaker determinants of major

[1] For example, Arcidiacono (2004); Long et al. (2015); Altonji et al. (2016), etc.

choice for women than men. In fact, high-ability men are more likely to sort into STEM majors; however, high-ability women are much more likely to choose non-STEM majors than high-ability men. Specifically, a one standard deviation increase in an average woman's general intelligence will increase her likelihood of graduating with a STEM degree by 17.2 percentage points while that number is 23.4 for an average man. A one standard deviation increase in the mathematical ability of an average woman will increase her probability of graduating from a STEM major by 9.5 percentage points; the same change will increase an average man's likelihood of graduating with a STEM degree by 14 percentage points. Consistent with the recent findings of Ahn et al. (2015), my finding could suggest that women are less sensitive to or more critical about their abilities. Alternatively, other characteristics unobserved by the researcher could be more significant to women's college major decision then men's. By choosing non-STEM majors, the high-ability women leave large amounts of money on the table. A counterfactual analysis shows that high-ability women give up $13,000–$20,000 in annual salary by choosing non-STEM majors. Those non-STEM high-ability women only make up 5.6% of the female sample, but their earning losses explain about 9.4% of the gender wage gap.

The existing literature on this topic has focused on college major choices and the policy implications of attracting students to STEM majors. Where STEM graduates end up remains unexplored. This model is able to assess the determinants of job choice by allowing the STEM graduates to make the choice between STEM and non-STEM jobs conditional on their major choice. Among both male and female STEM graduates, I find little evidence of sorting on abilities when making a job decision. Thus, the fact that female STEM graduates are less likely to stay in STEM compared to their male counterparts is *not* due to differences in ability sorting. It implies that other factors are more important to STEM graduates when making a job decision. Through full decomposition of the job decision equation, I find that the (Census) region where a student is from may be a major factor in a female STEM graduate's decision to pursue a STEM or non-STEM job. Those who go back to their home state are more likely to opt out of STEM fields. Although this finding is not conclusive, it paves the way for future research on female STEM graduates' trade-off between opting out of STEM and returning to their home state.

This paper contributes to the literature in several ways. First, it estimates an extended Roy model of unobserved heterogeneity allowing for endogenous choices with two sequential optimizing decisions: the choice between a STEM and non-STEM major and the choice between a STEM and non-STEM job. Second, it quantifies high-ability women's losses in annual salary due to their "poor sorting" on abilities. This suggests that there are large potential benefits in making high school girls aware of their abilities and more informed about the returns to a STEM education. Third, I find that differential ability sorting is not the reason that female STEM graduates are less likely to stay in STEM. Fourth, I further analyze the relationship between home region and job choice among female STEM graduates.

This paper is organized as follows. Section 2 reviews related literature on the subject. Section 3 describes the data I used for the analysis. I then present the model and the measurement system for the unobserved abilities in Section 4. In Section 5 and Section 6, I show my results and counterfactuals. Section 7 discusses the policy implications. Finally, Section 8 concludes.

2 Related Literature

This paper addresses three branches of literature: college major choices, gender differences in college major choices, and gender differences in job choices.

2.1 College Major Choices

There is extensive economic literature on college major choices. The college major premium and income differences between fields of study has been well documented. Differences in return to majors are as large as differences in return to different levels of education, and even larger than differences in return to college quality (Arcidiacono, 2004; Altonji et al., 2015; Daymont and Andrisani, 1984; James et al., 1989). Most studies find that college students' major decisions are related to expected earnings or their beliefs about future earnings (Altonji et al., 2016; Beffy et al., 2012; Long et al., 2015; Wiswall and Zafar, 2015a). Some studies focus on explaining major choices by abilities sorting. Arcidiacono (2004) finds that major selection depends on the monetary returns to various abilities, preferences in the workplace, and preferences for studying particular majors in college. He argues that major and workplace preferences are more dominant to major selection, which is consistent with my findings in this paper. Arcidiacono et al. (2012) and Wiswall and Zafar (2015b) show that sorting occurs both on expected earnings and on students' perceptions of their relative abilities to perform in particular majors. Using a similar framework as my paper, Humphries et al. (2017) decompose the college major premium into labor market returns from multi-dimensional abilities and finds that sorting on abilities primarily explains a college major's enrollment rate and about 50% of students graduating from a college major. However, they do not focus on gender differences in major choices and use only a male sample.

Furthermore, some studies suggest that students who perform worse than they expected are more likely to dropout or switch to a less difficult major (Stinebrickner and Stinebrickner, 2013; Arcidiacono, 2004). It is more likely for those with lower ability within a major to switch majors because they are closer to the margin of choosing one major over another (Arcidiacono et al., 2012).

2.2 Gender Differences in Major Choices

Gender differences within college majors and in the workplace have attracted extensive attention. On the one hand, women's college major choices appear to contribute to the persistent gender wage gap. On the other hand, it has been a concern of policymakers that women are underrepresented in STEM majors due to the reasons I mention in the introduction. A common view in the literature is that women are less likely to major in STEM and more likely to switch out of STEM majors, even after controlling for abilities (Dickson, 2010; Turner and Bowen, 1999; Ahn et al., 2015).

The gender gap in labor market positions, including the gender wage gap and the gender gap in certain types of jobs, is less attributed to discriminatory hiring practices, but rather more to gender-specific preferences in college majors (Polachek, 1978; Daymont and Andrisani, 1984). This viewpoint has been widely accepted by economists, yet some studies find that educational environments associated with discrimination or stereotyping have played an important role in gender segregation: women who attend coeducational colleges are more likely to remain in female-dominated fields than those who attended women's colleges (Solnick, 1995).

More effort has been made to explore gender-specific preferences in the workplace and gender differences in abilities or STEM readiness. For the former, studies have found that gender differences in fertility expectations affect gender differences in college major choices. Young female students with higher expected fertility tend to choose majors that are progressively less subject to atrophy and obsolescence (i.e. history and English), considering the expected time-out-of-the-labor force (Polachek, 1981; Blakemore and Low, 1984). Men care more about pecuniary outcomes and leadership in the workplace, while women are more likely to value opportunities to help others, to contribute to society, and to interact with people (Zafar, 2013; Daymont and Andrisani, 1984). Regarding the latter, some psychological and educational studies find that academic preparation in math and science are crucial determinants in choosing a quantitative college major; however, there is a gender differences in the effect of academic preparation in math and science on college major choices and persistency in chosen majors (Eccles, 2007; Trusty, 2002; Ethington and Woffle, 1988). Hanson et al. (1996) suggest that women avoid the sciences and mathematics because of inferior prior preparation, lack of innate ability, and biases against women in male-dominated subjects. Others, however, argue that the small gender differences in math course preparation does not explain the large gender differences in engineering majors (Xie et al., 2003; Kimmel et al., 2012). Besides that, a growing body of literature suggests that there are fewer women in STEM because they are less confident or more critical of their abilities and more sensitive to negative feedback than men (Roberts, 1991; Johnson and Helgeson, 2002).

2.3 Gender Differences in Job Choices

Compared to the rich literature on college major choices and the gender gap in major choices, a smaller fraction has been devoted to exploring gender differences in job choice. Similar to studies about gender differences in major choice, some argue that gender differences in occupational choice are dependent on differences in the distribution of scarce quantitative abilities (Paglin and Rufolo, 1990). However, minimal research has been done on the career path of STEM college graduates, especially the gender differences in job selection among STEM college graduates. Hanson et al. (1996) find that young women's participation decreases with each stage in the science pipeline with greater gender stratification in science occupations than in science education, which suggests factors other than training generate inequality in high-status science occupations. The literature indicates that the demands of family and children are major nonacademic barriers for women on the pathway to a STEM profession (Kimmel et al., 2012). Compared to previous studies, my model investigates students' entire career paths from endogenous major choice to endogenous job choice.

3 Data

I use a rich administrative data of Purdue Office of the Registrar that tracks the academic records of every Purdue University undergraduate students merged with their first destination survey conducted by the Purdue Center for Career Opportunities from 2005–2014. I observe individual information of undergraduate students, including their demographic characteristics, their date of enrollment, high school GPA, ACT scores, and applied major. I also observe every student's detailed education path within Purdue from transcript information including the entire list of courses taken and the corresponding grades received. Thereafter, I observe their graduation semester, graduation college and major as well as the self-reported first job information.

Table 1 shows some statistics regarding the sample selection. I start with 18904 Purdue graduates; among which, 10516 have complete information on test scores required by my measurement system. International students only make up 2.3% of this sample. I exclude all of them due to two reasons. First, international students have very distinct educational background compared to the domestic students. Second, I only observe first job destination within U.S., yet most of international students left U.S. after graduation. The first destination survey is voluntary. I end up with 4192 graduates taking the survey with a first job title. Among them, only 3055 reported a valid first job annual salary.

In total, there are 1145 women and 1910 men in this reduced sample, of which there are 37.03% of women graduated with a degree in a STEM major while there are 63.40% of men graduated in STEM. Among those who graduated with a STEM degree, 73.11% of women work in a STEM occupation and 81.17% of men work in a STEM occupation. As one of the top engineering schools, it is not surprising that the fractions of both Purdue female STEM graduates and Purdue male STEM graduates are much higher than the fractions in the national-representative survey. Moreover, the gender gap of staying in STEM field after graduating from a STEM major is much smaller in Purdue data—73.11% and 81.17%—than in the national data (26% and 40%).

Table 2 shows the descriptive statistics of the 6 test scores—ACT English, ACT Reading, ACT Math and ACT Science, high school GPA, and grade of COM114[2]—used to identify the two latent abilities in this paper. Overall, women and men have similar test scores, with women having slightly higher ACT English score, COM114 grades and high school GPA while men having slightly higher ACT Reading, ACT Science and ACT Math scores. Average salary of the female sample is smaller than that of the male sample.

[2]Communication 114, Fundamentals of Speech Communication, is a required course for all freshmen at Purdue. It is the study of communication theories as applied to speech, and involves practical communicative experiences ranging from interpersonal communication and small group processes to informative and persuasive speaking in standard speaker-audience situations. https://www.cla.purdue.edu/communication/undergraduate/com_114.html

3.1 STEM Major Definition

I use the first graduation major as student's major[3], regardless of what major one applied or what major one started with. I observe graduation major for every observation. Whoever dropped-out is not included in the sample. All Purdue majors are coded into 6-digit Classification of Instructional Programs (CIP) codes.

The STEM major dummy in this study is defined by the "STEM Designated Degree Program List Effective May 10, 2016" published by U.S. Immigration and Customs Enforcement (ICE, 2016). It is a complete list of fields of study that are considered by the Department of Homeland Security (DHS) to be STEM fields of study for purposes of the 24-month STEM optional practical training (OPT) extension described at 8 CFR 214.2(f)[4]. I define all Purdue undergraduate programs showing up in this list as STEM major and all the others as non-STEM major[5].

3.2 STEM Occupation Definition

The first destination survey provides self-reported first job title, employer (company name), job location (city and state), and annual salary[6].

[3]There are 2.76% students graduated with a double major, and 0.087% students graduated with a third major. The second and third major are not considered in this paper. Engineering majors cannot be listed a second major, because a student can only transfer out of an Engineering major but not transfer into one.

[4]Under 8 CFR 214.2(f)(10)(ii)(C)(2), a STEM field of study is a field of study "included in the Department of Education's Classification of Instructional Programs taxonomy within the two-digit series containing engineering, biological sciences, mathematics, and physical sciences, or a related field.

[5]There are some customization have been made according to Purdue's particular programs. "Nursing" is defined as non-STEM degree program by DHS, probably because there are many types of nursing degrees and most of them do not focus on medical training. Nursing major in Purdue only offers Bachelor of Science in Nursing degree and the placement of undergraduates is basically registered nurse (RN). Additionally, registered nurse is defined as a STEM occupation according to BLS. There are two Purdue majors that are not documented in the DHS's list, "Radiological Health Sciences" and "Health Sciences General". I treat both as STEM major based on the degrees both programs offer and the program requirements.

[6]There are only 35% observations reported full information of first job out of the whole registration record; among which, only 68.76% reported a valid salary (non-missing and non-zero).

The self-reported job titles are matched to a 6-digit level Standard Occupational Classification (SOC) title with a corresponding SOC code. I define a self-reported job as STEM/non-STEM occupation according to the "Detailed 2010 SOC occupations included in STEM"[7] published by Bureau of Labor Statistics (BLS, 2012).

4 Model

This general framework is inspired by the Roy model (Roy, 1951). The core of the empirical strategy follows Carneiro et al. (2003), Heckman et al. (2006), Sarzosa and Urzúa (2015) and Prada et al. (2017). Both latent abilities and observable variables determine outcomes of different degree holders in different occupations. The model captures how college students sort into two groups of majors (STEM majors and non-STEM majors) and given this, sort into two groups of occupations (STEM occupations and non-STEM occupations). Thus the outcome is considered a result of two optimizing decisions, rather than as exogenous causal relationships.

The extended Roy model I implement here can be described as a set of outcome equations linked by a factor structure with two underlying factors[8], θ^A, the general intelligence and, θ^B, the mathematical ability. For each individual, the main outcome variable, annual salary, is given by the following form:

$$Y = \boldsymbol{X_Y}\beta^Y + \alpha^{Y,A}\theta^A + \alpha^{Y,B}\theta^B + e^Y \tag{1}$$

where Y is the outcome variable, $\boldsymbol{X_Y}$ is vector of all observed controls affecting outcome, β^Y is the vector of returns associated with $\boldsymbol{X_Y}$, $\alpha^{Y,A}$ and $\alpha^{Y,B}$ are the factor loadings of each underlying factor θ^A and θ^B, and e^Y is the independent error term. I assume that e^Y is independent from the observable controls and the

[7] There are 840 6-digit SOC occupations and 184 of them are categorized as STEM occupations.
[8] I use "factors" and "latent abilities" interchangeably in the paper.

unobserved factors, i.e. $e^Y \perp\!\!\!\perp (\theta^A, \theta^B, \boldsymbol{X_Y})$. I further assume the factors θ^A and θ^B follow the distributions $f_{\theta^A}(.)$ and $f_{\theta^B}(.)$.

Choice of Major. The second model featuring the major choice is a specific case of the model above. To keep it simple, this paper only addresses the choice between two categories of majors, STEM majors and non-STEM majors. Let I_M denotes the net benefit associated with graduating with a STEM degree (relative to a non-STEM degree).

$$I_M = \boldsymbol{X_M}\beta^M + \alpha^{M,A}\theta^A + \alpha^{M,B}\theta^B + e^M \tag{2}$$

where $\boldsymbol{X_M}$ is vector of all observed controls affecting major choice, β^M is the vector of coefficients associated with $\boldsymbol{X_M}$, $\alpha^{M,A}$ and $\alpha^{M,B}$ are the factor loadings. Again, I assume independency of the error term, i.e. $e^M \perp\!\!\!\perp (\theta^A, \theta^B, \boldsymbol{X_M})$. D_M (= 1 if $I_M > 0$) is a binary variable that equals one if the individual chooses a STEM major and zero otherwise. Thus the major choice model can be re-written as

$$D_M = \mathbb{1}[\boldsymbol{X_M}\beta^M + \alpha^{M,A}\theta^A + \alpha^{M,B}\theta^B + e^M > 0] \tag{3}$$

Choice of Job. After graduating from college, students face the choice between STEM and non-STEM jobs, for simplicity of the model. It is important to mention that the major to job flow is not a two by two combination (STEM major to STEM job, STEM major to non-STEM job, non-STEM major to non-STEM job, non-STEM major to STEM job). According to the Purdue dataset, there are only around 3% of observations in the sample falls into the fourth category. I exclude this category due to two reasons. First, a STEM job requires certain techniques that are usually obtained from the training of a STEM program and can hardly be handled by one graduated with a degree in a non-STEM major, in general. Second, due to small sample size, it is computationally impossible to calculate the model with the fourth category included. Therefore, the choice between STEM and non-STEM job will only happen among graduates with a degree in STEM major. The job choice mode is straightforward:

$$D_J = \mathbb{1}[\boldsymbol{X_J}\beta^J + \alpha^{J,A}\theta^A + \alpha^{J,B}\theta^B + e^J > 0] \text{ if } D_M = 1 \tag{4}$$

where $\boldsymbol{X_J}$ is vector of all observed controls affecting job choice, β^J, $\alpha^{J,A}$ and $\alpha^{J,B}$ are defined in the same way as in the major choice model. The error term $e^J \perp\!\!\!\perp (\theta^A, \theta^B, \boldsymbol{X_J})$. D_J is a binary variable that equals one if the individual chooses a STEM job and zero otherwise, conditional on graduating with a STEM degree ($D_M = 1$).

Now, we can re-define the salary equation (1) in terms of salary from different combinations of major choices and job choices. Let Y_{11} denotes the salary for those $D_M = 1$ and $D_J = 1$ (i.e. choosing STEM major and STEM job), and Y_{10} denotes the outcome for those $D_M = 0$ and $D_J = 1$ (i.e. choosing STEM major and non-STEM job), and so on. Then we can combine the salary equations and the choices equations to construct a system of outcomes, [Y_{11}, Y_{10}, Y_{00}, D_M, D_J]' where:

$$Y_{11} = X_Y\beta^{Y_{11}} + \alpha^{Y_{11},A}\theta^A + \alpha^{Y_{11},B}\theta^B + e^{Y_{11}}, \text{ if } D_M = 1, D_J = 1 \tag{5}$$

$$Y_{10} = X_Y\beta^{Y_{10}} + \alpha^{Y_{10},A}\theta^A + \alpha^{Y_{10},B}\theta^B + e^{Y_{10}}, \text{ if } D_M = 1, D_J = 0 \tag{6}$$

$$Y_{00} = X_Y\beta^{Y_{00}} + \alpha^{Y_{00},A}\theta^A + \alpha^{Y_{00},B}\theta^B + e^{Y_{00}}, \text{ if } D_M = 0 \tag{7}$$

$$D_M = \mathbb{1}[\boldsymbol{X_M}\beta^M + \alpha^{M,A}\theta^A + \alpha^{M,B}\theta^B + e^M > 0] \tag{8}$$

$$D_J = \mathbb{1}[\boldsymbol{X_J}\beta^J + \alpha^{J,A}\theta^A + \alpha^{J,B}\theta^B + e^J > 0] \text{ if } D_M = 1 \tag{9}$$

where the error terms $e^{Y_{11}}$, $e^{Y_{10}}$, $e^{Y_{00}}$, e^{M} and e^{J} are jointly independent once the unobserved heterogeneity (θ^A and θ^B) are controlled.

I use maximum likelihood estimation (MLE) to estimate the model[9] by integrating the likelihood function over the distributions of the two factors. The likelihood function is

$$
\begin{aligned}
\mathcal{L} &= \prod_{i=1}^{N} \iint \begin{bmatrix} f_{e^{y00}}(X_{Yi}, Y_0 i, \theta^A, \theta^B) \\ \times Pr[D_{Mi} = 0 | X_{Mi}, \theta^A, \theta^B]^{1-D_{Mi}} \times Pr[D_{Ji} = 0 | X_{Ji}, \theta^A, \theta^B]^{1-D_{Mi}} \\ \times f_{e^{y10}}(X_{Yi}, Y_{10} i, \theta^A, \theta^B) \\ \times Pr[D_{Mi} = 1 | X_{Ji}, \theta^A, \theta^B]^{D_{Mi}} \times Pr[D_{Ji} = 0 | X_{Ji}, \theta^A, \theta^B]^{1-D_{Ji}} \\ \times f_{e_{y_{11}}}(X_{Yi}, Y_{11} i, \theta^A, \theta^B) \\ \times Pr[D_{Mi} = 1 | X_{Mi}, \theta^A, \theta^B]^{D_{Mi}} \times Pr[D_{Ji} = 1 | X_{Ji}, \theta^A, \theta^B]^{D_{Ji}} \end{bmatrix} dF(\theta^A) dF(\theta^B) \\
&= \prod_{i=1}^{N} \iint \begin{bmatrix} f_{e^{y00}}(X_{Yi}, Y_0 i, \theta^A, \theta^B) \times \Phi(-\mathcal{M})^{(1-D_{Mi})} \\ \times f_{e^{y10}}(X_{Yi}, Y_{10} i, \theta^A, \theta^B) \times \Phi(\mathcal{M}, \mathcal{J})^{(D_{Mi})(1-D_{Ji})} \\ \times f_{e_{y_{11}}}(X_{Yi}, Y_{11} i, \theta^A, \theta^B) \times \Phi(\mathcal{M}, \mathcal{J})^{D_{Mi} D_{Ji}} \end{bmatrix} dF(\theta^A) dF(\theta^B)
\end{aligned} \tag{10}
$$

where ($\mathcal{M}$) denotes $(X_{Mi}\beta^M + \alpha^{M,A}\theta^A + \alpha^{M,B}\theta^B)$ and $\mathcal{J}$ denotes $(X_{Ji}\beta^J + \alpha^{J,A}\theta^A + \alpha^{J,B}\theta^B)$.

4.1 The Measurement System of The Two Latent Abilities

To implement the two-factor model described above, I need to first estimate the distributions of the unobserved factors by a measurement system specified based on the nature of the data. The measurement system takes the following form:

$$\boldsymbol{T} = \boldsymbol{X_T}\beta^T + \alpha^{T,A}\theta^A + \alpha^{T,B}\theta^B + \boldsymbol{e^T} \tag{11}$$

[9] I use a modified version of the relative developed STATA command—heterofactor—by Sarzosa and Urzúa (2016)

where $\boldsymbol{T}$ is a $L \times 1$ vector that contains each of the test scores associated to unobserved factors θ^A and θ^B, $\boldsymbol{X_T}$ is a matrix with all observable controls, $\alpha^{T,A}$ and $\alpha^{T,B}$ are the loadings of the unobserved factors. I assume that the error terms $\boldsymbol{e^T} \perp\!\!\!\perp (\theta^A, \theta^B, \boldsymbol{X_T})$. All elements in $\boldsymbol{e^T}$ are mutually independent.

Following the identification strategy of Carneiro et al. (2003), the distribution of two latent abilities, $F(\theta_A)$ and $F(\theta_B)$, the set of loadings of both abilities in each test score equations, Λ^T, are identified from variances and covariances of the residuals from Equation system (11). They show that three restrictions have to be fulfilled to identify the factors:

1. Orthogonality of the factors (i.e.);
2. $L \geq 2k + 1$, where L is the number of scores and k is the number of factors;
3. The factor structure within the measurement system needs to follow a triangular pattern, indicating that the first three scores are affected by the first factor only, while the second three scores are affected by both factors.

I use 6 test scores to identify 2 factors here. The test scores representing abilities at the beginning of college are listed in (12). The first three test scores are $ACT_{English}$, $COM_1 14$, and $ACT_{Reading}$; and the second three test scores are $ACT_{Science}$, $HSGPA$, and ACT_{Math}.

$$\boldsymbol{T} = \begin{bmatrix} T_1 \\ T_2 \\ T_3 \\ T_4 \\ T_5 \\ T_6 \end{bmatrix} = \begin{bmatrix} ACT_{English} \\ COM114 \\ ACT_{Reading} \\ ACT_{Science} \\ HSGPA \\ ACT_{Math} \end{bmatrix} \tag{12}$$

The structure of the loadings, $\boldsymbol{\Lambda^T}$, takes the following pattern in (13), where the first factor, general intelligence, is allowed to affect all the 6 scores; while the second factor, mathematical ability, is only allowed to affect scores of $ACT_{Science}$, $HSGPA$, and ACT_{Math}. The triangular pattern of the loading system that describes how each of the abilities load onto the different scores in Table 3. $\alpha^{T_3,A}$ (i.e. the loading of $ACT_{Reading}$) and $\alpha^{T_6,B}$ (i.e. the loading of ACT_{Math}) are normalized to facilitate the identification.

$$\boldsymbol{\Lambda^T} = \begin{bmatrix} \alpha^{T_1,A} & \alpha^{T_1,B} \\ \alpha^{T_2,A} & \alpha^{T_2,B} \\ \alpha^{T_3,A} & \alpha^{T_3,B} \\ \alpha^{T_4,A} & \alpha^{T_4,B} \\ \alpha^{T_5,A} & \alpha^{T_5,B} \\ \alpha^{T_6,A} & \alpha^{T_6,B} \end{bmatrix} = \begin{bmatrix} \alpha^{T_1,A} & 0 \\ \alpha^{T_2,A} & 0 \\ 1 & 0 \\ \alpha^{T_4,A} & \alpha^{T_4,B} \\ \alpha^{T_5,A} & \alpha^{T_5,B} \\ \alpha^{T_6,A} & 1 \end{bmatrix} \tag{13}$$

The likelihood function is:

$$\mathcal{L} = \prod_{i=1}^{N} \iint \begin{bmatrix} f_{e^{T_1}}(X_{Ti}, T_1 i, \gamma^A, \gamma^B)\times \\ ... \times f_{e^{T_6}}(X_{Ti}, T_6 i, \gamma^A, \gamma^B) \end{bmatrix} dF(\theta^A)dF(\theta^B) \tag{14}$$

5 Main Results

5.1 Latent Abilities

Table 4 and Table 5 show the results of the estimation of the measurement system (11) used to identify general intelligence and mathematical ability for women and men, respectively. The set of controls X_T includes annual state-averaged freshmen graduation rate (AFGR) on the year of each student graduated from high school, home region[10] fix effects and first enrollment semester fix effects. (Table 6 lists the controls in each model and exclusion restrictions.)

Estimated distributions are shown in Figure 1 and Figure 2. They both show that the latent abilities are far from normal. Particularly, both women's and men's general intelligence distribution have a fat right tail. Especially for women, there is an obvious hump on the right tail. This implies women's general intelligence is very spread out. Also, the proportion of high-ability women is relatively big, compared to that of men.

One should be cautious when interpreting the two latent abilities in this paper. Mathematical ability is the factor assumed to be orthogonal to the other factor, general intelligence. It is measured by the "left over" variations of the test scores—ACT_{Math}, $ACT_{Science}$ and $HSGPA$—after general intelligence is measured. Thus, one could consider "mathematical ability" in this paper as the "extra mathematical ability" conditioning on a certain level of general intelligence.

5.2 The Roy Model

5.2.1 Model Fit

Tables 7 presents evidence on the models' goodness-of-fit on the first and second moments for major choice, job choice and salary. They are product of 10,000 simulations of the model based on as many different draws from the distributions of the two abilities. Comparing the "Data" and the "Model Prediction", it is clear that the model accurately predicts the means and standard deviations for each outcome of each gender. This provides confidence about the fact that the counterfactuals

[10] I define 6 home regions according to the Census regions: Northeast, South, West, Midwest, and Indiana. It is important to have Indiana as a home region itself, because there are many in-state students and they are likely to be different from out-of-state students in educational and family backgrounds.

predicted by the model are appropriate.

5.2.2 Major Selection

Table 8 shows the effect of abilities on selection between STEM and non-STEM majors. Column (1) and (2) show the marginal effects of the probit at the means for women and men, respectively. To take into consideration of cohort specific effects, I control for enrollment calendar year fixed effects, enrollment semester fixed effects, degree calendar year fixed effects, degree semester fixed effects, number of graduates in the same major[11] in the same year, and number of female graduates in the same major in the same year.

Both general intelligence and mathematical ability are significant determinants of the likelihood of graduating with a STEM degree. Specifically, a one standard deviation increase in an average woman's general intelligence will increase her probability of graduating with a STEM degree by 17.16 percentage points; and a one standard deviation increase in an average man's general intelligence will increase his likelihood of graduating with a STEM degree by 23.36 percentage points. These estimates are large and statistically significant. The marginal effect of general intelligence on major choice of men are larger than that of their female counterparts. Similarly, mathematical ability is an significantly more important determinant on major choice for men than for women. A one standard deviation increase in an average man's mathematical ability will raise his likelihood of graduating with a STEM degree by 14.02 percentage points; while that number is 9.52 for an average woman.

Therefore, both general intelligence and mathematical ability are weaker determinants of major selection for women than for men. Potential explanations could

[11] A major is defined by a 6-digit level CIP code (Classification of Instructional Programs).

be that, first, women are less sensitive to their abilities when making the decision between majoring in STEM and non-STEM. Second, other factors are more dominating for women's major decision, which is consistent to the literature on gender specific preference on college majors. Last, women might be more critical about their abilities or more easily to get discouraged about their performance on coursework (Ahn et al., 2015). Unfortunately, I do not capture the major switching behavior in this study; thus I cannot draw any conclusion about women.

5.2.3 Job Selection

Students who graduated with a degree in STEM face the choice between STEM and non-STEM jobs. As mentioned above, I restrict the model to only allow STEM graduates to choose between the two types of jobs. In this sense, non-STEM graduates are automatically filled in non-STEM jobs. To capture the macroeconomic condition and job market intensity in a certain year, I control for degree year fixed effects. I include controls for home state demand of STEM worker (number of STEM occupations in home state), home region fix effects, considering that people might take home location into account when making job decision. I also control for total number of Purdue graduates in the same major and number of Purdue female graduates in the same major.

Table 9 shows the marginal effects of latent abilities on probability of working in STEM for STEM major graduates. Compared to major selection, both latent abilities are much weaker determinants of the likelihood of working in a STEM job. The weak estimates imply that neither men nor women select between STEM and non-STEM job based on their abilities. This is not surprising: giving the fact that they have already graduated with a STEM degree, they should be similarly capable for a STEM job.

Specifically, a one standard deviation increase in general intelligence for an average female STEM graduate leads to an increase in her likelihood of working in STEM by 6.83 percentage points. For an average male STEM graduate, a one standard deviation increase in his general intelligence will increase his probability of staying STEM by 4.11 percentage points. The sorting on general intelligence when making job decision is not statistically different between women and men. Even though there is no gender differences in these level changes in likelihood of staying in STEM, the percent changes are quite different. The 6.83 percentage points increase in female STEM graduates' likelihood in staying in STEM will push up the fraction of Purdue female STEM graduates staying in STEM after graduation on the base of 73.1% by 9.34 percent. But in contrast, the 4.11 percentage points increase in men's probability in working in STEM will only increase the the fraction of Purdue male STEM graduates in STEM jobs on the base of 81.2% by 5.06 percent.

Compared to general intelligence, mathematical ability is a less important determinant in job decision for STEM graduates. A one standard deviation increase in an average female STEM graduate's mathematical ability will increase her likelihood of working in STEM by 5.17 percentage points; for men, that is 3.21 percentage points.

5.2.4 Salary

Table 10 and Table 11 show the salary returns to abilities for male and female who endogenously sort into different majors and jobs[12]. Column (1) to (3) in each table present the coefficients of interest for three types of men/women—graduating with a STEM degree and working in STEM, graduating with a STEM degree and working in non-STEM, and graduating with a non-STEM degree and working in non-

[12] The full table of estimates is in Appendix A.4, A.5, and A.6.

STEM—respectively. For simplicity, I denote these three types of men as $Male_{11}$, $Male_{10}$, and $Male_{00}$; same for women. I control for state-level annual unemployment rate, job region fixed effects[13], national annual total number of graduates, total number of graduates in STEM, total number of female graduates, total number of female STEM graduates, fraction of STEM employment in total employment, STEM and non-STEM total employment.

In general, both general intelligence and mathematical ability have positive returns to salary for all three types of women and men. Women are more rewarded for both of their abilities then men, comparing the magnitude of the estimates. One thing to note, all types of women—$Female_{11}$, $Female_{10}$ and $Female_{00}$—are rewarded for their mathematical ability. For an average woman who graduates with non-STEM degree and works in a non-STEM job, a one standard deviation increase in her mathematical ability will increase her annual salary by \$2474. In contrast, $Male_{00}$ has no significant return to mathematical ability. This can be one explanation that why women are less likely to enroll in STEM major: women with high mathematical ability are more rewarded outside of STEM field relative to men. Although the mechanism is inconclusive without further evidence, the suggestion here is interesting and straightforward: women should invest in mathematical ability.

Comparing within gender, $Male_{10}$ and $Male_{00}$ have smaller salary return to general intelligence, relative to $Male_{11}$. However, those estimates are not statistically different from each other. $Female_{11}$ and $Female_{10}$ have significantly higher returns to general intelligence compared to $Female_{00}$, again suggesting that high-ability women should major in STEM.

[13]I defined 10 job regions according to the Census regional devisions: "New England", "Mid-Atlantic", "East North Central", "West North Central", "South Atlantic", "East South Central", "West South Central", "Mountain", "Pacific", and "Indiana". It is important to have Indiana as a regional devision here, because there is a large fraction of in-state students; and a large fraction of them will hold a in-state job after graduation.

5.3 The Distributions of Abilities of The Three Career Paths

To reveal the link between latent abilities and the endogenous choices between STEM and non-STEM major and job, I construct Figure 3–Figure 6. Figure 3 presents the distributions of general intelligence of $Male_{00}$, $Male_{10}$, and $Male_{11}$, from the left to the right. All three distributions are far from normal. Comparing $Male_{00}$ to the other two, it is clear that men with a STEM degree are having significantly higher general intelligence compared to men with a non-STEM degree. Particularly, both the distributions of $Male_{10}$ and the $Male_{11}$ have a slight "swelling" on the right tails, indicating that men with relatively high general intelligence sort into STEM majors. Figure 4 shows the distributions of mathematical ability of the three categories of men. Similarly, Figure 4 shows that the distribution of $Male_{00}$ is apart from the distributions of $Male_{10}$ and $Male_{11}$, indicating men with high mathematical ability are more likely to be majoring in STEM.

Women's sorting behavior in major decision is surprisingly different from men's. Figure 5 shows general intelligence distributions of $Female_{00}$, $Female_{10}$, and $Female_{11}$. Remarkably, high-ability women are more likely to major in non-STEM, relative to their male counterparts. The hump on the right tail of the distribution of $Female_{00}$ suggests that a mass of women with high general intelligence graduate with non-STEM majors. We don't see this in the distribution of $Male_{00}$. Moreover, there is little evidence of sorting on mathematical ability among women: the three distributions in Figure 6 are equally apart from each other. This suggests that mathematical ability is a weaker determinant for women to make major decision relative to men.

Overall, the difference of the sorting behavior in major decision between men and women revealed by the ability distributions mirrors my finding in Table 8; that is, men sort on both abilities more than women. The high-ability women seem to be "ignoring" or misreading their abilities when making major decision. This is very interesting but not surprising: one potential explanation comes from the literature about women being too critical about their skills and less confident relative to men (Ahn et al., 2015). Furthermore, the fact that the distributions of 10 and 11—for both gender—are close to each other suggests that neither men nor women sort greatly on abilities when making job decision, which is consistent with estimates in Table 9.

6 Counterfactuals

6.1 Counterfacutals for Major Choice

Now let's get back to the question that why women are less likely to major in STEM than men. Table 12 presents the results of counterfactual analysis on likelihood of majoring in STEM, following the approach in Urzua (2008). The first row displays the model predicted proportion of graduates with a STEM major by gender, $D_M^f(\beta^{M,f}, X_M^f, \alpha^{M,A,f}, \alpha^{M,B,f}, \theta^{A,f}, \theta^{B,f})$ and $D_M^m(\beta^{M,m}, X_M^m, \alpha^{M,A,m}, \alpha^{M,B,m}, \theta^{A,m}, \theta^{B,m})$.

The second row shows that 37.49% of women would graduate in STEM when women are assumed to have the the same loadings as men ($D_M^f(\beta^{M,f}, X_M^f, \alpha^{M,A,m}, \alpha^{M,B,m}, \theta^{A,f}, \theta^{B,f})$). The third row shows women's proportion of graduates in STEM increases to 39.58% when women are assumed to have the same ability distributions as men ($D_M^f(\beta^{M,f}, X_M^f, \alpha^{M,A,f}, \alpha^{M,B,f}, \theta^{A,m}, \theta^{B,m})$). Furthermore, by assuming that women have the same ability distributions and the same returns to abilities, the proportion of graduates in STEM would be 40.37%. The counterfactuals above show that women would be slightly more likely to major in STEM, or the gender differences in STEM major would have shrunken, had they possessed the same ability distributions or evaluated their abilities in the same way as men; but the changes are not statistically different from the factual.

Giving that the gender differences in major choice is not primarily due to gender differences in the latent abilities and returns to abilities, I conduct the similar exercises on the observables. Substituting women's coefficients of the observables with men's ($D_M^f(\beta^{M,m}, X_M^f, \alpha^{M,A,f}, \alpha^{M,B,f}, \theta^{A,f}, \theta^{B,f})$), the fifth row shows that the proportion of STEM graduates in female graduates would have significantly increased to 42.53%. Besides that, the counterfactuals in row 6 and row 7 also suggest that gender differences in major decision can be attributed to observable characteristics, including economic conditions and cohort effects. There are more left as unexplained, however, could be due to unobserved personal preferences. Those unobserved gender-specific personal preferences are more dominating when women are making major choice, as shown in previous studies.

6.2 Counterfactuals for Job Choice

The weak determinants in the job model imply that neither men nor women select greatly between STEM and non-STEM job based on their abilities. This is very interesting, given the fact that they have already graduated with a STEM degree. Another question this paper intends to answer is why female STEM graduates choose different jobs than their male counterparts. Given that it is not due to the differential sorting behavior on abilities from the results shown in Table 9, no wonder that substituting women's latent abilities or men's returns to abilities with men's does not close the gender gap in job decision (see row 2 to row 4 in Table 13). I then seek answers from the gender differences in the observable characteristics.

To do so, I show the proportion of female STEM workers in female STEM graduates when compensating them with men's returns to the observable characteristics

$(D_J^f(\beta^{J,m}, X_J^f, \alpha^{J,A,f}, \alpha^{J,B,f}, \theta^{A,f}, \theta^{B,f}))$. Row 5 in Table 13 shows that women would have been more likely to stay in STEM when assumed they had the same returns to the observable characteristics as men. Particularly, there would be 75.12% female STEM graduates stay in STEM field, instead of the factual, 70.05%. This 5 percentage points increase explains 41.5% of gender gap of choosing between a STEM job and a non-STEM job among STEM graduates. The implication here is similar to the counterfactual analysis on major decision: gender differences in job choice among STEM graduates can be explained by gender differences in the coefficient of the observables but not the latent abilities.

After a full decomposition of the predictors in the job selection model, I find that the region where one is from is a major factor for female STEM graduates and their decision to pursue a STEM or non-STEM job. In Table 14, column (1) shows the counterfactuals of excluding the each variable, and column (2) shows the counterfactuals of substituting women's each coefficient with men's. Giving men's home region fixed effects to women, the gender gap on job choice is fully closed. Additionally, none of the other predictors significantly explains the gender gap. Although this is not conclusive, the potential mechanism is very interesting: there may be a trade-off between non-STEM job at home state and high-paying STEM job opportunity away from home for female STEM graduates. Table 16 also shows supportive evidence: those who go back to their home state are more likely to opt out of STEM fields. This finding sheds new light on the studies about career choices of female STEM graduates; and even on a broader topic of women's career choices.

6.3 The Effect of Majoring in STEM

I calculate the ATE (average treatment effect), TT (treatment effect on the treated) and TUT (treatment effect on the untreated) of majoring in STEM for women and men, respectively.

$$ATE_M = E[Y_{11} - Y_{00}|\theta]$$

$$TT_M = E[Y_{11} - Y_{00}|\theta, D_m = 1]$$

$$TUT_M = E[Y_{11} - Y_{00}|\theta, D_m = 0]$$

where the treatment is majoring in STEM, noted as subscript M. I show both specification of this treatment effect of majoring STEM, one is using the estimates of $Female_{11}$ (see Panel A in Table 15), the other is using the estimates of $Female_{10}$ (see Panel B in Table 15). Generally speaking, women are more rewarded than men for majoring in STEM, revealing by all treatment effects. Specifically, an average woman who is picked at random from the entire female sample would earn \$13,553 more if she works in STEM with a STEM degree rather than works in non-STEM with a non-STEM degree. That number is only \$9,932 for an average man. As expected, the TT is larger than the TUT, because the abilities of the treated group is higher than that of the untreated group. When computing the treatment effect of majoring in STEM based on the comparison between the 10 and the 00 groups (i.e. $ATE_M = E[Y_{10} - Y_{00}|\theta]$), the gender differences in treatment effects to majoring in STEM is not significantly different. Thus, two points have been made here: first, on average, both women and men have positive treatment effect of majoring and working in STEM; second, the gender differences in treatment effect in majoring in STEM can be attributed to gender differences in rewards for a STEM job.

Figure 7 shows the ATE of majoring in STEM for each gender, over the deciles of general intelligence. Similarly, Figure 8 shows that over the deciles of mathematical ability. Both curves on the left and right panels are upward sloping, indicating that the individuals possess higher ability are rewarded more than the others. In addition, again, women's curves are above the level of men's, indicating that women are more rewarded in majoring in STEM. Ironically, the fact is just the opposite.

To capture the counterfactuals for the individual on the margin of the treatment, I calculate the marginal treatment effect (MTE) of majoring in STEM for women and men, respectively.

$$MTE_i = E[Y_{11} - Y_{00} | Pr(X_{M,i}\beta^M + \alpha^{M,A}\theta_i^A + \alpha^{M,B}\theta_i^B = e_i^M) = 1]$$

where MTE_i is the treatment effect of majoring in STEM for an individual with observed characteristics $X_M = X_{M,i}$ and unobservable abilities $\theta^A = \theta_i^A$ and $\theta^B = \theta_i^B$, implying the individual is indifferent to majoring in STEM or not when having $X_{M,i}$, θ_i^A, and θ_i^B.

Figure 9 and Figure 10 present the MTE of majoring in STEM for each gender over the deciles of each abilities. There are several things stand out. First, MTE are positive and sufficiently large under both specifications for the entire ability space. Second, individuals at the higher quantiles of both ability distributions have higher MTE, except the MTE across mathematical ability in the left panel of Figure 10, which is rather flat. Third and most important, individuals at the right tail of each ability distribution, the high-ability ones, are having significantly large MTE. This suggests that women with high ability have MTE up to $20,000 in terms of annual salary. Those high-ability non-STEM women I am referring to are exactly the ones distributed under the mass on the right tail of the $Female_{00}$ curve in Figure 5.

Men's MTE of majoring in STEM is significantly lower than that of women, comparing the left and right panels on both Figure 9 and Figure 10. This suggests, again, women's gain from majoring in STEM is significantly larger than that of male's, conditioning on that they are indifferent of being treated. In addition, it might not be that obvious on these figures, but women's MTE of women are slightly larger than ATE, especially on the left tail of the general intelligence distribution.

Meanwhile, the MTE of men are slightly smaller than the ATE of men.

6.4 The Effect of Working in STEM

In the Section 5.2.3, I address the fact that women are less likely to stay in STEM after they graduated with a STEM degree and point out that it is not due to gender differences in sorting on abilities. The next question is "how much do they lose by opting out STEM?" To answer that, I calculate the ATE and TT and TUT of having a STEM job relative to having a non-STEM job for those who graduated with a STEM degree.

$$ATE_J = E[Y_{11} - Y_{10}|X_J = x, D_m = 1]$$

$$TT_J = E[Y_{11} - Y_{10}|X_J = x, D_m = 1, D_j = 1]$$

$$TUT_J = E[Y_{11} - Y_{10}|X_J = x, D_m = 1, D_j = 0]$$

Panel C in Table 15 shows that for a woman who is picked at random from the sample of women who graduated with a STEM degree, working in a STEM job increases her annual salary by \$7,459. Although this number is not particularly large, compared to men, the salary foregone for women who left STEM after graduation is much more than that of their male counterpart. Figure 11 and Figure 12 reveal the same implication. One may notice that the ATE is downward sloping across deciles of mathematical ability. This is due to the fact that the salary return to mathematical ability among the 10 group is higher than that of the 11 group. This implies that the returns to working in STEM is positive across the entire distribution of mathematical ability; but with a declining marginal return. Figure 13 and Figure 14 depict the marginal treatment effect of working in STEM for each gender over the deciles of each abilities. They look similar to the figures of ATE, besides that the MTE of working in STEM across each ability distribution for women is slightly larger than the corresponding ATE. Yet this is not true for the males.

Since there is not much selection on abilities between STEM and non-STEM jobs, it is not surprising that the treatment on an average treated woman, \$7449, is no different than the treatment on an average untreated woman, \$7495 (see Panel C in Table 15). Thus, by opting out STEM, an average female STEM graduate loses \$7495 salary per year. Alternatively, assuming $Female_{10}$ are making their optimal decision, the nonpecuniary value that an average woman gains by leaving STEM field after graduation, is at least as much as \$7495 per year. Hypothetically, a female STEM graduate takes a low-pressure non-STEM job to take care of her family. The interesting question here is if that family time worths \$7495 per year to her; perhaps yes, then how would the STEM industry compensate the female workers to retain them?

6.5 Foregone Earnings of the High-Ability Women And the Gender Wage Gap

As mentioned above, high-ability women in the distribution of $Female_{00}$ group could have earned a lot more had they got a STEM degree. To quantify the total losses in terms of salary by this group, I integrate the marginal treatment effect of majoring in STEM over the shadowed area on Figure 15. This shadowed area created by the interaction of the general intelligence distribution of $Male_{00}$ with that of $Female_{00}$, where there is a mass of the women distributed on the hump shaped region of general intelligence distribution of the $Female_{00}$. Assuming high-ability women act like high-ability men when making major decision (i.e. the individuals distributed on the right tail of general intelligence distribution of $Female_{00}$ be like that of $Male_{00}$), how much would they gain?

The value generated by the shadowed area is \$772.4168, which explains 9.42% of the gender wage gap. The gender wage gap, \$8198, is calculated by subtracting Purdue male graduates' average annual salary by Purdue female graduates' average annual salary. Although 9.42% is not a gigantic number at the first glance, one should not take it for granted: the 9.42% of the gender wage gap is only contributed by the high-ability women who make up the mass on the right tail of $Female_{00}$ distribution; those high-ability women only make up 5.6% of the Purdue female sample. Thus, one should not interpret as every woman gains \$772.4168 per year by majoring in STEM, which is clearly minuscule. Instead, the 9.42% is all attributed to the 5.6% high-ability women, who are most likely to be capable of majoring in STEM; and each of them would have gained about \$13,000–\$20,000 per year.

7 Policy Implications

A possible policy implication of the findings in this paper is to encourage programs or activities that improve the awareness of their own abilities of high school girls. Transcripts of SAT and ACT informs high school students about their percentile rankings in these standardized tests, which indicate how they did compared to everyone else. However, that is not informative enough for college major decision. High school students and their parents may not know what those scores and percentile rankings mean in terms of potential careers.

The Career Mapping Visualization System created by a research group[14] funded by Eli Lilly has made a visualization tool to help high school students understand the requirements for graduating from a certain major and the requirements for

[14] Lilly Endowment for "Transforming Indiana into a Magnet for High Technology Jobs".

each occupation[15]. This facilitates high school students, parents and teachers to comprehend the requirement of each career path and the expected abilities among their peers, and to have an appropriate expectation on their career outcome.

Also, it is crucial to make high school girls more informed about the returns to a STEM education. It is costly to train students to be "ready" for STEM, why don't we attract the "already-ready" ones—the high-ability women in this study—to major in STEM? Considering how much would have been made by the high-ability women, we should encourage state funded program designed to attract high-ability high school girls to STEM majors, which could be financed by the tax revenue equivalent to the tax from the 9.4% gain. For instance, state funded program for campus visit of middle or high school girls; for instance, UT Austin's Girl's Day[16].

8 Conclusion

This paper investigates the gender differences in ability sorting in major and job choices by applying a semi-structural model of unobserved heterogeneity to explore the endogenous sequential decisions: the choice between a STEM and non-STEM major and the choice between a STEM and non-STEM job. I find that women sort less on abilities when making major decisions; and high-ability women are more likely to choose non-STEM major, compared to men. By majoring in non-STEM majors, high-ability women have as much as \$13,000–\$20,000 annual salary foregone, which explains about 9.4% of the gender wage gap. There are several potential explanations for this sorting behavior among high-ability women. First, they may have a poor judgment on their ability. Second, they may be not informed well about the pecuniary value of the career paths associated with their abilities.

[15] https://va.tech.purdue.edu/careerVis/
[16] https://girlday.utexas.edu

Last but not least, those high-ability women could intentionally choose the non-STEM career path to have the nonpecuniary value of pursuing their ideal but low-paying jobs or taking care of family, as suggested in the literature.

Another contribution of this paper is to affirm that gender gap on job choice is *not* due to different sorting on abilities, but to other observable or unobserved characteristics. The region where one is from is a major factor for female STEM graduates and their decision to pursue a STEM or non-STEM job. Those who go back to their home state are more likely to opt out of STEM fields. The future research should investigate the effect of family on female STEM graduates' job choice and seek answers for whether they are going back home for a familiar social network, marriage or access to child care.

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Table 1: Sample Selection

Sample	**Total**	**Female**	**Male**
All	18,904	8,763	10,141
Six Scores Complete	10,516	4,682	5,834
Six Scores Complete (Domestic Student)	10,282	4,565	5,640
First Destination Survey Complete	4,192	1,687	2,505
Valid Self-Reported Salary	3,055	1,145	1,910

Note: The sample includes undergraduate cohorts graduated from 2005–2014. Six scores include: ACT English, Com114, ACT Reading, ACT Science, high school GPA, and ACT Math. A valid self-reported salary means an annual salary>zero.

Table 2: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Panel A. Females					
ACT_E	25.661	4.617	11	36	1145
COM114 grade points	3.526	0.570	1	4	1145
ACT_R	25.94	4.944	12	36	1145
ACT_S	24.668	3.960	12	36	1145
HS_GPA	3.532	0.426	2	4	1145
exp(HS_GPA)	36.971	13.043	7.389	54.598	1145
ACT_M	25.645	4.517	15	36	1145
Self-reported Annual Salary	45179.963	14365.635	8000	101000	1145
STEM Major	0.370	0.483	0	1	1145
STEM Job	0.271	0.445	0	1	1145
STEM Major, STEM Job	0.731	0.444	0	1	424
Panel A. Males					
ACT_E	25.507	4.64	11	36	1910
COM114 grade points	3.339	0.63	1	4	1910
ACT_R	26.278	4.951	8	36	1910
ACT_S	26.73	4.398	11	36	1910
HS_GPA	3.483	0.427	2	4	1910
exp(HS_GPA)	35.29	12.868	7.389	54.598	1910
ACT_M	28.237	4.185	15	36	1910
Self-reported Annual Salary	53427.169	13178.711	5250	107000	1910
STEM Major	0.634	0.482	0	1	1910
STEM Job	0.516	0.5	0	1	1910
STEM Major, STEM Job	0.812	0.391	0	1	1211

Note: The sample includes undergraduate cohorts graduated from 2005–2014. COM114 grade points range from 2-4. Whoever fail the class has to re-take the class in order to graduate; and I do not observe dropouts. "exp(HS_GPA)" is the exponential of high school GPA. Self-reported Annual Salary is nominal and in USD.

Table 3: Structure of Measurement System of Abilities

Scores	General Intelligence	Mathematical Ability
$ACT_{English}$	X	
$COM114$	X	
$ACT_{Reading}$	X	
$ACT_{Science}$	X	X
$HSGPA$	X	X
ACT_{Math}	X	X

Note: The loading of $ACT_{Reading}$ is normalized to one; so as the loading of ACT_{Math}.

Table 4: Identification of Abilities at College Entrance, Female

	ACT_E	COM114	ACT_R	ACT_S	HSGPA	ACT_M
Home Region: Indiana	-0.569	-0.128	-0.660	-1.209***	1.889	-0.801
	(0.773)	(0.094)	(0.827)	(0.449)	(1.832)	(0.510)
Home Region: Midwest	1.044	-0.171*	0.210	-0.201	-3.313*	0.335
	(0.783)	(0.099)	(0.853)	(0.477)	(1.946)	(0.547)
Home Region: Northeast	-1.389	-0.260*	-0.893	-0.897	-1.779	0.0322
	(1.158)	(0.147)	(1.264)	(0.709)	(2.892)	(0.797)
Home Region: South	2.594**	-0.073	1.918*	1.141**	2.550	1.839***
	(1.066)	(0.120)	(1.108)	(0.573)	(2.334)	(0.656)
AFGR	0.122***	0.013**	0.103**	0.113***	0.566***	0.111***
	(0.039)	(0.005)	(0.043)	(0.0255)	(0.103)	(0.030)
First Term Semester: Fall	2.042*	-0.112	2.557*	1.550*	8.124**	2.827**
	(1.084)	(0.178)	(1.327)	(0.942)	(3.727)	(1.306)
First Term Semester: Spring	-1.536	-0.050	0.597	-1.167	-4.794	-1.524
	(1.552)	(0.258)	(1.905)	(1.301)	(5.257)	(1.648)
General Intelligence	1.127***	0.045***	1	0.771***	1.780***	0.832***
	(0.020)	(0.005)	X	(0.025)	(0.097)	(0.029)
Math Ability				0.361***	1.199***	1
				(0.043)	(0.161)	X
Constant	14.043***	2.754***	15.706***	15.13***	-13.83	14.54***
	(3.088)	(0.427)	(3.486)	(2.128)	(8.585)	(2.620)
Observations	1,145	1,145	1,145	1,145	1,145	1,145

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Note: The sample includes undergraduate cohorts graduated from 2005–2014. Column (1) and column (2) show the marginal effect of probit at the means for the female and male sample, respectively. All marginal effects reflect to changes in probability of working in STEM with one unit increase in the corresponding ability of STEM graduates. The standard deviation of female's and male's general intelligence is 3.496 and 3.349; the standard deviation of female's and male's mathematical ability is 2.723 and 2.771. The dependent variable in both column (1) and (2) is dummy of majoring in STEM. Number of Purdue graduates in the same major, number of Purdue female graduates in the same major, home state STEM demand, degree year fixed effects, home region fixed effects are controlled but not shown in this table for short (see Appendix for the full table). The factor loadings are also shown in the full table in Appendix. Home region at West and first term semester at Summer are omitted because of collinearity.

Table 5: Identification of Abilities at College Entrance, Male

	ACT_E	COM114	ACT_R	ACT_S	HSGPA	ACT_M
Home Region: Indiana	-2.216***	-0.071	-1.981***	-1.831***	-0.180	-1.388***
	(0.687)	(0.080)	(0.703)	(0.397)	(1.437)	(0.394)
Home Region: Midwest	-0.995	-0.206**	-1.111	-0.427	-5.342***	-0.267
	(0.736)	(0.085)	(0.748)	(0.421)	(1.519)	(0.421)
Home Region: Northeast	-1.441	-0.204*	-1.138	-0.290	-3.640*	-0.415
	(0.978)	(0.119)	(1.013)	(0.577)	(2.120)	(0.536)
Home Region: South	0.0362	-0.013	-0.068	0.188	-0.141	0.704
	(0.742)	(0.093)	(0.777)	(0.479)	(1.699)	(0.518)
AFGR	0.169***	0.019***	0.089**	0.108***	0.654***	0.124***
	(0.031)	(0.004)	(0.034)	(0.0224)	(0.0810)	(0.0226)
First Term Semester: Fall	4.941***	0.210	3.610**	5.844***	13.67***	6.089***
	(1.011)	(0.179)	(1.237)	(0.853)	(3.228)	(0.670)
First Term Semester: Spring	2.794**	-0.232	1.270	4.297***	10.26**	4.402***
	(1.315)	(0.225)	(1.578)	(1.110)	(4.100)	(1.019)
General Intelligence	1.151***	0.045***	1	0.831***	1.557***	0.729***
	(0.017)	(0.004)	X	(0.022)	(0.078)	(0.021)
Math Ability				0.455***	1.107***	1
				(0.029)	(0.103)	X
Constant	9.045***	2.204***	17.235***	13.607***	-25.932***	13.383***
	(2.582)	(0.379)	(2.880)	(1.888)	(6.891)	(1.810)
Observations	1,910					

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Note: The sample includes undergraduate cohorts graduated from 2005–2014. Column (1) and column (2) show the marginal effect of probit at the means for the female and male sample, respectively. All marginal effects reflect to changes in probability of working in STEM with one unit increase in the corresponding ability of STEM graduates. The standard deviation of female's and male's general intelligence is 3.496 and 3.349; the standard deviation of female's and male's mathematical ability is 2.723 and 2.771. The dependent variable in both column (1) and (2) is dummy of majoring in STEM. Number of Purdue graduates in the same major, number of Purdue female graduates in the same major, home state STEM demand, degree year fixed effects, home region fixed effects are controlled but not shown in this table for short (see Appendix for the full table). The factor loadings are also shown in the full table in Appendix. Home region at West and first term semester at Summer are omitted because of collinearity.

Table 6: Observed Controls in Each Model (Exclusion Restrictions)

Variables	Controls			
	X_T	X_M	X_J	X_Y
Averaged Freshmen Graduation Rate (AFGR)	Yes			
First Enrollment Year Fixed Effects		Yes		
First Enrollment Semester Fixed Effects	Yes	Yes		
Home (Census) Region Fixed Effects	Yes		Yes	
Degree Year Fixed Effects		Yes	Yes	
Degree Semester Fixed Effects		Yes	Yes	
# Purdue Graduates in Same Major		Yes	Yes	
# Purdue Female Graduates in Same Major		Yes	Yes	
State-level STEM Employment			Yes	
STEM Fraction of Total Employment				Yes
# STEM Total Employment				Yes
# nonSTEM Total Employment				Yes
# Total Graduates				Yes
# STEM Major Graduates				Yes
# Female Graduates				Yes
# Female STEM Major Graduates				Yes
State Annual Unemployment Rate				Yes
Job Location Region Fixed Effects				Yes

Table 7: The Fit of the Model

	Female	Male
Panel A. STEM Major		
Data	0.3703 (0.4831)	0.6340 (0.4818)
Model Prediction	0.3705 (0.4830)	0.6354 (0.4813)
N	1145	1910
Panel B. STEM Job		
Data	0.7311 (0.4439)	0.8117 (0.3911)
Model Prediction	0.7005 (0.4579)	0.8020 (0.3984)
N	424	1211
Panel C. $Salary_{11}$		
Data	58280 (11298.910)	58669.21 (11072.49)
Model Prediction	56513.93 (11362.94)	57991.49 (10969.02)
N	310	983
Panel D. $Salary_{10}$		
Data	48180.07(14031.83)	54357.9 (13285.75)
Model Prediction	47347.81 (13460.25)	54247.45 (13196.58)
N	114	228
Panel E. $Salary_{00}$		
Data	39038.96(11370.31)	45558.46 (11758.58)
Model Prediction	39573.29 (11398.77)	46375.31 (11647.44)
N	721	699

Note: The sample includes undergraduate cohorts graduated from 2006-2015. Panel A shows the estimates from the female sample and Panel B shows the male sample. Standard deviations are in the parenthesis.

Table 8: Likelihood of Graduating with A STEM Major

	(1) Female	(2) Male
	Marginal Effects at the Mean	
General Intelligence	0.048***	0.066***
	(0.0058)	(0.0056)
Mathematical Ability	0.034***	0.049***
	(0.0084)	(0.0063)
N	1145	1910

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Note: The sample includes undergraduate cohorts graduated from 2005–2014. Column (1) and column (2) show the marginal effect of probit at the means for the female and male sample, respectively. All marginal effects reflect to changes in probability of graduating in STEM with one unit increase in the corresponding ability. The standard deviation of female's and male's general intelligence is 3.576 and 3.539; the standard deviation of female's and male's mathematical ability is 2.801 and 2.862. The dependent variable in both column (1) and (2) is dummy of majoring in STEM. Number of Purdue graduates in the same major, number of Purdue female graduates in the same major, degree year fixed effects, home state STEM demand (number of STEM occupations in home state), home region fix effects are controlled but not shown in this table for short (see Appendix for the full table). The factor loadings are also shown in the full table in Appendix.

Table 9: Likelihood of STEM Major Graduates Working in A STEM Occupation

	(1) Female	(2) Male
	Marginal Effects at the Mean	
General Intelligence	0.0191*	0.0116**
	(0.0109)	(0.0059)
Mathematical Ability	0.0190	0.0116*
	(0.0159)	(0.0070)
N	1145	1910

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Note: The sample includes undergraduate cohorts graduated from 2005–2014. Column (1) and column (2) show the marginal effect of probit at the means for the female and male sample, respectively. All marginal effects reflect to changes in probability of working in STEM with one unit increase in the corresponding ability of STEM graduates. The standard deviation of female's and male's general intelligence is 3.496 and 3.349; the standard deviation of female's and male's mathematical ability is 2.723 and 2.771. The dependent variable in both column (1) and (2) is dummy of majoring in STEM. Number of Purdue graduates in the same major, number of Purdue female graduates in the same major, home state STEM demand, degree year fixed effects, home region fixed effects are controlled but not shown in this table for short (see Appendix for the full table). The factor loadings are also shown in the full table in Appendix.

Table 10: Salary for Males

VARIABLES	(1) Salary11	(2) Salary10	(3) Salary00
Unemployment Rate at Job State	-838.5**	-1,059	-143.3
	(357.7)	(883.3)	(575.4)
STEM Employment Fraction	-178,101	-2.582e+06	-51,061
	(1.719e+06)	(4.308e+06)	(2.321e+06)
# Employment in STEM Occupations	-0.000123	0.0257	0.00205
	(0.0141)	(0.0360)	(0.0190)
# Employment in nonSTEM Occupations	-3.45e-05	-0.000972	-5.34e-05
	(0.000584)	(0.00149)	(0.000789)
# Graduates	1.208*	2.879	0.130
	(0.663)	(1.764)	(0.932)
# STEM Major Graduates	-1.200	-3.630	-1.450
	(1.278)	(2.982)	(1.795)
# Female Graduates	-2.124	-6.176	-0.834
	(1.524)	(3.882)	(2.114)
# Female STEM Major Graduates	2.515	10.05	4.488
	(3.606)	(8.119)	(4.967)
General Intelligence	422.7***	156.1	172.7
	(129.1)	(343.3)	(175.4)
Mathematical Ability	716.3***	1,102***	303.6
	(160.3)	(374.5)	(192.7)
Constant	58,383	454,814	182,691
	(116,660)	(313,697)	(159,320)
Observations	1,910	1,910	1,910

Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: The sample includes undergraduate cohorts graduated from 2005–2014. Column (1) shows the estimates from the female sample and Column (2) shows the male sample. The dependent variable in both column (1) and (2) is annual salary.

Table 11: Salary for Females

VARIABLES	(1) Salary11	(2) Salary10	(3) Salary00
Unemployment Rate at Job State	-134.2	241.1	-998.8
	(619.7)	(1,577)	(614.0)
STEM Employment Fraction	-3.019e+06	-2.606e+06	-2.052e+06
	(2.969e+06)	(7.243e+06)	(2.284e+06)
# Employment in STEM Occupations	0.0177	0.0240	0.0140
	(0.0241)	(0.0597)	(0.0190)
# Employment in nonSTEM Occupations	-0.000925	-0.000850	-0.000669
	(0.00100)	(0.00248)	(0.000786)
# Graduates	1.090	0.333	0.966
	(1.858)	(1.778)	(1.002)
# STEM Major Graduates	0.480	1.015	-0.749
	(3.639)	(2.448)	(1.670)
# Female Graduates	-1.460	-0.488	-1.561
	(4.362)	(3.534)	(2.129)
# Female STEM Major Graduates	-1.776	-2.775	1.300
	(10.32)	(6.050)	(4.369)
General Intelligence	779.0***	310.3	154.7
	(218.4)	(418.4)	(158.2)
Mathematical Ability	932.5***	1,513**	888.6***
	(320.6)	(600.8)	(216.1)
Constant	16,546	202,269	75,694
	(289,424)	(385,859)	(158,521)
Observations	1,145	1,145	1,145

Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: The sample includes undergraduate cohorts graduated from 2005–2014. Column (1) shows the estimates from the female sample and Column (2) shows the male sample. The dependent variable in both column (1) and (2) is annual salary.

Table 12: Counterfactuals of Majoring in STEM

	(1) Female	(2) Male
Proportion of STEM Graduates by Gender		
Factual:	0.3704	0.6354
	(0.0143)	
Counterfactual: swapping $\alpha^{M,A}$, $\alpha^{M,B}$	0.3749	
	(0.0143)	
Counterfactual: swapping θ^{A}, θ^{B}	0.3958	
	(0.0145)	
Counterfactual: swapping $\alpha^{M,A}$, $\alpha^{M,B}$,θ^{A} ,θ^{B}	0.4037	
	(0.0145)	
Counterfactual: swapping β_M	0.4253***	
	(0.0146)	
Counterfactual: swapping X_M	0.5763***	
	(0.0146)	
Counterfactual: swapping β_M and X_M	0.6450***	
	(0.0141)	
N	1145	1910

Standard errors in parentheses.

Note: The sample includes undergraduate cohorts graduated from 2005–2014. Column (1) shows the estimates from the female sample and Column (2) shows the male sample. Significant level of the test—$H_0 = factual$; $H_1 = counterfactual$—are shown as *** p<0.01, ** p<0.05, * p<0.1.

Table 13: Counterfactuals of Working in STEM

	(1) Female	(2) Male
Proportion of STEM Workers in STEM Graduates by Gender		
Factual:	0.7005	0.8020
	(0.0222)	(0.3984)
Counterfactual: Swap $\alpha_{J,A}$, $\alpha_{J,B}$	0.6926	
	(0.0224)	
Counterfactual: swapping θ^A, θ^B	0.7057	
	(0.0221)	
Counterfactual: swapping $\alpha^{J,A}$, $\alpha^{J,B}$, θ^A, θ^B	0.6958	
	(0.0223)	
Counterfactuals: Swap β_J	0.7512*	
	(0.0210)	
N	424	1211

Standard errors in parentheses.

Note: The sample includes undergraduate cohorts graduated from 2005–2014. Column (1) shows the estimates from the female sample and Column (2) shows the male sample. Significant level of the test—$H_0 = factual$; $H_1 = counterfactual$—are shown as *** p<0.01, ** p<0.05, * p<0.1.

Table 14: Decomposition of Job Decision

	(1) Exclude	(2) Replace with Male's
Fraction of Graduates in STEM Job		
Factual:	0.7005	
	(0.0222)	
Counterfactual: $\beta_{\text{\#Purdue Graduates in the Same Major}}$	0.4894	0.6440
	(0.0243)	(0.0233)
Counterfactual: $\beta_{\text{\#Purdue Female Graduates in the Same Major}}$	0.8152***	0.6951
	(0.0188)	(0.0224)
Counterfactual: $\beta_{\text{Home State STEM Demand}}$	0.7330	0.7047
	(0.0215)	(0.0222)
Counterfactuals: Year Fixed Effects	0.7492	0.7473
	(0.0210)	(0.0211)
Counterfactuals: Home Region Fixed Effects	0.7671**	0.8209***
	(0.0205)	(0.0186)
N	424	424

Note: The sample includes undergraduate cohorts graduated from 2005–2014. Column (1) shows the counterfactual fraction of female STEM graduates working in STEM for excluding the corresponding predictor. Column (2) shows the counterfactuals of replacing female's coefficient of interest with male's. Standard errors in parentheses. Significant level of the test—$H_0 = factual$; $H_1 = counterfactual$—are shown as *** p<0.01, ** p<0.05, * p<0.1.

Table 15: Average Treatment Effects

	(1) Female	(2) Male
Panel A. Average Treatment Effects of Majoring in STEM (11 vs. 00)		
ATE	13553	9932
	(4479.5)	(4112)
TT	15049	10570
	(4473)	(4013)
TUT	12921	9037
	(4322.8)	(4080)
N	1145	1910
Panel B. Average Treatment Effects of Majoring in STEM (10 vs. 00)		
ATE	7055	6773
	(5861)	(5625)
TT	6938	7383
	(6086)	(5669)
TUT	7073	6557
	(5804)	(5595)
N	1145	1910
Panel C. Average Treatment Effects of Working in STEM (11 vs. 10)		
ATE	7459	2732
	(7589)	(4433)
TT	7449	2813
	(7529)	(4466)
TUT	7495	2483
	(7728)	(4338)
N	424	1211

Standard deviation in parentheses.

Note: The sample includes undergraduate cohorts graduated from 2005–2014.

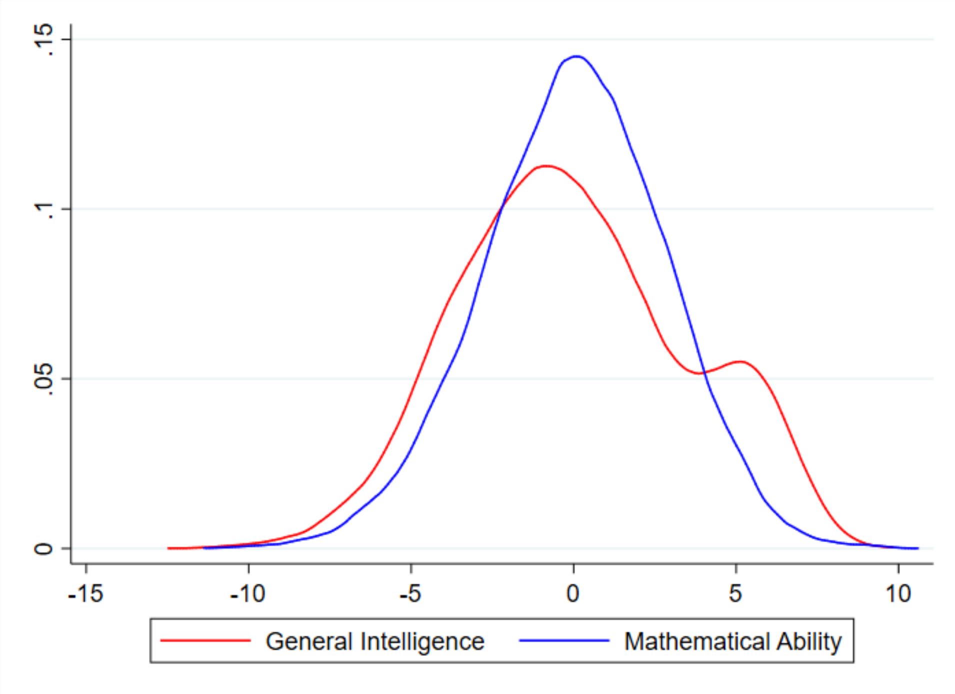
Table 16: Home Away

	(1) non-STEM	(2) STEM
Panel A. Males		
Away	133	587
	(18.44%)	(81.56%)
Home	95	396
	(19.35%)	(80.65%)
N	228	983
Panel B. Females		
Away	71	220
	(24.4%)	(75.6%)
Home	43	90
	(32.3%)	(67.7%)
N	114	310

Fraction in parentheses.

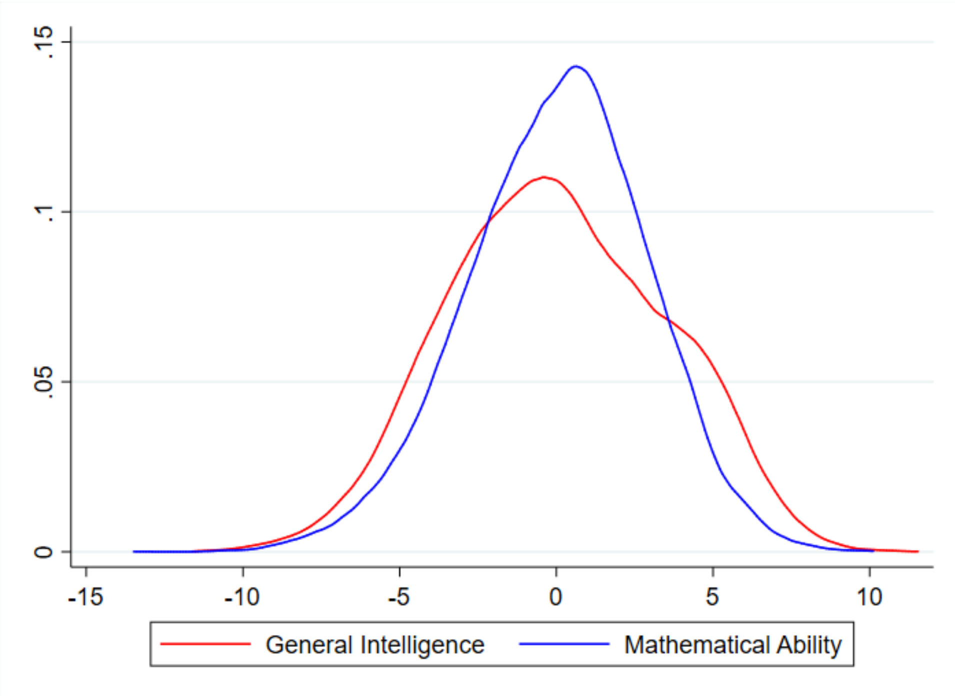
Note: The sample includes undergraduate cohorts graduated from 2005–2014. Column (1) shows the number or fraction of STEM graduates working in a non-STEM job. Column (2) shows the number or fraction of STEM graduates working in a STEM job.

Figure 1: Distributions of Female's Two Abilities



Distributions are centered at mean zero. $sd(f1) = 3.576$; $sd(f2) = 2.801$

Figure 2: Distributions of Male's Two Abilities



Distributions are centered at mean zero. $sd(f1) = 3.539$; $sd(f2) = 2.862$

Figure 3: Distribution of Male Factor 1 by Group

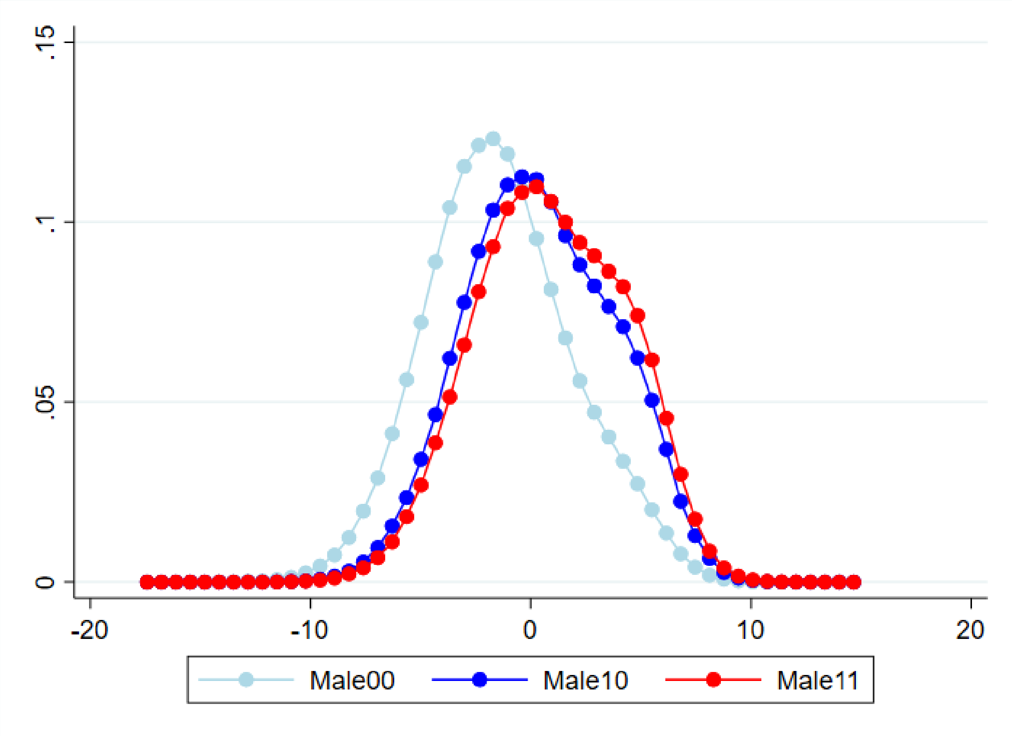


Figure 4: Distribution of Male Factor 2 by Group

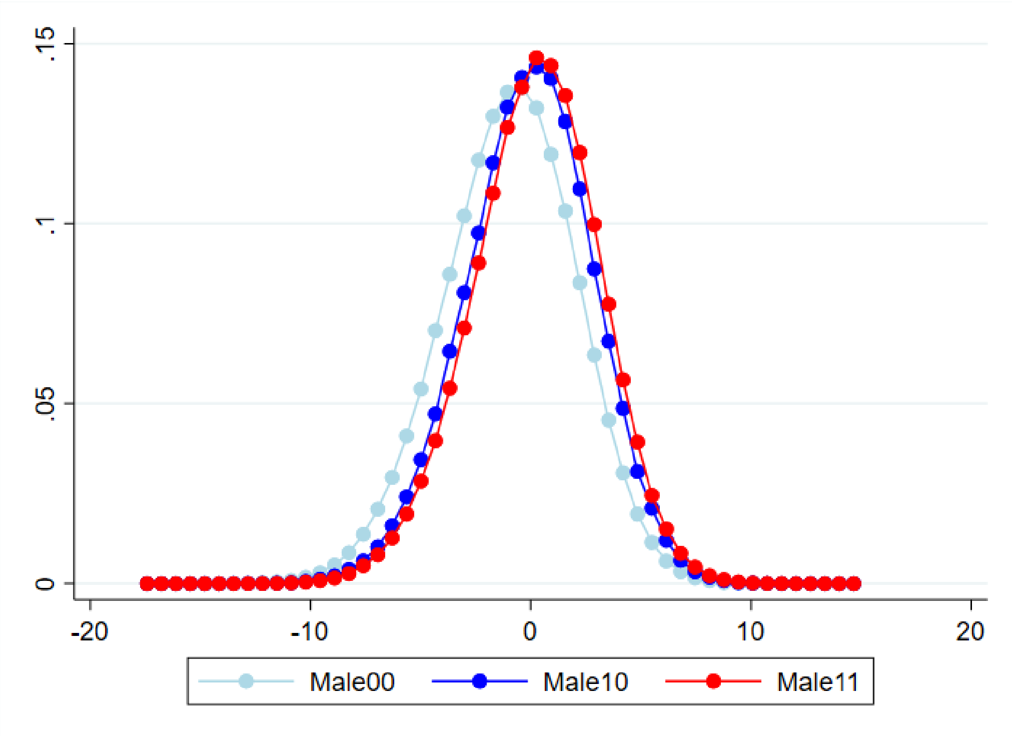


Figure 5: Distribution of Female Factor 1 by Group

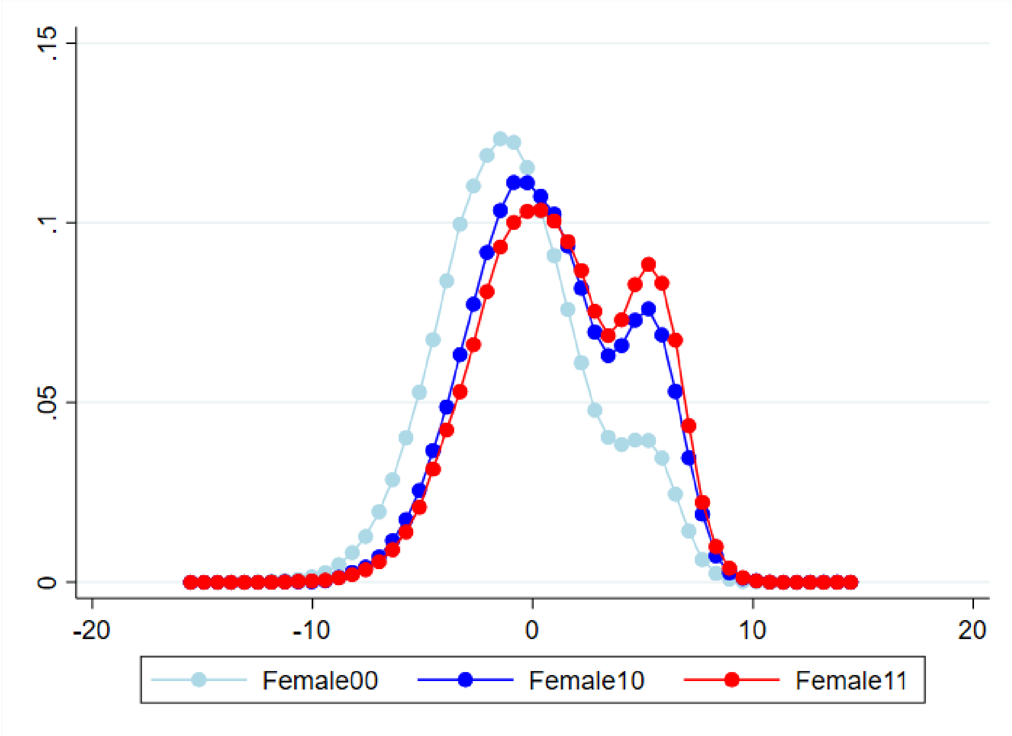


Figure 6: Distribution of Female Factor 2 by Group

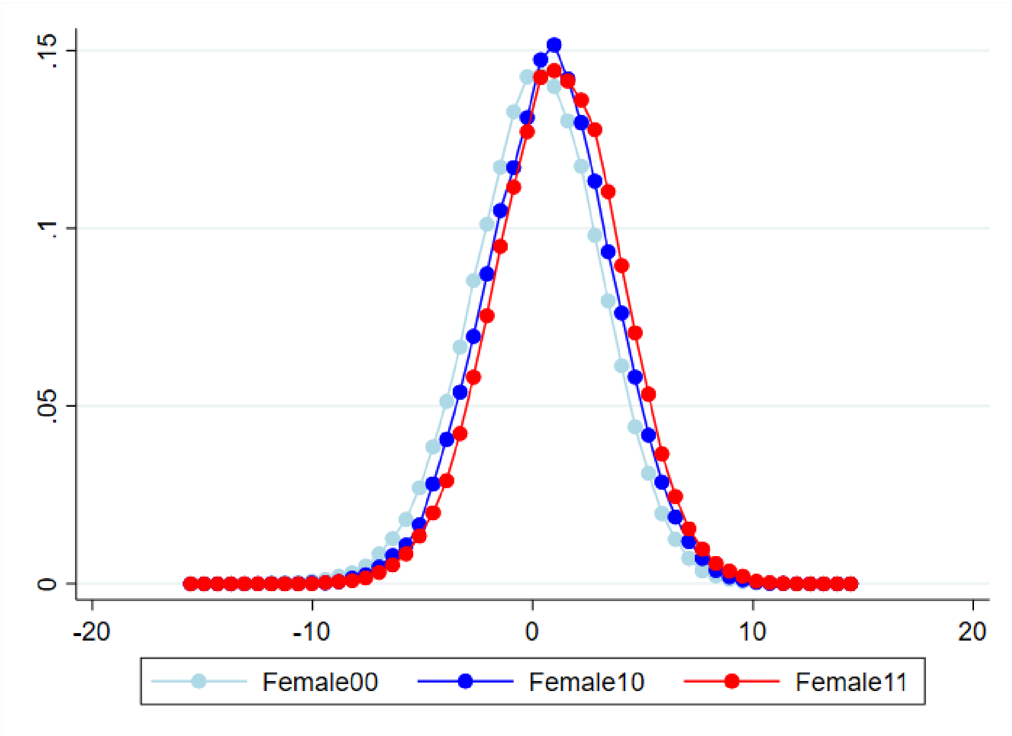


Figure 7: ATE of Majoring in STEM, on General Intelligence

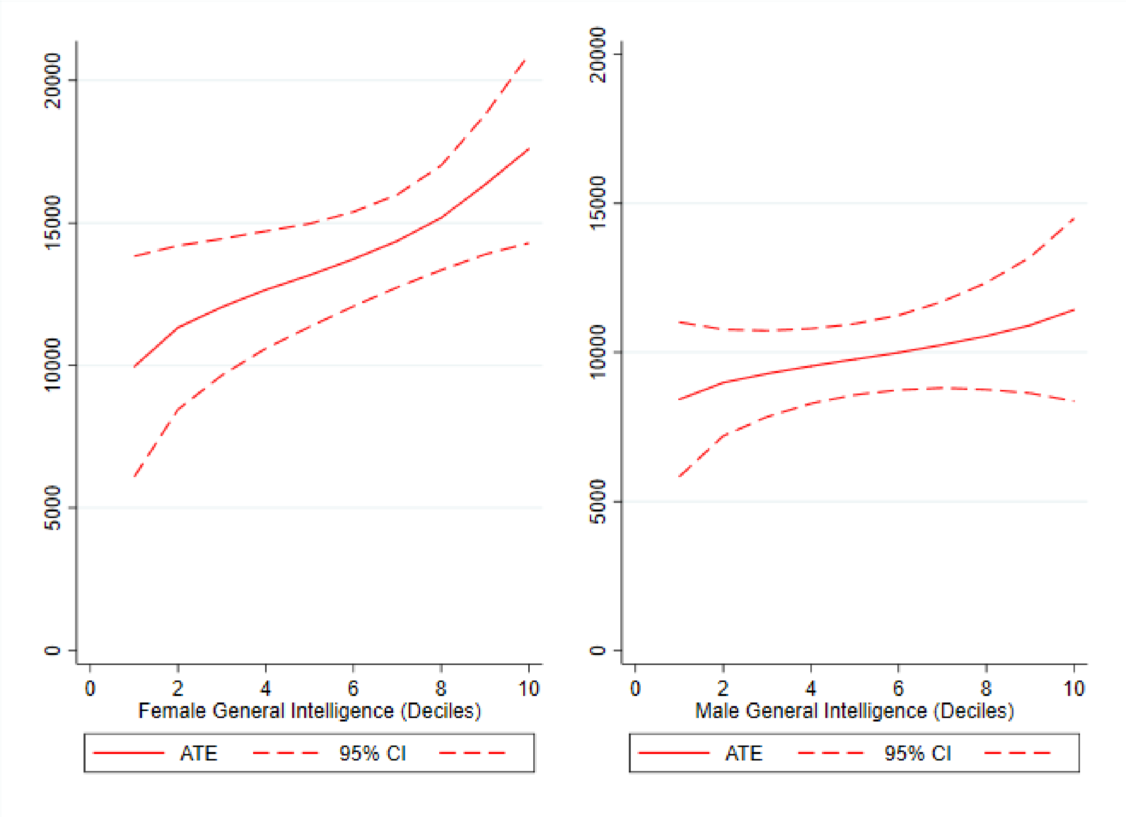


Figure 8: ATE of Majoring in STEM, on Mathematical Ability

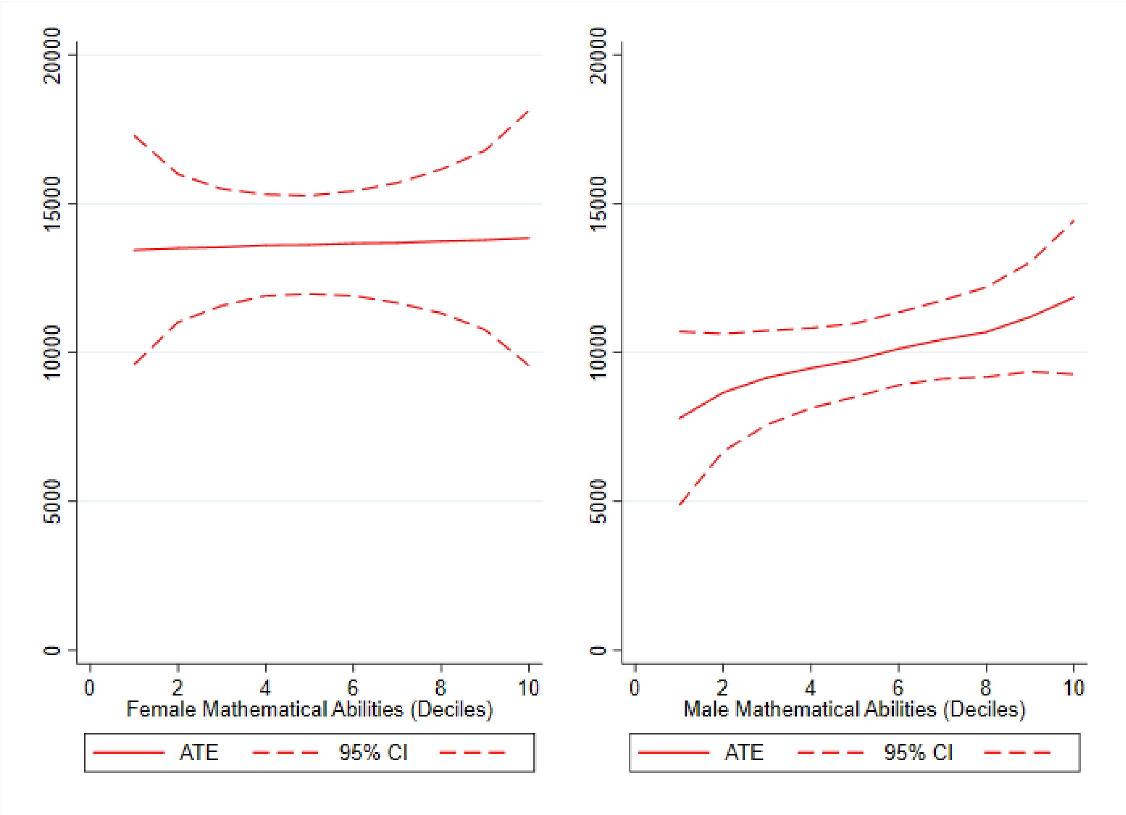


Figure 9: MTE of Majoring in STEM, on General Intelligence

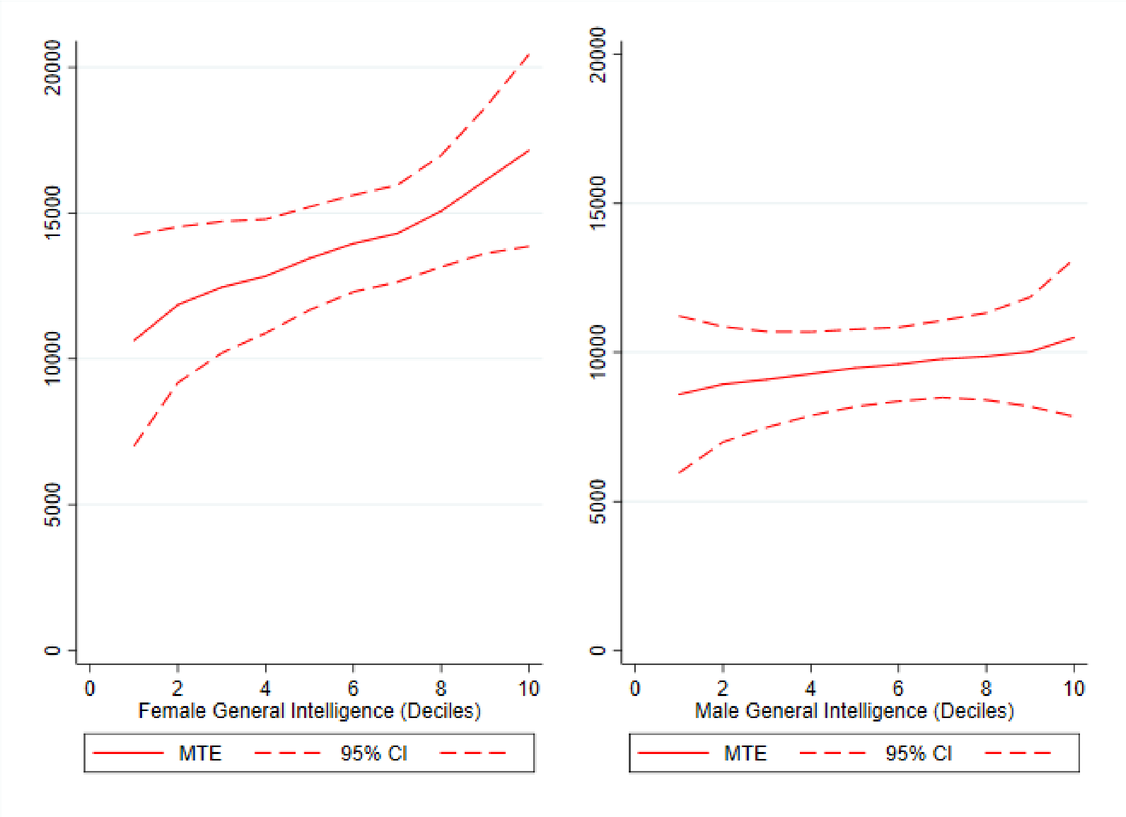


Figure 10: MTE of Majoring in STEM, on Mathematical Ability

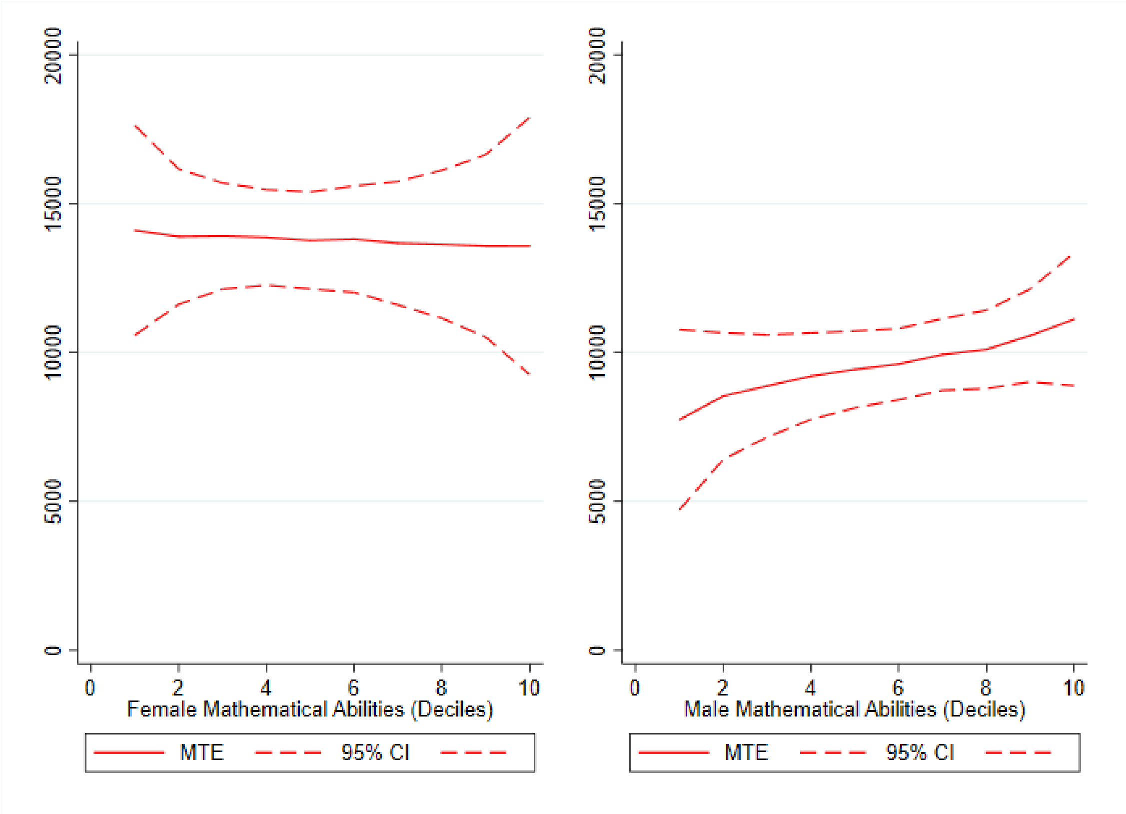


Figure 11: ATE of Working in STEM, on General Intelligence

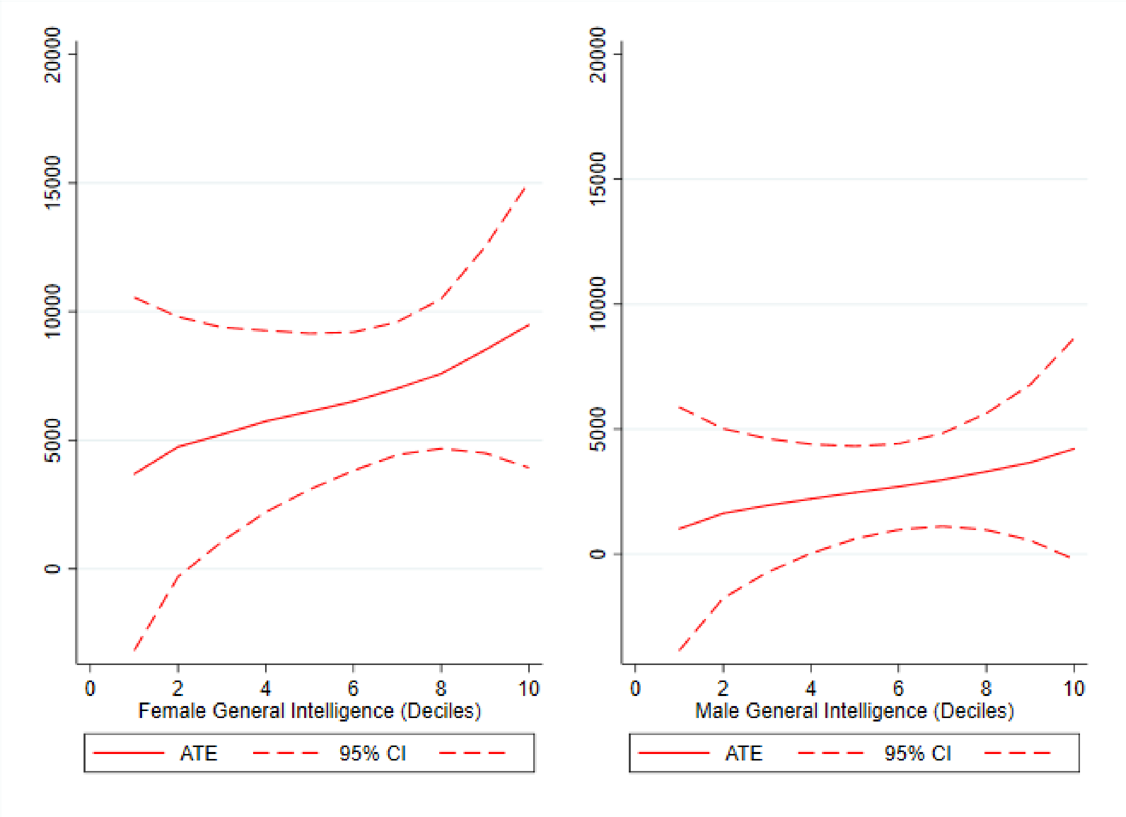


Figure 12: ATE of Working in STEM, on Mathematical Ability

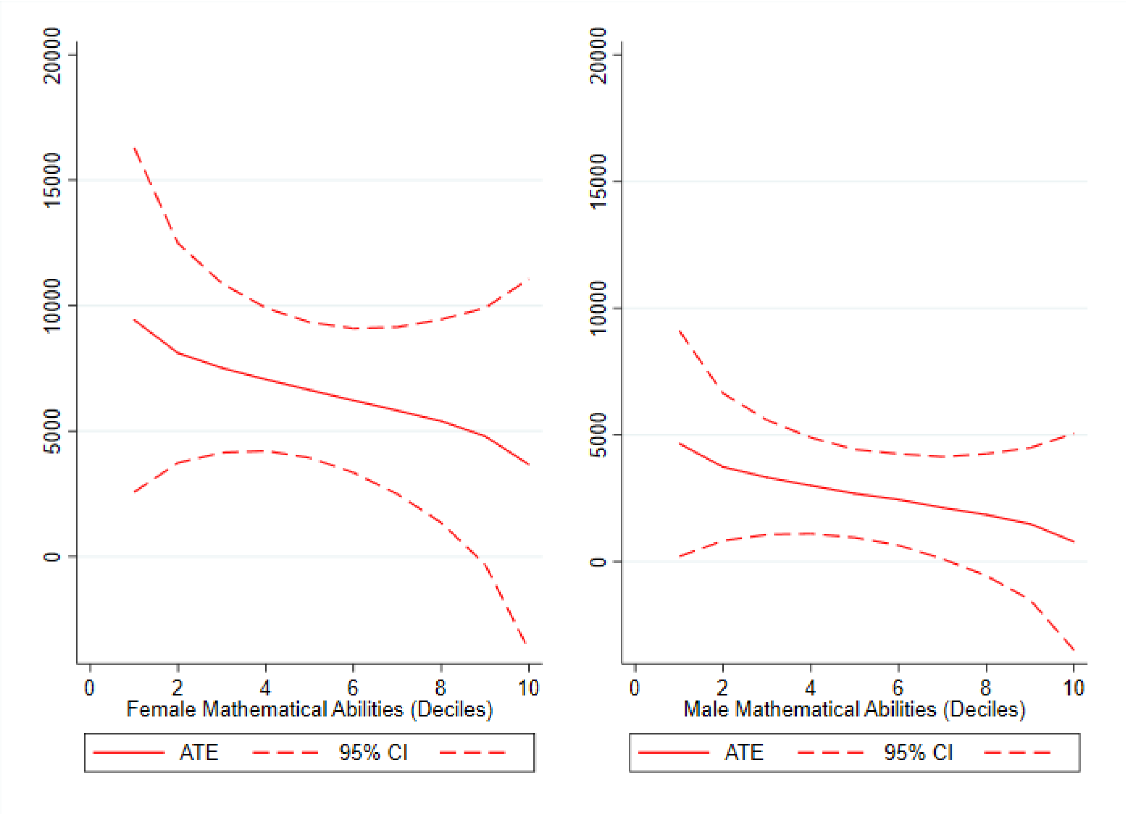


Figure 13: MTE of Working in STEM, on General Intelligence

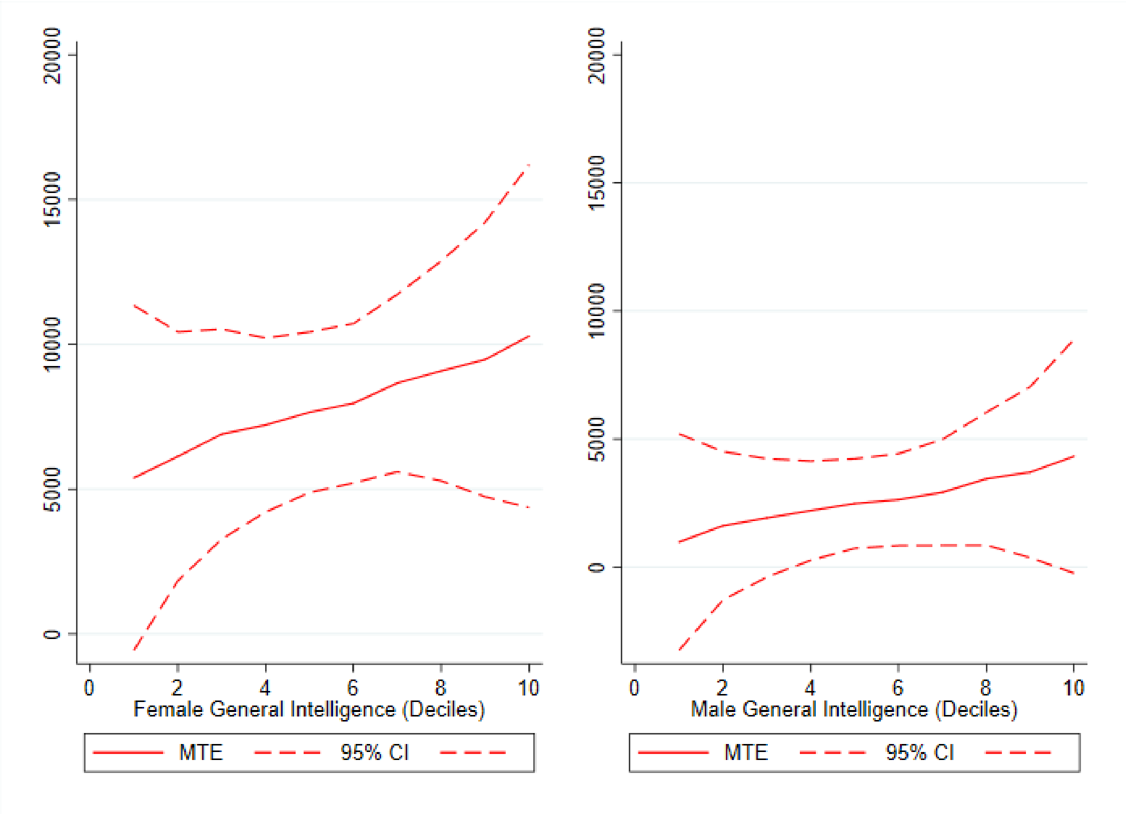


Figure 14: MTE of Working in STEM, on Mathematical Ability

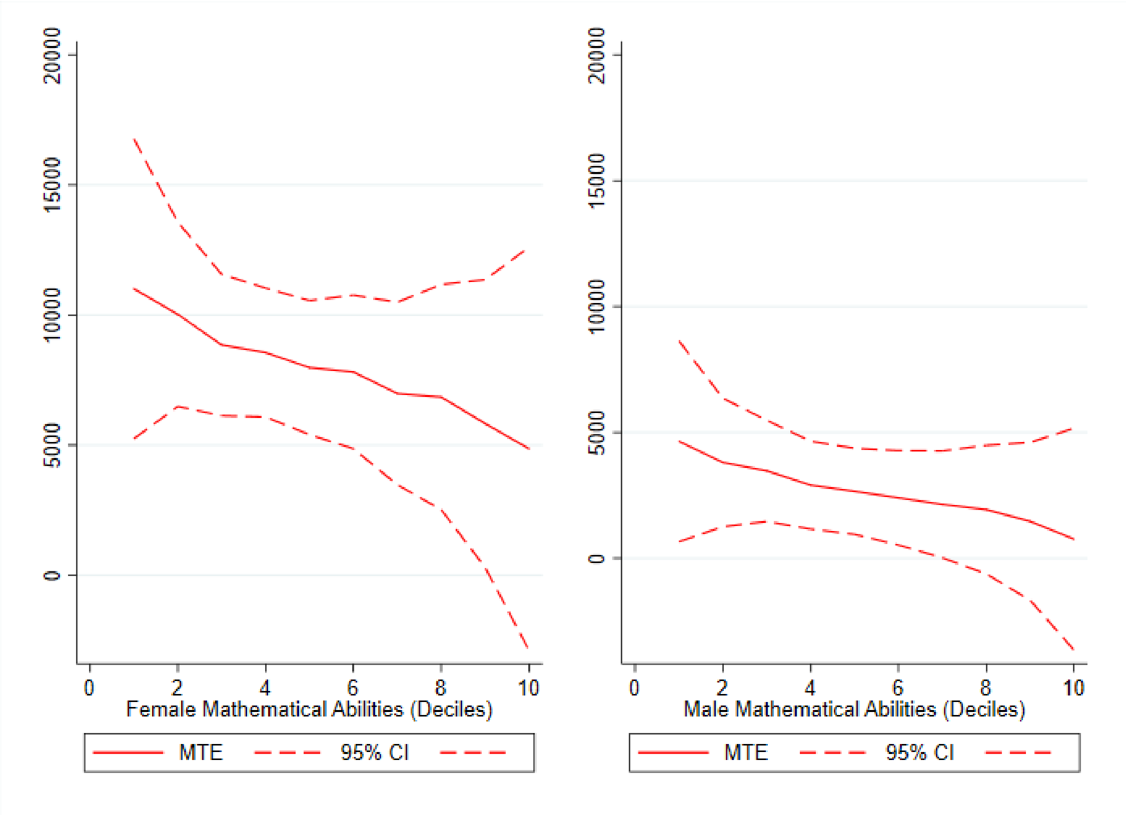
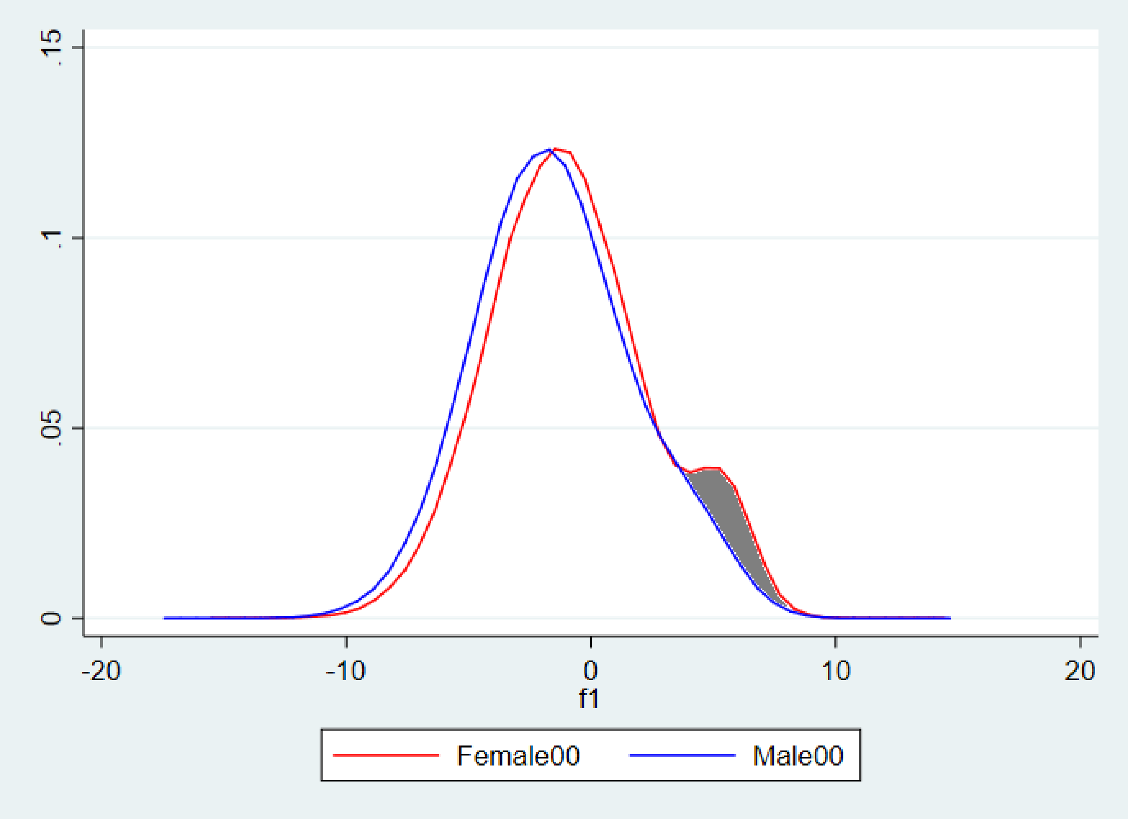


Figure 15: Poor-Sorted High-Ability Women



A Appendix

Table A.1: Selection: Self-report First Job Information

	(1) Female	(2) Male
General Intelligence	0.0070428	-0.0057017
	(0.0083508)	(0.0077115)
Mathematical Ability	0.0007466	0.0153035**
	(0.0072008)	(0.006406)
N	4565	5640

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Note: The sample includes undergraduate cohorts graduated from 2005–2014. Column (1) and column (2) show the factor loadings but not the marginal effects. The dependent variable in both column (1) and (2) is dummy of self-reporting first job information. Number of Purdue graduates in the same major, number of Purdue female graduates in the same major, first enrolled year fixed effect, first enrolled semester fixed effects, degree year fixed effects, degree semester fixed effects, and home region fix effects are controlled but not shown in this table for short.

Table A.2: Likelihood of Graduating with A STEM Major

	(1)	(2)
	Female	Male
# Purdue Graduates in Same Major	0.00812***	0.00838***
	(0.000959)	(0.000789)
# Purdue Female Graduates in Same Major	-0.0322***	-0.0366***
	(0.00224)	(0.00218)
First Enrollment Year = 2001	1.881	1.227*
	(1.429)	(0.739)
First Enrollment Year = 2002	1.764*	1.159
	(0.933)	(0.717)
First Enrollment Year = 2003	1.192*	0.903*
	(0.706)	(0.493)
First Enrollment Year = 2004	1.064*	0.869*
	(0.612)	(0.446)
First Enrollment Year = 2005	0.711	0.949**
	(0.542)	(0.397)
First Enrollment Year = 2006	0.289	0.632*
	(0.473)	(0.355)
First Enrollment Year = 2007	0.535	0.632**
	(0.440)	(0.316)
First Enrollment Year = 2008	0.437	0.609**
	(0.362)	(0.284)
First Enrollment Year = 2009	0.185	0.643**
	(0.292)	(0.259)
First Enrollment Semester = Fall	4.899	1.369**
	(91.41)	(0.651)
First Enrollment Semester = Spring	4.293	1.385*
	(91.42)	(0.751)
Degree Year = 2007	0.241	-1.361**
	(0.750)	(0.498)
Degree Year = 2008	0.464	-0.998**
	(0.791)	(0.455)
Degree Year = 2009	0.954	-1.098**
	(0.864)	(0.401)
Degree Year = 2010	0.810	-0.796**
	(0.911)	(0.356)
Degree Year = 2011	1.554*	-0.625**
	(0.936)	(0.316)
Degree Year = 2012	1.355	-0.704**
	(0.963)	(0.275)
Degree Year = 2013	1.511	-0.683**
	(0.977)	(0.243)
Degree Year = 2014	1.956*	0.2958
	(1.021)	(0.9227457)
Degree Semester = Fall	0.203	-0.161
	(0.373)	(0.287)
Degree Semester = Spring	-0.0614	-0.328
	(0.343)	(0.270)
General Intelligence	0.144***	0.182***
	(0.0175)	(0.0155)
Mathematical Ability	0.102***	0.135***
	(0.0253)	(0.0173)
Constant	-6.372	-0.408
	(91.42)	(0.714)
N	1145	1910

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Note: The sample includes undergraduate cohorts graduated from 2005–2014. Column (1) and column (2) show the coefficients and the loadings for the female and male sample, respectively. The dependent variable in both column (1) and (2) is a dummy of graduating in a STEM major. First enrollment year = 2010, Degree Year = 2005 and Degree Year = 2006 are omitted due to collinearity.

Table A.3: Likelihood of STEM Major Graduates Working in A STEM Occupation

	(1)	(2)
	D_job	D_job
# Purdue Graduates in The Same Major	0.00563***	0.00390***
	(0.00118)	(0.000758)
# Purdue Female Graduates in The Same Major	-0.0148***	-0.0155***
	(0.00404)	(0.00416)
Home State STEM Demand	-0.000000573	-0.000000500
	(0.000000787)	(0.000000431)
Degree Year = 2005	-4.086	0*
	(3.79)	(.)
Degree Year = 2006	-3.795	-1.644**
	(13.69)	(0.673)
Degree Year = 2007	0.424	-0.158
	(0.386)	(0.196)
Degree Year = 2008	0.290	0.0687
	(0.333)	(0.191)
Degree Year = 2009	-0.215	-0.0344
	(0.303)	(0.193)
Degree Year = 2010	-0.0269	0.00299
	(0.340)	(0.181)
Degree Year = 2011	-0.314	-0.112
	(0.265)	(0.171)
Degree Year = 2012	-0.401*	0.0933
	(0.242)	(0.153)
Degree Year = 2013	-0.230	0.0106
	(0.236)	(0.142)
Home Region = Indiana	-0.652	-0.214
	(0.641)	(0.263)
Home Region = Midwest	-0.495	-0.0814
	(0.574)	(0.244)
Home Region = Northeast	-1.116	-0.364
	(0.706)	(0.329)
Home Region = South	-0.700	0.178
	(0.590)	(0.279)
General Intelligence	0.0492*	0.0366**
	(0.0282)	(0.0186)
Mathematical Ability	0.0490	0.0365*
	(0.0410)	(0.0221)
Constant	1.171	0.919**
	(0.718)	(0.302)
N	424	1211

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The sample includes undergraduate cohorts graduated from 2005–2014. Column (1) and column (2) show the coefficients and the loadings for the female and male sample, respectively. The dependent variable in both column (1) and (2) is a dummy of working in a STEM occupation. Degree Year = 2014, and Home Region = West are omitted due to collinearity.

Table A.4: Salary of 11 Type (STEM Major, STEM Job)

	(1) Female	(2) Male
State Annual Unemployment Rate	-136.0	-838.7**
	(608.5)	(358.5)
STEM Fraction of Total Employment	-3004239.8	-181322.5
	(2962201.5)	(1713905.1)
# STEM Total Employment	0.0176	-0.0000960
	(0.0242)	(0.0140)
# non-STEM Total Employment	-0.000920	-0.0000357
	(0.00100)	(0.000582)
# Total Graduates	1.091	1.209*
	(1.382)	(0.668)
# Total STEM Graduates	0.477	-1.201
	(2.689)	(1.296)
# Female Graduates	-1.464	-2.126
	(3.218)	(1.536)
# Female STEM Graduates	-1.766	2.517
	(7.639)	(3.655)
Job Region = New England	7929.5**	6977.5**
	(3272.5)	(2449.5)
Job Region = Mid-Atlantic	13217.5***	7353.3***
	(3136.3)	(1570.9)
Job Region = East North Central	6957.2***	6077.3***
	(1465.9)	(844.5)
Job Region = West North Central	8486.6***	4197.4**
	(2447.5)	(1707.9)
Job Region = South Atlantic	9137.6***	7310.8***
	(2113.0)	(1200.1)
Job Region = East South Central	8825.2**	5050.3**
	(3875.7)	(1697.4)
Job Region = West South Central	13856.0***	12931.2***
	(2195.1)	(1289.0)
Job Region = Mountain	8118.4**	3855.0*
	(2847.4)	(2139.1)
Job Region = Pacific	14331.6***	17012.6***
	(2502.0)	(1261.4)
General Intelligence	775.7***	424.6**
	(217.6)	(129.1)
Mathematical Ability	-938.0**	-714.4***
	(319.6)	(160.4)
Constant	16264.1	58553.7
	(227334.2)	(115951.0)
N	310	983

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The sample includes undergraduate cohorts graduated from 2005–2014. Column (1) and column (2) show the coefficients and the loadings for the female and male sample, respectively. The dependent variable in both column (1) and (2) is self-reported annual salary. Job Region = Indiana is omitted due to collinearity.

Table A.5: Salary of 10 Type (STEM Major, non-STEM Job)

	(1) Female	(2) Male
State Annual Unemployment Rate	245.0	-1059.2
	(1579.2)	(883.1)
STEM Fraction of Total Employment	-2565034.6	-2578088.3
	(7425402.7)	(4294849.1)
# STEM Total Employment	0.0237	0.0257
	(0.0612)	(0.0358)
# non-STEM Total Employment	-0.000836	-0.000970
	(0.00254)	(0.00148)
# Total Graduates	0.321	2.874
	(1.904)	(1.756)
# Total STEM Graduates	1.025	-3.618
	(2.614)	(2.976)
# Female Graduates	-0.466	-6.163
	(3.790)	(3.866)
# Female STEM Graduates	-2.796	10.01
	(6.468)	(8.101)
Job Region = New England	12727.1	2751.4
	(8286.8)	(12191.4)
Job Region = Mid-Atlantic	14399.8**	1883.4
	(4673.7)	(4474.4)
Job Region = East North Central	15747.4***	5746.9**
	(2576.2)	(2091.6)
Job Region = West North Central	7791.1	3538.6
	(5275.8)	(3523.7)
Job Region = South Atlantic	7551.8	13629.4***
	(6036.8)	(3423.8)
Job Region = East South Central	10576.4**	-980.4
	(5255.9)	(5541.4)
Job Region = West South Central	8632.4	6063.9
	(6521.1)	(3884.3)
Job Region = Mountain	11319.4	15231.7**
	(12051.8)	(4770.5)
Job Region = Pacific	6931.7	14658.0***
	(5406.7)	(4276.6)
General Intelligence	301.1	164.0
	(420.0)	(343.3)
Mathematical Ability	-1518.6**	-1095.8**
	(606.1)	(374.6)
Constant	200091.5	453778.7
	(401613.8)	(312401.1)
N	114	228

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The sample includes undergraduate cohorts graduated from 2005–2014. Column (1) and column (2) show the coefficients and the loadings for the female and male sample, respectively. The dependent variable in both column (1) and (2) is self-reported annual salary. Job Region = Indiana is omitted due to collinearity.

Table A.6: Salary of 00 Type (non-STEM Major, non-STEM Job)

	(1) Female	(2) Male
State Annual Unemployment Rate	-998.7*	-31.02
	(586.9)	(578.5)
STEM Fraction of Total Employment	-2051633.9	-137548.0
	(2227097.8)	(2321971.8)
# STEM Total Employment	0.0140	0.00263
	(0.0185)	(0.0190)
# non-STEM Total Employment	-0.000669	-0.0000751
	(0.000764)	(0.000790)
# Total Graduates	0.965	-0.150
	(0.737)	(1.022)
# Total STEM Graduates	-0.749	-0.879
	(1.258)	(1.951)
# Female Graduates	-1.561	-0.200
	(1.565)	(2.316)
# Female STEM Graduates	1.300	2.954
	(3.300)	(5.391)
Job Region = New England	6053.4**	6089.6*
	(2989.4)	(3266.6)
Job Region = Mid-Atlantic	6998.5**	7861.3**
	(2425.6)	(2978.0)
Job Region = East North Central	7027.8***	7453.3***
	(986.2)	(1072.5)
Job Region = West North Central	6465.0**	9657.1***
	(2338.5)	(2243.7)
Job Region = South Atlantic	4876.7**	6405.3***
	(1656.4)	(1782.5)
Job Region = East South Central	4275.7*	6027.3**
	(2320.4)	(2843.8)
Job Region = West South Central	4799.1*	9642.3***
	(2510.7)	(2253.3)
Job Region = Mountain	4597.0*	3237.2
	(2462.7)	(2028.4)
Job Region = Pacific	7462.1**	7880.8***
	(2459.5)	(2175.9)
General Intelligence	154.7	153.4
	(158.1)	(175.7)
Mathematical Ability	-888.6***	-302.8
	(216.0)	(193.0)
Constant	75672.5	152025.6
	(134046.8)	(168848.6)
N	721	699

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The sample includes undergraduate cohorts graduated from 2005–2014. Column (1) and column (2) show the coefficients and the loadings for the female and male sample, respectively. The dependent variable in both column (1) and (2) is self-reported annual salary. Job Region = Indiana is omitted due to collinearity.

Figure A.1: Visualization Tool