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ABSTRACT

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This dissertation is composed of three independent chapters in the field of labor economics, focusing on educational decisions, gender differences and gender differences in educational decisions.

The first chapter investigates gender differences in college major choice and job choice. 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.

The second chapter exploits China's One-Child Policy to study the relationship between fertility expectation and educational attainment of the mothers of the "siblingless generation". One-Child Policy was China's most intensive family planning policy which implemented by the end of 1979 and only restricted Han families to have one child. I use two difference-in-differences approaches—one compares gender difference among Han, the other compares ethnicity differences between Han women and non-Han women—to estimate how Han women changed their educational choice in response to the policy. The OCP explains 53.6% of the 2.38 year average increase in education for women born between 1960–1980. Potential mechanisms include delaying entry to the first marriage, motherhood and increasing labor force participation. This study highlights the policy's positive externality on women's education.

The third chapter studies how China's Open Door Policy's implementation at the end of 1978 affected the skill composition for workers born 1960-1970. Using measures of local labor markets' export exposure, we find that export growth increased high school completion rates but had no effect on middle school completion rates. For every $1000 increase in exports per worker, high school completion rates decreased by 4.76 p.p. for workers born in 1970 compared to those born in 1960, explaining about 10.4% of the national decline in high school completion for 1960s birth cohorts. This suggests a tradeoff between education and labor market opportunities in China. China's growth was likely dampened during the early industrialization of the 1980s and 1990s, as the Open Door Policy simultaneously reduced the availability of skilled labor.

1. PLANTING THE SEEDS FOR SUCCESS: WHY WOMEN IN STEM DON'T STICK IN THE FIELD

1.1 Introduction

Women are underrepresented in Science, Technology, Engineering and Mathematics (STEM) college majors and occupations. While nearly as many women hold college degrees as men overall, they make up only about 30 percent of all STEM degree holders. Women fill 47 percent of all U.S. jobs but hold only 24 percent of STEM jobs. Moreover, women with STEM college degrees are less likely than their male counterparts to work in a STEM occupation. About 40 percent of men with STEM college degrees work in STEM jobs, while only 23 percent of women with STEM degrees work in STEM jobs. (Noonan, 2017).

Why is the lack of women in the STEM field a concern? First, we face a scarcity of STEM workers in many industries, even though STEM jobs are among the best-paying jobs (Xue & Larson, 2015). Attracting and retaining more women in STEM will help with unfilled positions. Second, when women are not seen as equal 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 & Williams, 2012). Last, when women are not involved in STEM, products, services and solutions are mostly designed by men and according to their user experiences. The needs and desires that are unique to women may be overlooked (Fisher & Margolis, 2002; Clayton et al., 2014).

The first research question of this paper is how much of the gender gap in college major choice and job choice can be explained by gender differences in sorting on abilities. There is abundant literature that covers the issue of ability sorting in college major choices (Arcidiacono, 2004; Arcidiacono et al., 2012; Wiswall & Zafar, 2015a; Humphries et al., 2017) and that of gender differences in college major choices (Polachek, 1978, 1981; Daymont & Andrisani, 1984; Blakemore & Low, 1984; Turner & Bowen, 1999; Dickson, 2010; Ahn et al., 2015; Eccles, 2007; Trusty, 2002; Ethington & Woffle, 1988; Hanson et al., 1996). Yet the two elements—*ability sorting in college major choices* and *gender differences*—have rarely been linked. My second question is, by not choosing a STEM major or a STEM job, do women leave any money on the table; and how much? Third, why are female STEM degree holders more likely to leave STEM than their male counterparts?

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 separately estimated for men and women: one chooses between graduating with a STEM degree and a non-STEM degree; after getting a STEM degree, one chooses between a STEM occupation and a non-STEM occupation. My model relies on the identification of two latent abilities, general intelligence and extra mathmatical ability, to deal with sequential selections of major and job. Most of the literature (Arcidiacono, 2004; Long et al., 2015; Altonji et al., 2016) use 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 & Urzúa, 2015; Prada et al., 2017). Moreover, the identification strategy here assumes a mixture of normals for the distributions of both latent abilities, which avoids the restriction for them being normal and guarantees the flexibility of the functional forms the latent abilities could take.

The data—Purdue University's administrative (Registrar) data—I am using fulfill the requirement of the identification of the two latent abilities. They contain the academic records of Purdue undergraduate students who graduated between 2005–2014 and is linked to their first destination survey conducted by the Purdue Center for Career Opportunities. The data provide rich information on individuals' high school GPA, standardized test scores (ACT English, ACT Reading, ACT Math and ACT Science) and entire college transcripts data.

I find the distributions of abilities at the start of college are 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 choice for women than for men. In fact, high-ability men are more likely to choose STEM majors relative to high-ability women. 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 extra 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. This is consistent with the recent findings in Ahn et al. (2015), which suggests that women are less sensitive to or more critical about their abilities. Alternatively, other characteristics unobserved by the researcher could be more dominant to women's college major decision. For my second research question, I find that high-ability women leave large amounts of money on the table by choosing non-STEM majors. A counterfactual analysis shows that a high-ability woman gives up \$13,000–\$20,000 in annual salary by choosing non-STEM majors. These 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[1].

The existing literature on this topic has focused on students' college major choices and the policy implications of attracting students to STEM majors. However, the career outcomes of STEM graduates remains unexplored. My 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

[1]The gender wage gap—\$8198—is calculated by subtracting the averaged Purdue's female graduates annual salary by the averaged Purdue's male graduates annual salary.

stay in STEM compared to their male counterparts is *not* due to differences in ability sorting. This implies that other factors are more important to STEM graduates when making a job decision. Based on full decomposition of the job decision equation, I find that the (Census) region where a student came from[2] 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 after graduation 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 study makes three main contributions to the existing literature. First, to the best of my knowledge, this is the first attempt to estimate the gender differences of ability sorting in job choices. Second, I am the first to document that there is a disproportionate and considerable number of high-ability women choose non-STEM majors, an able to quantify the total gains if they had made the same choices as high-ability men. I then use these total gains to explain the gender wage gap. Third, I provide empirical evidence to answer the question of why female STEM graduates are more likely to opt-out.

This paper is organized as follows. Section 1.2 reviews related literature on this subject. Section 1.3 describes the data I used for the analysis. I then present the model and the measurement system for the unobserved abilities in Section 1.4. In Section 1.5 and Section 1.6, I show my results and counterfactual analysis. Section 1.7 discusses the policy implications. Finally, Section 1.8 concludes.

1.2 Related Literature

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

[2] This is based on the place the student went for high school.

1.2.1 College Major Choice

There is an extensive economic literature on college major choice. 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 & 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 & Zafar, 2015b). 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 & Zafar (2015a) show that sorting occurs both on expected earnings and on students' perceptions of their relative abilities to perform in particular majors. Based on 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 address gender differences in major choices and only focus on a male sample.

Major switching behavior has been well documented too. Some studies suggest that students who perform worse than they expected are more likely to dropout or switch to a less difficult major (Stinebrickner & 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).

1.2.2 Gender Differences in Major Choices

Gender differences within college majors and in the workplace have attracted extensive attention. On 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 & 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 & 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 & 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 & Andrisani, 1984). Regarding the latter, psychological and educational literature finds 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 & Woffle, 1988). Hanson et al. (1996) argue 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 & Helgeson, 2002).

1.2.3 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 & Rufolo, 1990). Yet minimal research has been done on the career path of STEM college graduates, especially the gender differences in job selection among STEM college graduates. 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 demands of family and children are major nonacademic barriers for women on the pathway to a STEM profession Hanson et al. (1996); Kimmel et al. (2012). Compared to previous studies, my paper investigates students' entire career paths from endogenous major choice to endogenous job choice.

1.3 Data

I use a rich administrative data from Purdue Office of the Registrar that tracks the academic records of every Purdue University undergraduate student. The academic records are linked to the First Destination Survey conducted by the Purdue Center for Career Opportunities. The sample includes undergraduate students who graduated between 2005–2014. The data provides individual pre-college information including demographic characteristics, date of enrollment, high school GPA, ACT and SAT subject scores, and applied major.

Table 1.1 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 responded to the survey and reported a meaningful first job title. Among them, only 3055 reported a valid first job annual salary[3].

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,

[3]With concerns of selection in reporting first job, I estimate the model with dummy of reporting first job as dependent variable, two latent abilities and other characteristics as independent variables. Table B.1 shows that women who reported to the survey do not differ on abilities from women who did. Although we see a positive and significant effect on men's extra math ability, the magnitude is too small to have significant economic meaning: one standard deviation increase in extra math ability will increase the probability for an average man to report his first job information by 1.5 percentage points.

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 1.2 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[4]—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[5]. Average self-reported annual salary of female is lower than that of male. The Purdue gender wage gap is $8198.

1.3.1 STEM Major Definition

I use the first graduation major as student's major[6], 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) exten-

[4]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

[5]In the whole sample, there are 41% of students have taken ACT when they applied to Purdue (including those who took both). The rest of them took only SAT. There is no selection on abilities of taking ACT over SAT; especially, there is no gender difference in selection on abilities of taking ACT over SAT. I will get into more details of the reason of using ACT scores in Section 1.4.1.

[6]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 unless the first major is engineering as well. A student can not transfer into an engineering major if he's not originally an engineering student.

sion described at 8 CFR 214.2(f)[7]. I categorize all Purdue undergraduate programs showing up on this list as STEM major and the others as non-STEM major with some exceptions[8].

1.3.2 STEM Occupation Definition

The first destination survey provides self-reported first job title, employer (company name), job location (city and state), and annual salary[9].

I match the self-reported job titles to a 6-digit level Standard Occupational Classification (SOC) title with a corresponding SOC code by using O*NET search. I define a self-reported job as STEM/non-STEM occupation according to the "Detailed 2010 SOC occupations included in STEM"[10] published by Bureau of Labor Statistics (BLS, 2012).

1.4 Model

This general framework is inspired by the Roy model (Roy, 1951), in which individuals make choices to maximize their expected labor outcomes based on their comparative advantages. The core of the empirical strategy follows Carneiro et al. (2003), Heckman et al. (2006), Sarzosa & Urzúa (2015) and Prada et al. (2017). The model captures how college students sort into two groups of majors (STEM majors

[7]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.

[8]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.

[9]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).

[10]There are 840 6-digit SOC occupations and 184 of them are categorized as STEM occupations.

and non-STEM majors) and given this, sort into two groups of occupations (STEM occupations and non-STEM occupations). Particularly, at the start of college, students choose between a STEM major and a non-STEM major; after getting a STEM degree, students choose between a STEM occupation and a non-STEM occupation. Students maximize their expected outcome by making these sequential choices, based on their latent abilities and observable characteristics.

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[11]: θ^A, the general intelligence and, θ^B, the extra mathematical ability. For each individual, the main outcome variable, annual salary, is given by the following form:

$$Y = \boldsymbol{X_Y}\beta^Y + \alpha^{Y,A}\theta^A + \alpha^{Y,B}\theta^B + e^Y \tag{1.1}$$

where Y is the outcome variable, $\boldsymbol{X_Y}$ is a vector of all observable 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 error term. I assume that e^Y is independent from the observable controls and the 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 $f_{\theta^B}(.)$, which both are mixture of two normal distributions.

Choice of Major. The second model featuring the major choice is a specific case of the model above. For simplicity, I classify college major choices dichotomously as STEM majors and non-STEM majors, so as the occupation choices. Let I_M denotes the net benefit associated with graduating with a STEM degree (relative to a non-STEM degree).

$$I_M = \boldsymbol{X_M}\beta^M + \alpha^{M,A}\theta^A + \alpha^{M,B}\theta^B + e^M \tag{1.2}$$

where $\boldsymbol{X_M}$ is vector of all observable 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. I

[11] I use "factors" and "latent abilities" interchangeably in the paper.

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

$$D_M = \mathbb{1}[\boldsymbol{X_M}\beta^M + \alpha^{M,A}\theta^A + \alpha^{M,B}\theta^B + e^M > 0] \tag{1.3}$$

Choice of Job. After graduating from college, students face the choice between STEM and non-STEM jobs. It is important to note that the major to job flow is not a two by two matrix (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 data, there are only around 3% of observations 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, only graduates with a STEM degree will make a choice between STEM and non-STEM job. Non-STEM graduates are considered to work in non-STEM jobs. The job choice model is straightforward:

$$D_J = \mathbb{1}[\boldsymbol{X_J}\beta^J + \alpha^{J,A}\theta^A + \alpha^{J,B}\theta^B + e^J > 0] \text{ if } D_M = 1 \tag{1.4}$$

where $\boldsymbol{X_J}$ is vector of all observable 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. Again, I assume independency of the error term, i.e. $e^J \perp\!\!\!\perp (\theta^A, \theta^B, \boldsymbol{X_J})$. 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} denote the salary when $D_M = 1$ 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, $[Y_{11}, Y_{10}, Y_{00}, D_M, D_J]$':

$$Y_{11} = X_Y \beta^{Y_{11}} + \alpha^{Y_{11},A}\theta^A + \alpha^{Y_{11},B}\theta^B + e^{Y_{11}}, \text{ if } D_M = 1, D_J = 1 \tag{1.5}$$

$$Y_{10} = X_Y \beta^{Y_{10}} + \alpha^{Y_{10},A}\theta^A + \alpha^{Y_{10},B}\theta^B + e^{Y_{10}}, \text{ if } D_M = 1, D_J = 0 \tag{1.6}$$

$$Y_{00} = X_Y \beta^{Y_{00}} + \alpha^{Y_{00},A}\theta^A + \alpha^{Y_{00},B}\theta^B + e^{Y_{00}}, \text{ if } D_M = 0 \tag{1.7}$$

$$D_M = \mathbb{1}[\boldsymbol{X_M}\beta^M + \alpha^{M,A}\theta^A + \alpha^{M,B}\theta^B + e^M > 0] \tag{1.8}$$

$$D_J = \mathbb{1}[\boldsymbol{X_J}\beta^J + \alpha^{J,A}\theta^A + \alpha^{J,B}\theta^B + e^J > 0] \text{ if } D_M = 1 \tag{1.9}$$

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

I use maximum likelihood estimation (MLE) to estimate the model[12] by integrating the likelihood function below over the distributions of the two factors. The likelihood function is

$$
\begin{aligned}
\mathcal{L} &= \prod_{i=1}^{N} \iint \left[\begin{array}{l} f_{e^{y00}}(X_{Yi}, Y_0 i, \theta^A, \theta^B) \\ \times Pr[D_{Mi} = 0 | X_{Mi}, \theta^A, \theta^B]^{1-D_{Mi}} \times Pr[D_{Ji} = 0 | X_{Ji}, \theta^A, \theta^B]^{1-D_{Mi}} \\ \times f_{e^{y10}}(X_{Yi}, Y_{10} i, \theta^A, \theta^B) \\ \times Pr[D_{Mi} = 1 | X_{Ji}, \theta^A, \theta^B]^{D_{Mi}} \times Pr[D_{Ji} = 0 | X_{Ji}, \theta^A, \theta^B]^{1-D_{Ji}} \\ \times f_{e_{y11}}(X_{Yi}, Y_{11} i, \theta^A, \theta^B) \\ \times Pr[D_{Mi} = 1 | X_{Mi}, \theta^A, \theta^B]^{D_{Mi}} \times Pr[D_{Ji} = 1 | X_{Ji}, \theta^A, \theta^B]^{D_{Ji}} \end{array} \right] dF(\theta^A) dF(\theta^B) \\
&= \prod_{i=1}^{N} \iint \left[\begin{array}{l} f_{e^{y00}}(X_{Yi}, Y_0 i, \theta^A, \theta^B) \times \Phi(-\mathcal{M})^{(1-D_{Mi})} \\ \times f_{e^{y10}}(X_{Yi}, Y_{10} i, \theta^A, \theta^B) \times \Phi(\mathcal{M}, \mathcal{J})^{(D_{Mi})(1-D_{Ji})} \\ \times f_{e_{y11}}(X_{Yi}, Y_{11} i, \theta^A, \theta^B) \times \Phi(\mathcal{M}, \mathcal{J})^{D_{Mi} D_{Ji}} \end{array} \right] dF(\theta^A) dF(\theta^B)
\end{aligned} \tag{1.10}
$$

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

1.4.1 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 factors, $F(\theta^A)$ and $F(\theta^B)$, by a measurement system specified based on the nature of the data. The measurement system takes the following form:

$$
\boldsymbol{T} = \boldsymbol{X_T}\beta^T + \alpha^{T,A}\theta^A + \alpha^{T,B}\theta^B + \boldsymbol{e^T} \tag{1.11}
$$

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

[12] I use a modified version of the relative developed STATA command, **heterofactor**, by Sarzosa & Urzúa (2016)

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 (1.11). 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.

In order to identify $k = 2$ factors, I will need $L \geq 5$ test scores here. The test scores representing abilities at the beginning of college are listed in (1.12). The first set of test scores are $ACT_{English}$, $COM114$, and $ACT_{Reading}$; and the second set of test scores are $ACT_{Science}$, $HSGPA$, and ACT_{Math}. The intention of using ACT scores is to gather enough number of test scores (Otherwise, using SAT scores—SAT verbal and SAT math—would not fulfill the second restriction.) to identify two factors. The purpose of identifying two factors is to capture two latent abilities—one representing general abilities and the other representing math related abilities—and their varying effects on the choices.

$$\boldsymbol{T} = \begin{bmatrix} T_1 \\ T_2 \\ T_3 \\ T_4 \\ T_5 \\ T_6 \end{bmatrix} = \begin{bmatrix} ACT_{English} \\ COM114 \\ ACT_{Reading} \\ ACT_{Science} \\ HSGPA \\ ACT_{Math} \end{bmatrix} \tag{1.12}$$

The structure of the loadings, $\boldsymbol{\Lambda^T}$, takes the following pattern in (1.13), where the first factor is allowed to affect all 6 scores while the second factor is only allowed to affect scores of $ACT_{Science}$, $HSGPA$, and ACT_{Math}. For example, if one increases her first latent ability, all her 6 scores will increase; if one increase her second latent ability, her $ACT_{Science}$, $HSGPA$, and ACT_{Math} wil increase. More specifically, the first factor is identified from the covariances of all 6 scores; and the second factor is identified form the "left-over" covariances of the second set of scores—$ACT_{Science}$, $HSGPA$, and ACT_{Math}—after the first factor is identified. In this sense, I call the first latent ability as general intelligence, and the second as extra mathematical ability. I assume individuals need "general intelligence" to study and comprehend every subjects.

This is the triangular pattern of the loading system mentioned above. Note that $\alpha^{T_3,A}$ (i.e. the loading of $ACT_{Reading}$) and $\alpha^{T_6,B}$ (i.e. the loading of ACT_{Math}) are normalized to 1 to facilitate the identification.

$$\boldsymbol{\Lambda^T} = \begin{bmatrix} \alpha^{T_1,A} & \alpha^{T_1,B} \\ \alpha^{T_2,A} & \alpha^{T_2,B} \\ \alpha^{T_3,A} & \alpha^{T_3,B} \\ \alpha^{T_4,A} & \alpha^{T_4,B} \\ \alpha^{T_5,A} & \alpha^{T_5,B} \\ \alpha^{T_6,A} & \alpha^{T_6,B} \end{bmatrix} = \begin{bmatrix} \alpha^{T_1,A} & 0 \\ \alpha^{T_2,A} & 0 \\ 1 & 0 \\ \alpha^{T_4,A} & \alpha^{T_4,B} \\ \alpha^{T_5,A} & \alpha^{T_5,B} \\ \alpha^{T_6,A} & 1 \end{bmatrix} \tag{1.13}$$

I use MLE to estimate the measurement system. The likelihood function is:

$$\mathcal{L} = \prod_{i=1}^{N} \iint \begin{bmatrix} f_{e^{T_1}}(X_{Ti}, T_1 i, \gamma^A, \gamma^B) \times \\ ... \times f_{e^{T_6}}(X_{Ti}, T_6 i, \gamma^A, \gamma^B) \end{bmatrix} dF(\theta^A) dF(\theta^B) \tag{1.14}$$

I include an alternative setting of the factors in Appendix A, which takes the non-triangular pattern of the loading system.

1.5 Main Results

1.5.1 Latent Abilities

Table 1.3 and Table 1.4 show the estimates of the measurement system (1.11) used to identify the two latent abilities—general intelligence and extra 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[13] fix effects and first enrollment semester fix effects[14]. The loadings of general intelligence on all six test scores are significantly positive, meaning that both increase in general intelligence and extra mathematical ability will increase the 6 scores, as expected. Specifically, for example, one standard deviation increase in an average woman's general intelligence will increase her $ACT_{English}$ by 3.94 points and her ACT_{Math} by 2.91 points. One standard deviation increase in an average woman's extra mathematical ability will increase her ACT_{Math} by 2.72 points. Again, one should be cautious when interpreting the estimates of the two latent abilities in this paper. Extra math ability is the factor assumed to be orthogonal to 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, we should interpret the estimates of extra mathematical ability as conditioning on average level of general intelligence.

The predicted distributions of the latent abilities are shown in Figure 1.1 and Figure 1.2. They both show that the latent ability distributions are far from normal. Particularly, both female and male general intelligence distribution have a fat right tail. Especially for women, there is an obvious hump on the right tail. This implies the proportion of high-ability women is relatively big, compared to that of men.

[13]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.

[14]Table 1.5 lists the controls in each model and exclusion restrictions.

1.5.2 The Roy Model

Major Selection

Table 1.6 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[15] in the same year, and number of female graduates in the same major in the same year.

Both general intelligence and extra 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, extra 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 extra 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.

On average, women sort less on both general intelligence and extra mathematical ability than their male counterparts. Potential explanations could be that, first, women are less sensitive to their abilities when making the decision between majoring in STEM and non-STEM. I cannot rule out the possibility that they may think they are not good enough for STEM. Second, other factors are more dominating

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

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.

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 1.7 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, extra 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 extra mathematical ability will increase her likelihood of working in STEM by 5.17 percentage points; for men, that is 3.21 percentage points.

Salary

Table 1.8 and Table 1.9 show the salary returns to abilities for male and female who endogenously sort into different majors and jobs[16]. 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-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[17], national annual total number of graduates, total number of graduates in STEM, total number of female graduates, total number of female

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

[17]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.

STEM graduates, fraction of STEM employment in total employment, STEM and non-STEM total employment.

In general, both general intelligence and extra 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 extra 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 extra mathematical ability will increase her annual salary by $2474. In contrast, $Male_{00}$ has no significant return to extra mathematical ability. This can be one explanation that why women are less likely to enroll in STEM major: women with high extra 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 extra 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.

Model Fit

Table 1.11 shows that the model fits the actual data well, with respect to the test scores. Both the first and second moments are close to the data. Figures 1.8, and Figure 1.7 show the cumulative distribution of the test scores, for male and female. Generally speaking, Male's fits better than female's. The data for high school GPA and communication 114 grade points are lumpy because these two variables are discrete. Tables 1.10 presents evidence on the models' goodness-of-fit on the first and second moments of major choice (D_M), job choice (D_J) and salary ($Salary_{11}$,

$Salary_{10}$, and $Salary_{00}$). They are product of 1,000,000 simulations of the model based on bootstrapping 1000 times from the estimates and 1000 random draws from the factor distributions within each bootstrap. Comparing the "Data" and the "Model Prediction", it is clear that the model accurately predicts the means and standard deviations for each outcome of both genders. This provides confidence about the fact that the counterfactuals predicted by the model are appropriate.

1.5.3 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 1.3–Figure 1.6. Figure 1.3 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 hump on the right tails, indicating that men with relatively high general intelligence sort into STEM majors. Figure 1.4 shows the distributions of extra mathematical ability of the three categories of men. Similarly, the distribution of $Male_{00}$ is apart from the distributions of $Male_{10}$ and $Male_{11}$, indicating men with high extra mathematical ability are more likely to be majoring in STEM.

Women's sorting behavior in major decision is surprisingly different from men's. Figure 1.5 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 extra mathematical ability among women: the three distributions in Figure 1.6 are equally apart from each other. This suggests that extra 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 1.6; that is, on average, men sort more on both abilities than women. Furthermore, women of every level of ability are less likely to major in STEM or work in STEM, compared to their male counterparts. Evidence is provided by Table 1.12 and 1.13, which show the predicted values of majoring in STEM (working in STEM) by general intelligence deciles and extra mathematical ability deciles, respectively. We see that women's probability of majoring in STEM (Panel A) or probability of working in STEM (Panel B) is smaller than men's from ability decile 1 to 10. Moreover, the gender difference on the right tail of the ability distribution is slightly larger. High-ability (right tail) 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 1.7.

1.6 Counterfactuals

1.6.1 The Effect of Majoring in STEM

To understand the effect of majoring in STEM, I calculate the ATE (average treatment effect)of majoring in STEM for women and men, respectively.

$$ATE_M = E[Y_{10} - Y_{00}|\theta, x]$$

where the treatment is majoring in STEM, noted as subscript M. Panel A in Table 1.14 shows the averaged ATE of majoring in STEM over the whole distribution of ability. An average female majoring in non-STEM and working in non-STEM would have earned \$7,171 more if she had majoring in STEM and working in non-STEM. That number is \$7,312 to an average male. On average, there is no gender difference in the ATE of majoring STEM.

To show the variation of ATE across the ability distribution, I calculate ATE by each ability decile. Figure 1.9 shows the ATE of majoring in STEM for both genders over the deciles of f_1, general intelligence. Similarly, Figure 1.10 shows the ATE of majoring in STEM for both genders over the deciles of f_2, extra mathematical ability. Both curves on the left and right panels are upward sloping, indicating positive returns to abilities. There is barely any gender difference on the level of ATE of majoring in STEM. Female's ATE over both ability distributions have slightly larger standard deviation, implying that among individuals with the same ability, female's returns to STEM degree varies more than male's.

To capture the counterfactuals for individuals on the margin of the treatment, I calculate the MTE (marginal treatment effect) of majoring in STEM for female and male, respectively.

$$MTE_i = E[Y_{10} - Y_{00} | Pr(X_{M,i}\beta^M + \alpha^{M,A}\theta_i^A + \alpha^{M,B}\theta_i^B = e_i^M) = 1]$$

where MTE_i is the treatment effect of majoring in STEM for individuals who are indifferent of majoring in STEM, having observable characteristics $X_{M,i}$, and unobserved abilities θ_i^A and θ_i^B.

Figure 1.11 and Figure 1.12 present the MTE of majoring in STEM for both genders across the deciles of general intelligence and math ability. In general, MTEs are upward sloping, except male's MTE across general intelligence ability (the right panel of Figure 1.11, which is insignificantly downward slopping. Comparing ATE of majoring in STEM (Figure 1.9 and Figure 1.10) and MTE of majoring in STEM

(Figure 1.11 and Figure 1.12), they are very similar except that the MTEs have significant larger standard deviations. This is probably because 1. we are comparing fewer individuals on the margin within the same ability deciles; 2. the observable characteristics of individuals on the margin vary a lot more than an average individual.

1.6.2 The Effect of Working in STEM

In the Section 1.5.2, I discuss the fact that women are less likely to stay in STEM after they graduated with a STEM degree and argue that it is not due to gender differences in sorting on abilities. The next question is "how much do people lose by opting out of STEM after getting STEM degrees?" To answer that, I calculate the ATE of having a STEM job relative to having a non-STEM job for those who graduated with a STEM degree.

$$ATE_J = E[Y_{11} - Y_{10}|\theta, x, D_M = 1]$$

Panel B in Table 1.14 shows the averaged ATE of working in STEM over the whole ability space. For a woman who is picked at random from the sample of women who graduated with a STEM degree, working in a STEM job would increase her annual salary by \$6,480 than working in a non-STEM job. Although this number is not extraordinarily large, compared to male's averaged ATE, \$2,612, the effect of working in STEM for an average female STEM graduate is significantly larger than that of her male counterpart.

Figure 1.13 and Figure 1.14 also shows that female's ATE of working in STEM is larger than male's across deciles of both abilities. One may notice that the ATE is downward sloping across deciles of extra mathematical ability. This is due to the fact that the salary return to extra mathematical ability for group 10 (STEM degree and non-STEM job) is higher than that for group 11 (STEM degrees and STEM jobs). This implies that the returns to working in STEM is positive across the entire distribution of extra mathematical ability; but with a declining marginal return.

Again, I present the MTE of working in STEM, which can be written as follows.

$$MTE_i = E[Y_{11} - Y_{10}|Pr(X_{J,i}\beta^J + \alpha^{J,A}\theta_i^A + \alpha^{J,B}\theta_i^B = e_i^J) = 1, D_M = 1]$$

Figure 1.15 and Figure 1.16 depict the marginal treatment effect of working in STEM for each gender over the deciles of each abilities. The trends look similar to the figures of ATE above. However, female's MTE of working in STEM at each ability decile is slightly larger than female's ATE of working in STEM. Yet this is not true for the males. Additionally, we can see the gender differences in the MTE of working in STEM as in the ATE. Male's MTE of majoring in STEM is significantly lower than that of female, suggesting that the effect of working in STEM for females who are on the margin is significantly larger than that of their male counterparts.

1.6.3 The Effect of Majoring and Working in STEM

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

Now I compare two groups in distance, one work in STEM jobs with STEM degrees, the other work in non-STEM jobs with non-STEM degrees. This is the counterfactural of working in STEM for those who do not have STEM degrees. Generally speaking, an average woman is more rewarded than an average man for majoring in STEM, revealing by Panel C in Table 1.14. Specifically, an average woman who is picked at random from the entire female sample would earn \$13,651 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 \$9,925 for an average man, which is statistically lower. It is important to notice that there is no gender difference in treatment effect of majoring in STEM; and the gender difference of treatment effect of working in STEM is close to the gender differences in treatment effects to majoring and working in STEM. Thus, to sum up: 1. on average, both women and men have positive treatment effect of majoring and working in STEM; 2. the gender differences in treatment effect in majoring in STEM can be attributed to gender differences in rewards for a STEM job.

Figure 1.17 and Figure 1.18 show the ATE of majoring and working in STEM across ability deciles. Again, the level of female's ATE are above the level of male's ATE, indicating that women are more rewarded in majoring and working in STEM. Ironically, the fact is that women are less likely to major in STEM and more to opt out.

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

Having seen the effect of majoring and working in STEM by ability deciles, I argue that high-ability women could have earned a lot more had they got a STEM degree and worked in STEM. Recall the simulated general intelligence distribution of $Female_{00}$ group in Figure 1.5. Compared with $Male_{00}$ group in Figure 1.3, $Female_{00}$ has a lump on the right tail, implying high-ability women are less likely to majoring in STEM than high-ability men. To quantify the total losses in terms of salary for high-ability non-STEM women, I integrate the average treatment effect of majoring in STEM over the shadowed area on Figure 1.19. This area created by the interaction of 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 $Female_{00}$. 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, 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 5.60% of the Purdue female sample. Thus, one should not interpret as every woman gains \$772 per year by majoring in STEM, which is clearly minuscule. Instead, the 9.42% is all attributed to the 5.60% 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.

1.6.5 Counterfacutals of Major Choice

Now let's get back to the question that why women are less likely to major in STEM than men. From the estimates in Table 1.6, we see that women and men sort on abilities differently when making major choice. What if women had sorted the same as men? What if women and men had the same distributions of abilities? Table 1.15 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 for female and male, respectively. For easy understanding, I write out the expressions as follows.
$D_M^f(\beta^{M,f}, X_M^f, \alpha^{M,A,f}, \alpha^{M,B,f}, \theta^{A,f}, \theta^{B,f})$ and $D_M^m(\beta^{M,m}, X_M^m, \alpha^{M,A,m}, \alpha^{M,B,m}, \theta^{A,m}, \theta^{B,m})$, where superscripts denote the gender.

The second row answers the question that what if women had sorted the same as men. It 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 answers that what if women had had men's abilities. It 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 had both the same abilities and the same loadings of abilities, the proportion of graduates in STEM would be 40.37%. These counterfactuals indicate 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 or the sorting on abilities, I conduct the similar exercises on the observables. Substituting men's coefficients of the observables for women's ($D^f_M(\beta^{M,m}, X^f_M, \alpha^{M,A,f}, \alpha^{M,B,f}, \theta^{A,f}, \theta^{B,f})$), the proportion of female majoring in STEM would have significantly increased to 42.53%. Substituting men's observable variables for women's, we get the proportion of female majoring in STEM as 57.63%. Given both male's observable variables and the corresponding coefficients to women, the counterfactual estimate increases even more. Thus, the counterfactuals in row 5–row 7 suggest that gender differences in major decision can be primarily attributed to observable characteristics, including economic conditions, labor demand for STEM workers, and cohort effects. Besides these, there is still unexplained gender gap in major choice, which 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 the literature.

1.6.6 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 1.7, 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 1.16). 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 1.16 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 1.17, 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 1.18 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.

1.7 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[18] 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 each occupation[19]. 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[20].

1.8 Conclusion

This paper investigates the gender differences in ability sorting in major and job choices by applying an extended Roy 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

[18]Lilly Endowment for "Transforming Indiana into a Magnet for High Technology Jobs".
[19]https://va.tech.purdue.edu/careerVis/
[20]https://girlday.utexas.edu

to choose non-STEM major, compared to men. By majoring in non-STEM majors, high-ability women give up as much as \$13,000–\$20,000 annual salary, which in total explains about 9.4% of the gender wage gap.

There are several potential explanations for this sorting behavior among high-ability women. I cannot rule out the possibility that they may think they are not good enough for STEM. Additionally, they may be not informed well about the pecuniary value of the career paths associated with their abilities. 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. Home region is important in the job decision for women; women STEM graduates who go back home are more likely to opt out of STEM. 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, or marriage or access to child care.

Table 1.1.: 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 students graduated between 2005–2014. Six scores are: ACT English, ACT Reading, ACT Science, ACT Math, grade points of Communication 114 (required for all Purdue freshmen) and high school GPA. A valid self-reported salary means the graduate self-reported a positive annual salary.

Table 1.2.: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Panel A. Females					
ACT_English	25.661	4.617	11	36	1145
COM114 grade points	3.526	0.570	1	4	1145
ACT_Reading	25.940	4.944	12	36	1145
ACT_Science	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_Math	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_English	25.507	4.640	11	36	1910
COM114 grade points	3.339	0.630	1	4	1910
ACT_Reading	26.278	4.951	8	36	1910
ACT_Science	26.730	4.398	11	36	1910
HS_GPA	3.483	0.427	2	4	1910
exp(HS_GPA)	35.290	12.868	7.389	54.598	1910
ACT_Math	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 students graduated from 2005–2014. Standard test of ACT English, ACT Reading, ACT Science, and ACT Math have minimum of 0 and maximum of 36. COM114 grade points range from 2-4. Whoever fail the class (grade points less than 2) 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, which is used in the estimation instead of HS_GPA. Self-reported Annual Salary is nominal and in USD.

Table 1.3.: Identification of Abilities at College Entrance, Female

Dependent Var	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)
Extra 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					

Note: Each column is a separate regression specified in Equation 1.11. All columns have the same observations: 1145. The loading of General Intelligence is normalized to one in regression of $ACT_{Reading}$, so that General Intelligence takes the metrics of $ACT_{Reading}$. The loading of Extra Mathematical Ability is normalized to one in regression of ACT_{Math}, so that Extra Mathematical Ability takes the metrics of ACT_{Math}. I control for annual state-averaged freshmen graduation rate (AFGR) on the year of each student graduated from high school, home census region fixed effects and first enrollment semester fix effects.

Table 1.4.: 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					

Note: Each column is a separate regression specified in Equation 1.11. All columns have the same observations: 1910. The loading of General Intelligence is normalized to one in regression of $ACT_{Reading}$, so that General Intelligence takes the metrics of $ACT_{Reading}$. The loading of Extra Mathematical Ability is normalized to one in regression of ACT_{Math}, so that Extra Mathematical Ability takes the metrics of ACT_{Math}. I control for annual state-averaged freshmen graduation rate (AFGR) on the year of each student graduated from high school, home census region fixed effects and first enrollment semester fix effects.

Table 1.5.: 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 1.6.: 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)
Extra Math 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: 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 Extra 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, first enrollment year, first enrollment semester, degree year fixed effects are controlled but not shown in this table for short. See Table B.2 for the full table. The factor loadings are also shown in the full table.

Table 1.7.: Likelihood of STEM Graduates Work in STEM Occupations

	(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: 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 Extra 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 Table B.3 for the full table. The factor loadings are also shown in the full table.

Table 1.8.: Salary for Males

VARIABLES	(1) $Salary_{11}$	(2) $Salary_{10}$	(3) $Salary_{00}$
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		

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

Note: Column (1)–(3) separately show the estimates for men who graduate in STEM and work in STEM ($Salary_{11}$), men who graduate in STEM and work in non-STEM ($Salary_{10}$), and men who graduates in non-STEM and work in non-STEM ($Salary_{00}$). The dependent variable in all columns is annual salary in USD. Census region of job fixed effects are included but not shown. See Table B.4 for full table.

Table 1.9.: Salary for Females

VARIABLES	(1) $Salary_{11}$	(2) $Salary_{10}$	(3) $Salary_{00}$
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		

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

Note: Column (1)–(3) separately show the estimates for women who graduate in STEM and work in STEM ($Salary_{11}$), women who graduate in STEM and work in non-STEM ($Salary_{10}$), and women who graduates in non-STEM and work in non-STEM ($Salary_{00}$). The dependent variable in all columns is annual salary in USD. Census region of job fixed effects are included but not shown. See Table B.4 for full table.

Table 1.10.: The Fit of the Model, Decisions and Salaries

	Female	Male
Panel A. Prob(STEM Major)		
Data	0.3703 (0.4831)	0.6340 (0.4818)
Model Prediction	0.3762 (0.4843)	0.6348 (0.4814)
Panel B. Prob(STEM Job)		
Data	0.7311 (0.4439)	0.8117 (0.3911)
Model Prediction	0.6936 (0.4603)	0.7984 (0.4008)
Panel C. $Salary_{11}$		
Data	58280 (11299)	58669 (11072)
Model Prediction	53797 (12089)	56822 (11095)
Panel D. $Salary_{10}$		
Data	48180 (14032)	54358 (13286)
Model Prediction	47307 (14921)	54209 (13865)
Panel E. $Salary_{00}$		
Data	39039 (11370)	45558 (11759)
Model Prediction	40146 (11790)	46902 (11847)

Note: Predicted means and standard deviations (in the parenthesis) are not statistically different from the actual means and standard deviations at any conventional level of significance, except the predicted mean for female $Salary_{11}$ is different from the actual at 10% level. The predicted values come from 1,000,000 simulations based on 1000 bootstraps of the estimated parameters of the model and 1000 random draws from the two ability distributions within each bootstrap.

Table 1.11.: The Fit of the Model, Test Scores

	Female	Male
Panel A. ACT English		
Data	25.661 (4.617)	25.507 (4.640)
Model Prediction	25.683 (4.352)	25.518 (4.343)
Panel B. Communication 114 Grade Points		
Data	3.526 (0.570)	3.339 (0.630)
Model Prediction	3.523 (0.625)	3.339 (0.525)
Panel C. ACT Reading		
Data	25.940 (4.944)	26.278 (4.951)
Model Prediction	25.973 (3.906)	26.278 (3.837)
Panel D. ACT Science		
Data	24.668 (3.960)	26.730 (4.398)
Model Prediction	24.668 (3.408)	26.736 (3.547)
Panel E. exp(High School GPA)		
Data	36.971 (13.043)	35.290 (12.868)
Model Prediction	37.107 (8.895)	35.330 (7.288)
Panel F. ACT Math		
Data	25.645 (4.517)	28.237 (4.185)
Model Prediction	25.666 (5.227)	28.237 (4.017)

Note: The predicted values come from 5,000 simulations based on 50 bootstraps of the estimated parameters of the model and 100 random draws from the two ability distributions within each bootstrap.

Table 1.12.: The Predicted STEM Major Choice by General Intelligence (θ_1) Deciles

Decile	1	2	3	4	5	6	7	8	9	10
Panel A. STEM Major										
Female	0.185	0.246	0.283	0.315	0.346	0.378	0.415	0.462	0.528	0.605
	(0.043)	(0.045)	(0.045)	(0.046)	(0.046)	(0.047)	(0.048)	(0.049)	(0.052)	(0.054)
Male	0.356	0.472	0.535	0.584	0.627	0.668	0.709	0.752	0.797	0.848
	(0.044)	(0.040)	(0.038)	(0.037)	(0.036)	(0.035)	(0.034)	(0.033)	(0.033)	(0.029)
Panel B. STEM Job										
Female	0.627	0.646	0.658	0.667	0.675	0.685	0.694	0.707	0.723	0.743
	(0.129)	(0.105)	(0.094)	(0.087)	(0.081)	(0.076)	(0.071)	(0.068)	(0.067)	(0.070)
Male	0.755	0.770	0.778	0.784	0.791	0.796	0.803	0.810	0.819	0.830
	(0.065)	(0.052)	(0.046)	(0.042)	(0.039)	(0.038)	(0.036)	(0.036)	(0.037)	(0.040)

Note: This predicted values come from 1000,000 replications: 1000 bootstraps each with 1000 replications. Column 1 to 10 present the predicted probability of majoring in STEM (working in STEM) by General Intelligence decile 1–10. Panel A and B show the predicted values of probability of majoring in STEM and probability of working in STEM, respectively.

Table 1.13.: The Predicted STEM Major Choice by Extra Math Ability (θ_2) Deciles

Decile	1	2	3	4	5	6	7	8	9	10
Panel A. STEM Major										
Female	0.253	0.303	0.328	0. 348	0.367	0.384	0.403	0.423	0.450	0.505
	(0.054)	(0.049)	(0.047)	(0.047)	(0.046)	(0.047)	(0.048)	(0.049)	(0.052)	(0.061)
Male	0. 462	0.540	0.579	0.608	0.632	0.655	0.677	0.699	0.726	0.770
	(0.044)	(0.039)	(0.037)	(0.036)	(0.0356)	(0.035)	(0.035)	(0.035)	(0.035)	(0.034)
Panel B. STEM Job										
Female	0.629	0.654	0.667	0.677	0.685	0.693	0.701	0.710	0.720	0.741
	(0.123)	(0.098)	(0.087)	(0.081)	(0.077)	(0.074)	(0.072)	(0.071)	(0.073)	(0.083)
Male	0.758	0.775	0.783	0.789	0.795	0.800	0.805	0.810	0.816	0.828
	(0.060)	(0.048)	(0.043)	(0.041)	(0.039)	(0.038)	(0.037)	(0.037)	(0.038)	(0.041)

Note: This simulation results come from 1000,000 replications: 1000 bootstraps each with 1000 replications. Column 1 to 10 present the predicted probability of majoring in STEM (working in STEM) by Extra Math Ability decile 1–10. Panel A and B show the predicted values of probability of majoring in STEM and probability of working in STEM, respectively.

Table 1.14.: Averaged (across ability distribution) Average Treatment Effects

	(1) Female	(2) Male
Panel A. Averaged ATE of Majoring in STEM (10 vs. 00)		
ATE	7171	7312
	(2240)	(1727)
N	1145	1910
Panel B. Averaged ATE of Working in STEM (11 vs. 10)		
ATE	6480	2612
	(2903)	(1850)
N	424	1211
Panel C. Averaged ATE of Majoring&Working in STEM (11 vs. 00)		
ATE	13651	9925
	(2601)	(1401)
N	1145	1910

Note: This predicted values come from 1000,000 replications: 1000 bootstraps each with 1000 replications. Panel A shows the averaged ATE of majoring in STEM; Panel B shows the averaged ATE of working in STEM; Panel C shows the averaged ATE of majoring and working in STEM. Column (1) and (2) separately show predicted values for female and male. Standard deviations are in parentheses.

Table 1.15.: Counterfactuals of Majoring in STEM

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

Standard errors are in parentheses.

Note: This predicted values come from 1000,000 replications: 1000 bootstraps each with 1000 replications. Column (1) shows female predicted probability of majoring in STEM (factual) and counterfactuals. Column (2) shows male predicted probability of majoring in STEM (factual). Row 2–5 show the probability of majoring in STEM when replacing female parameters with the corresponding male parameters. Significant level of the test—$H_0 = H_1$ where $H_0 = female - factual$; $H_1 = female - counterfactual$—are shown as *** p<0.01, ** p<0.05, * p<0.1.

Table 1.16.: 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)	(0.0398)
Counterfactual: replacing $\alpha_{J,A}$, $\alpha_{J,B}$	0.6926	
	(0.0224)	
Counterfactual: replacing θ^A, θ^B	0.7057	
	(0.0221)	
Counterfactual: replacing $\alpha^{J,A}$, $\alpha^{J,B}$, θ^A, θ^B	0.6958	
	(0.0223)	
Counterfactuals: replacing β_J	0.7512*	
	(0.0210)	
N	424	1211

Standard errors in parentheses.

Note: This predicted values come from 1000,000 replications: 1000 bootstraps each with 1000 replications. Column (1) shows female predicted probability of working in STEM (factual) and counterfactuals. Column (2) shows male predicted probability of majoring in STEM (factual). Row 2–5 show the probability of working in STEM when replacing female parameters with the corresponding male parameters. Significant level of the test—$H_0 = H_1$ where $H_0 = female - factual$; $H_1 = female - counterfactual$—are shown as *** p<0.01, ** p<0.05, * p<0.1.

Table 1.17.: 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 1.18.: Fraction of STEM Graduates being Home or 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

Note: Panel A and B separately show summary statistics for males and females. Column (1) shows the number (fraction in parenthesis) of STEM graduates who work in a non-STEM job. Column (2) shows the number (fraction in parenthesis) of STEM graduates who work in a STEM job. "Home" means working in a state where one's home located (reported at college entrance); "Away" means working in another state.

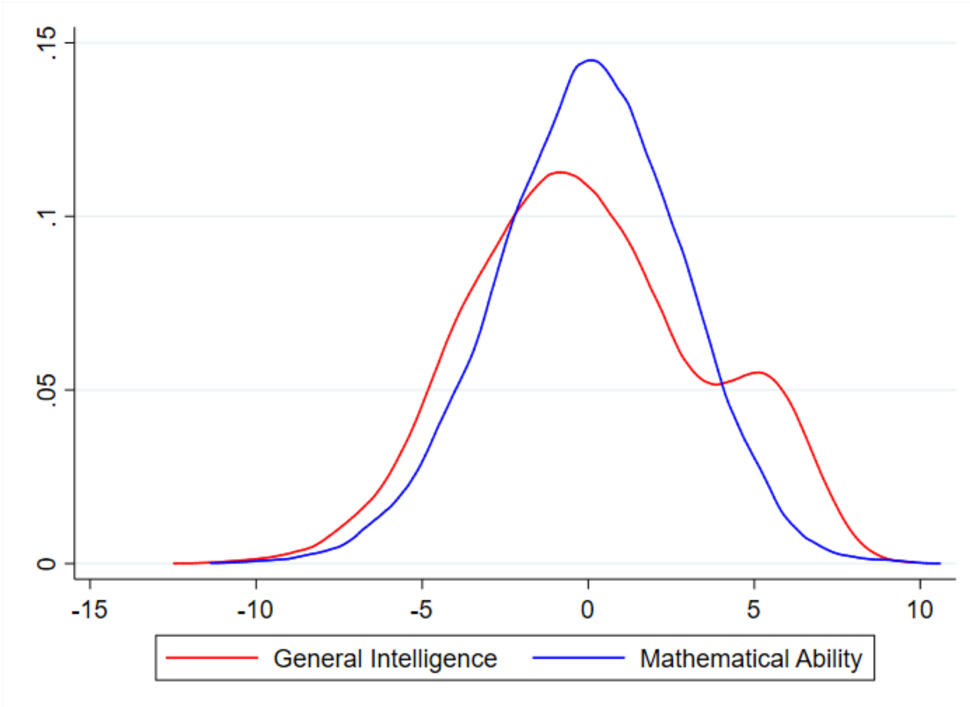

Figure 1.1.: Distributions of Female's Two Abilities

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

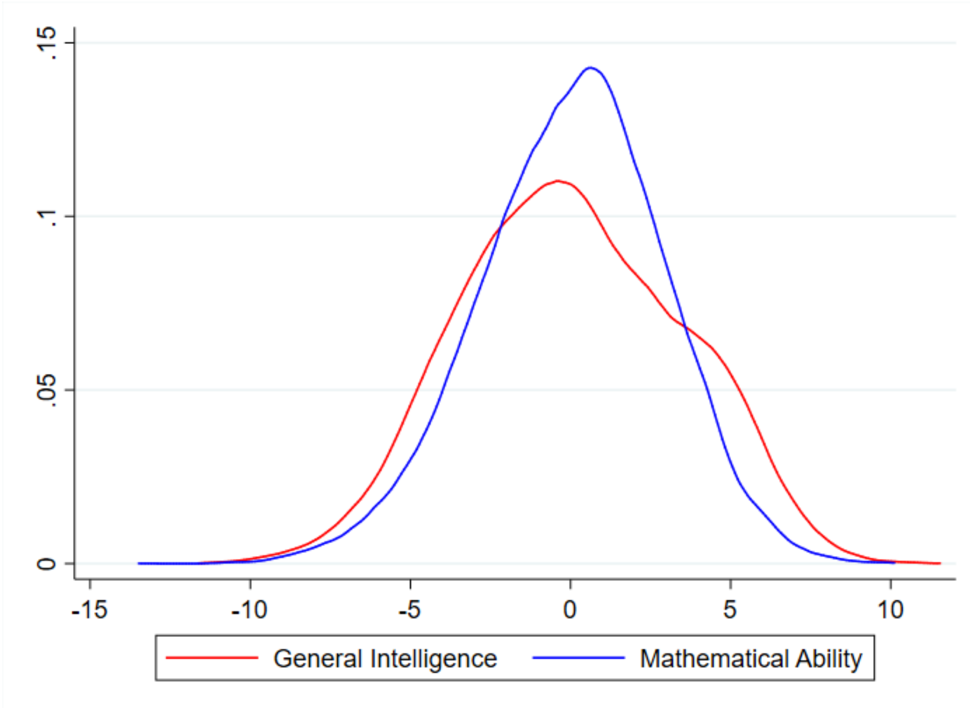

Figure 1.2.: Distributions of Male's Two Abilities

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

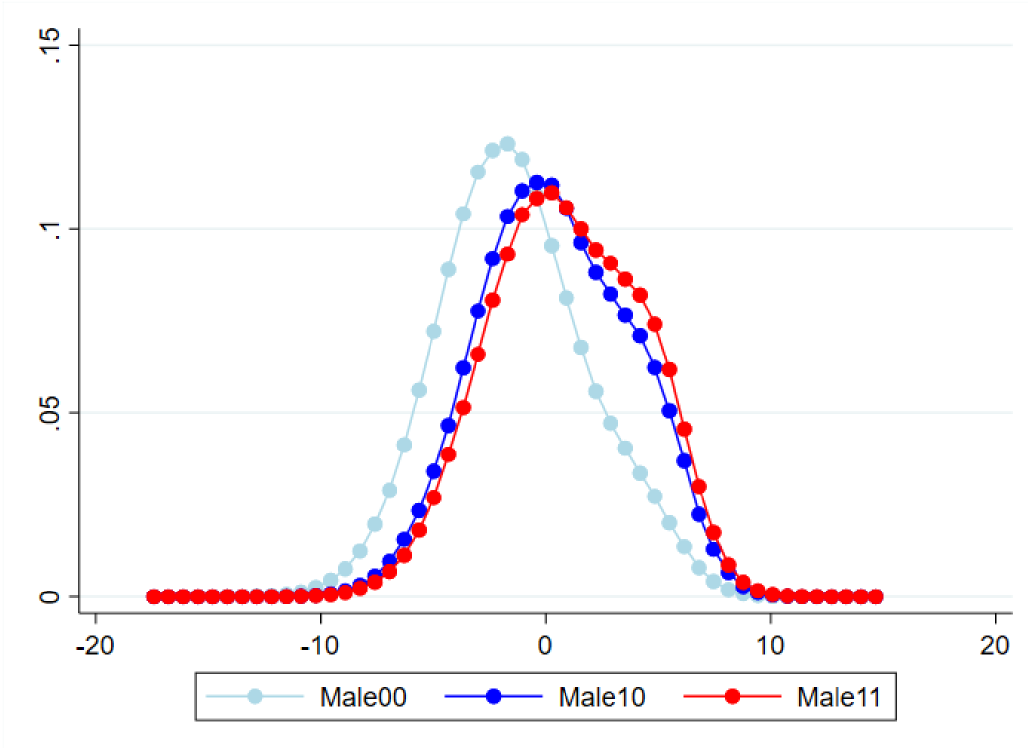

Figure 1.3.: Distribution of Male Factor 1 by Group

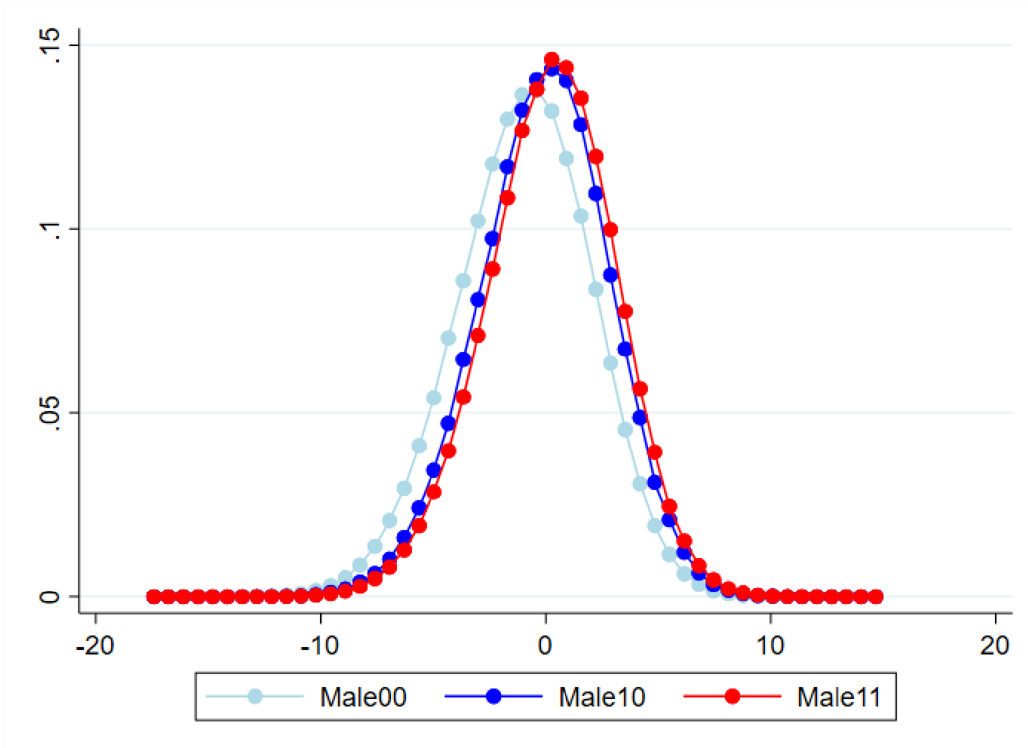

Figure 1.4.: Distribution of Male Factor 2 by Group

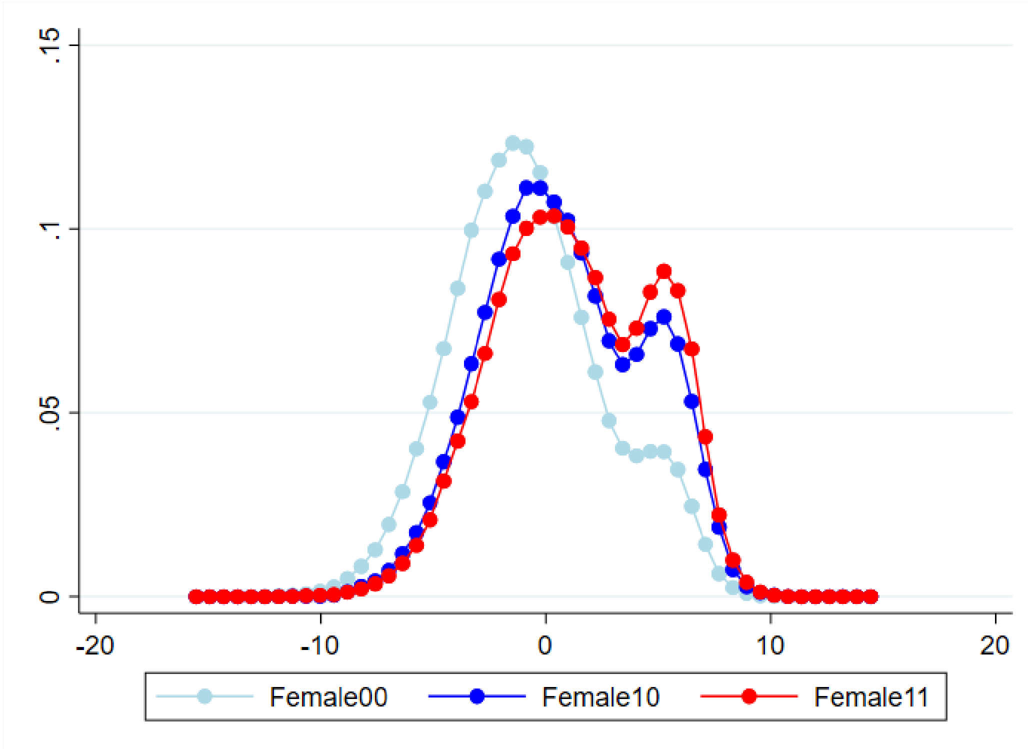

Figure 1.5.: Distribution of Female Factor 1 by Group

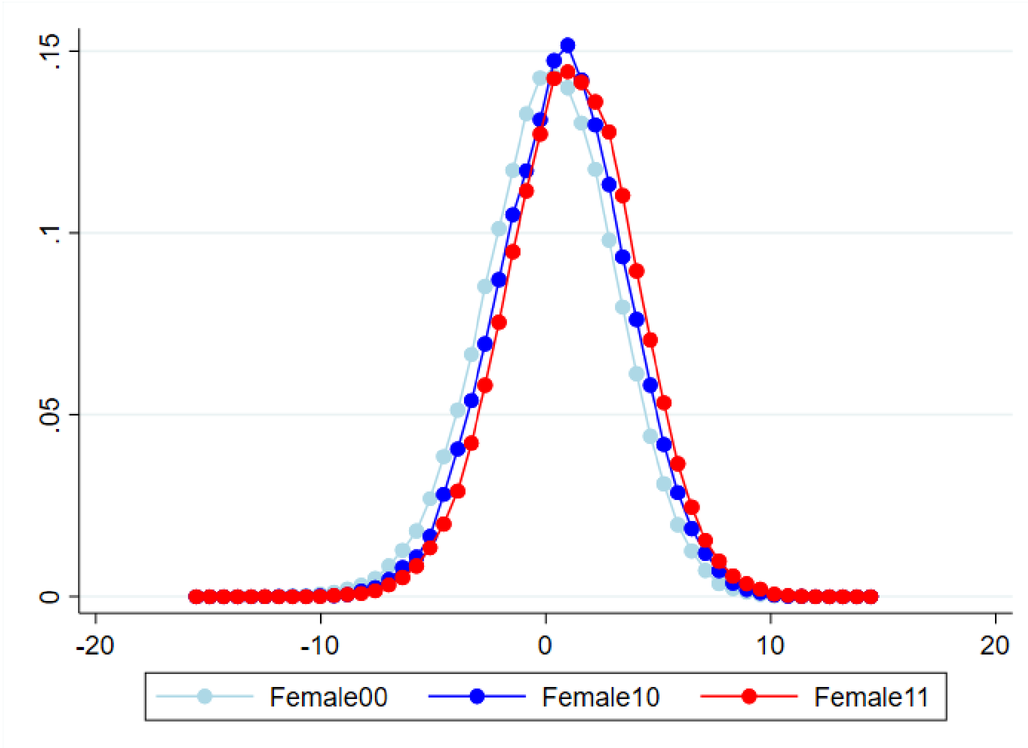

Figure 1.6.: Distribution of Female Factor 2 by Group

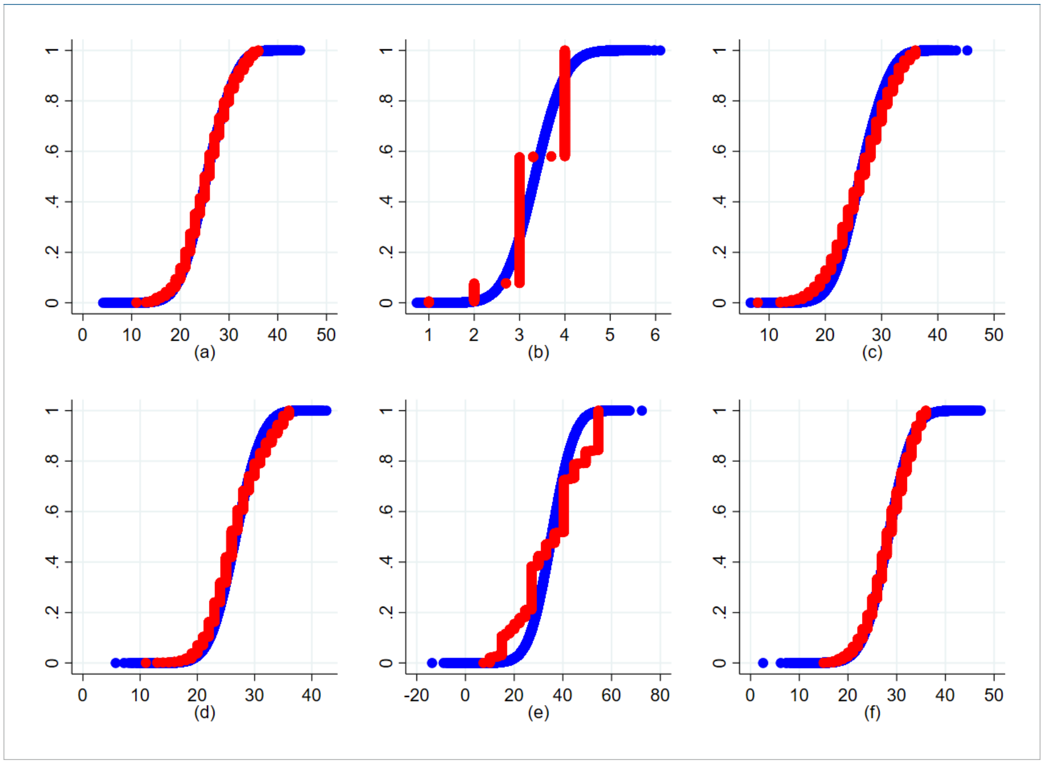

Figure 1.7.: Fit of the Model, Male Test Scores

Notes: Actual (red, dash) and predicted (blue, line) cumulative distributions plotted of the following test scores: (a) ACT English (b) Communication 114 grade points (c) ACT Reading (d) ACT Science (e) exponential high school GPA, and (f) ACT Math. The predicted values come from simulations based on the estimated parameters of the model.

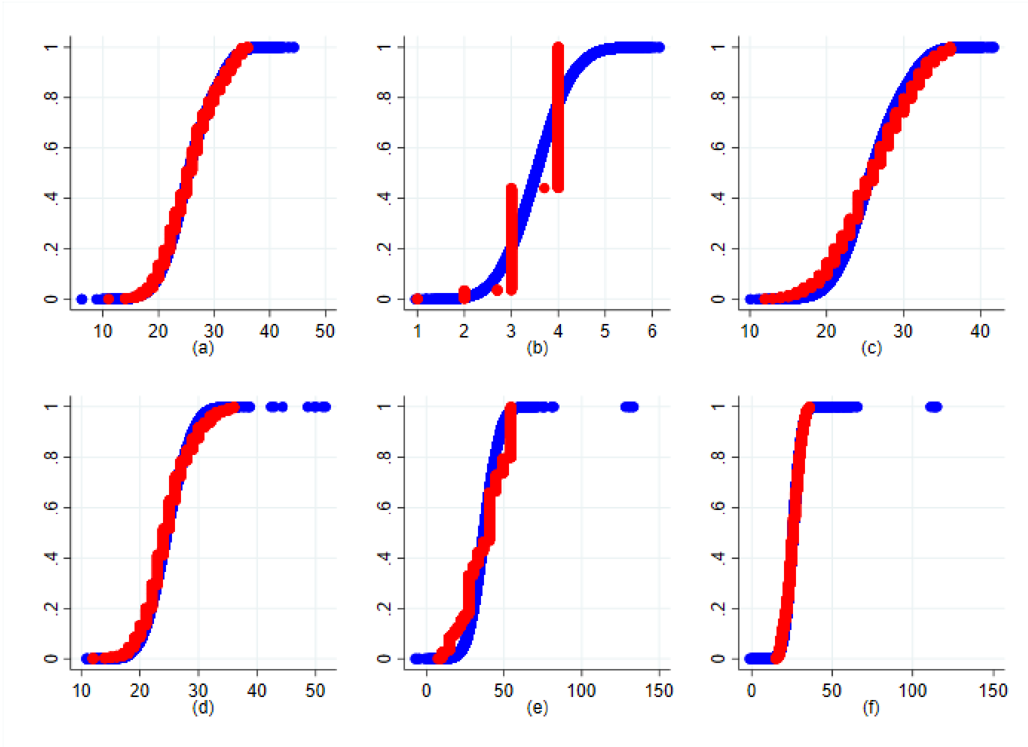

Figure 1.8.: Fit of the Model, Female Test Scores

Notes: Actual (red, dash) and predicted (blue, line) cumulative distributions plotted of the following test scores: (a) ACT English (b) Communication 114 grade points (c) ACT Reading (d) ACT Science (e) exponential high school GPA, and (f) ACT Math. The predicted values come from simulations based on the estimated parameters of the model.

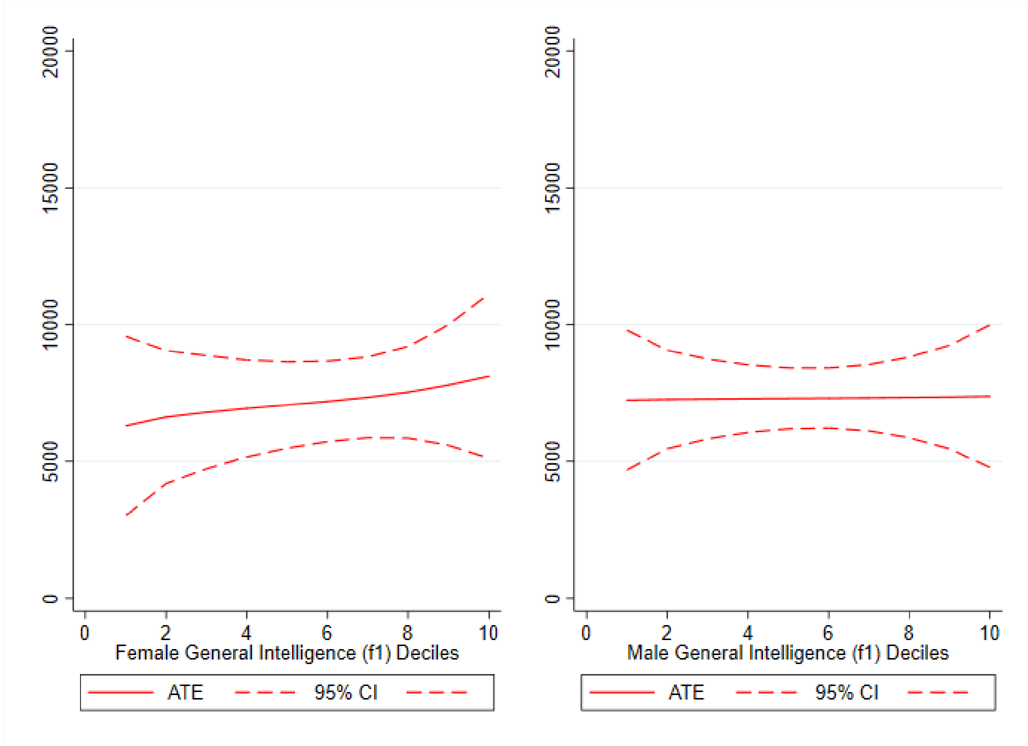

Figure 1.9.: ATE of Majoring in STEM, on General Intelligence

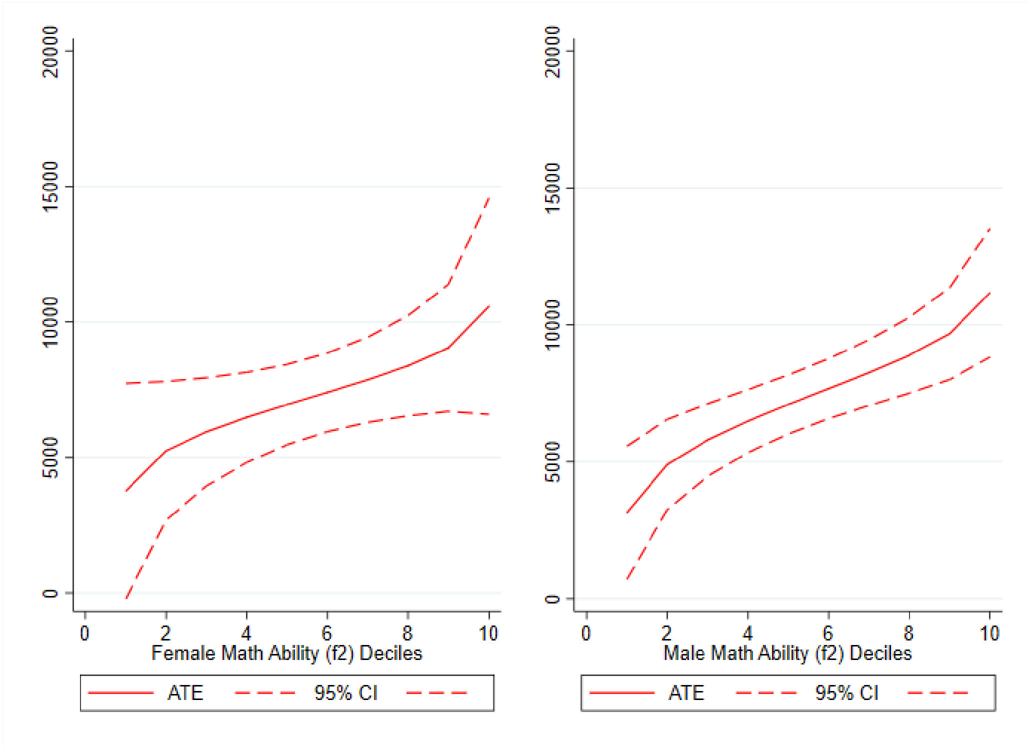

Figure 1.10.: ATE of Majoring in STEM, on Mathematical Ability

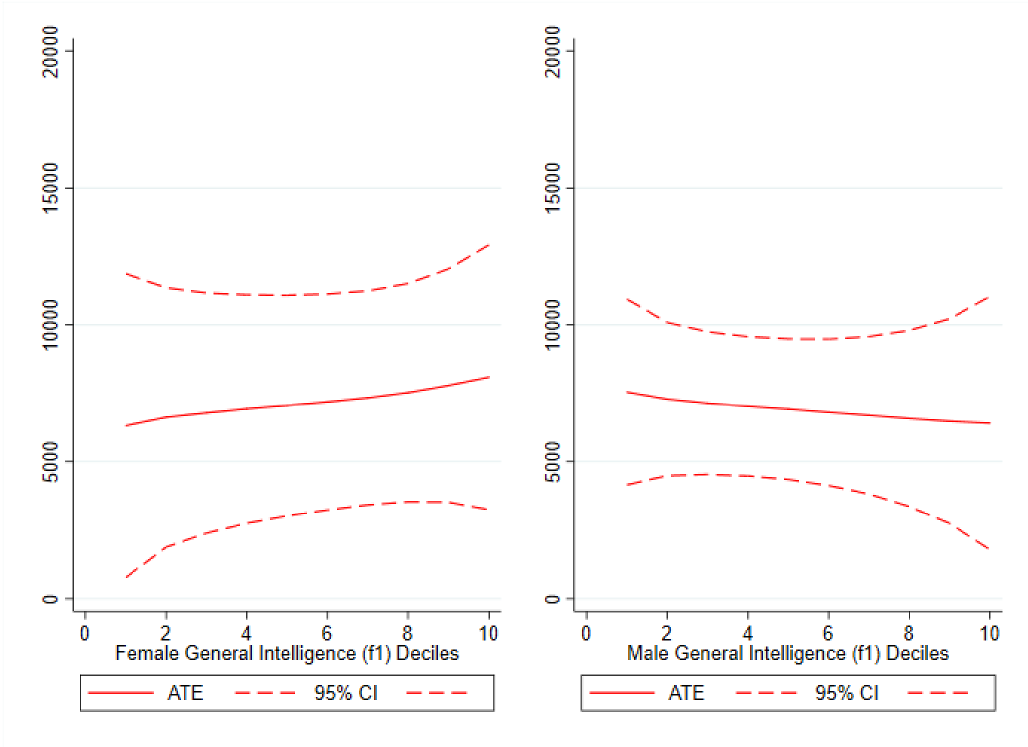

Figure 1.11.: MTE of Majoring in STEM, on General Intelligence

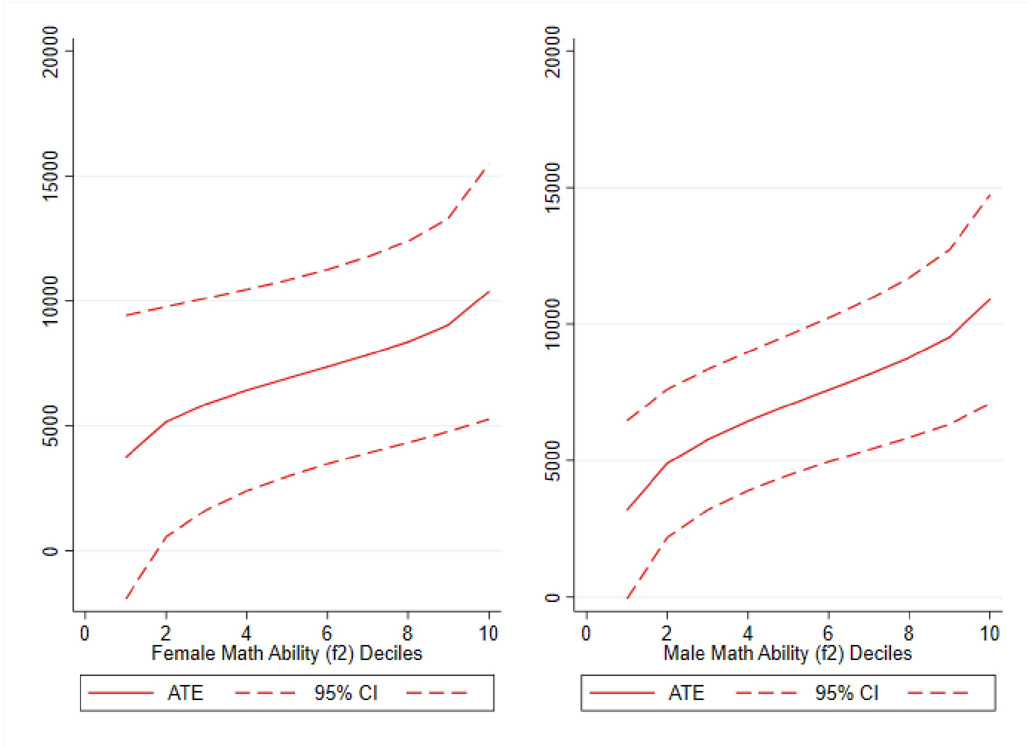

Figure 1.12.: MTE of Majoring in STEM, on Mathematical Ability

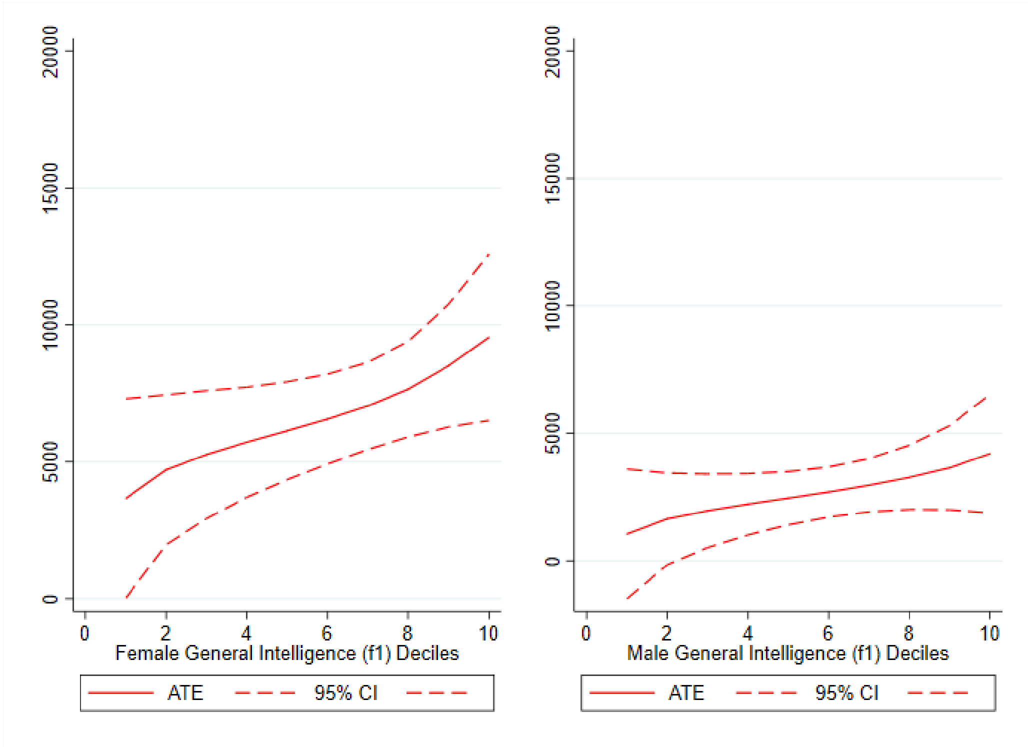

Figure 1.13.: ATE of Working in STEM, on General Intelligence

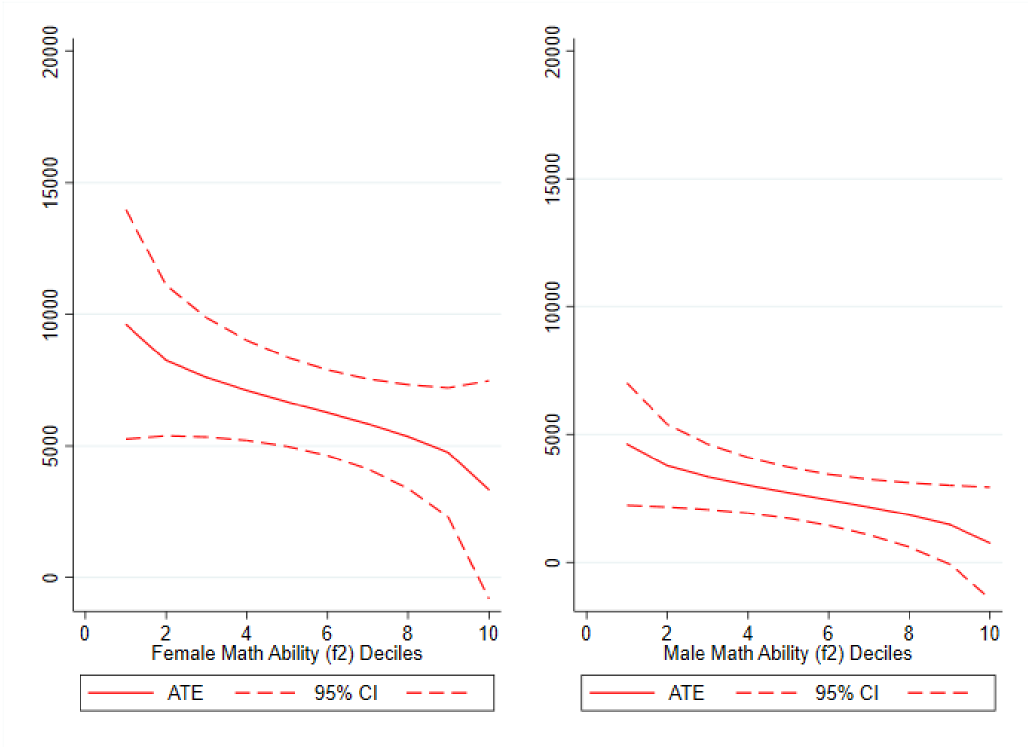

Figure 1.14.: ATE of Working in STEM, on Mathematical Ability

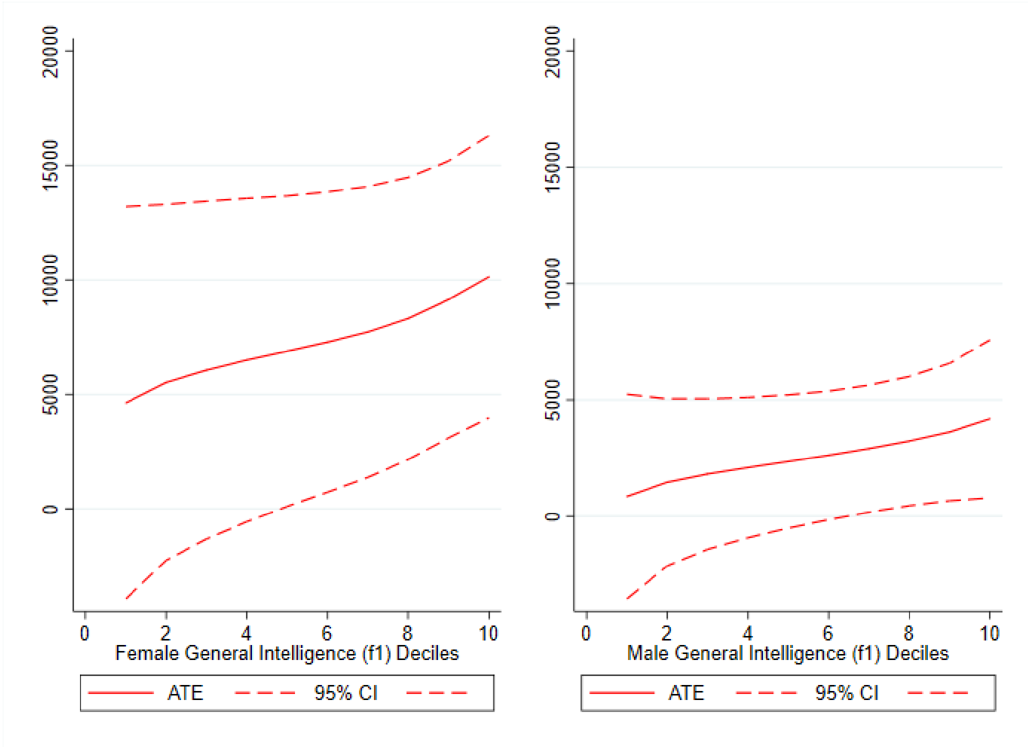

Figure 1.15.: MTE of Working in STEM, on General Intelligence

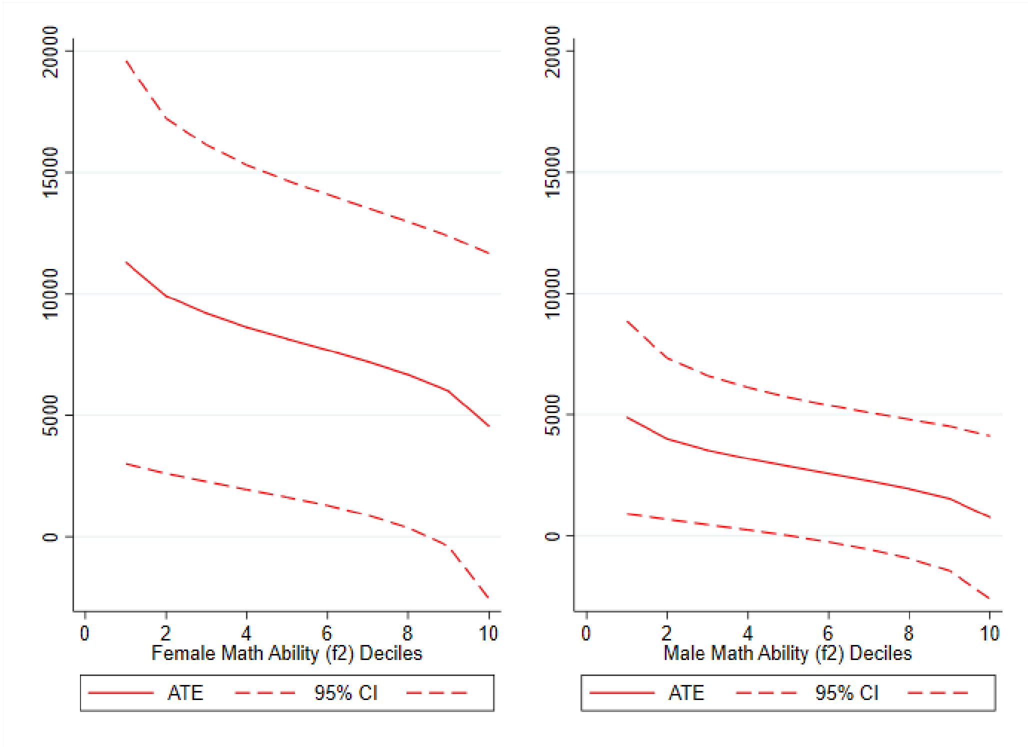

Figure 1.16.: MTE of Working in STEM, on Mathematical Ability

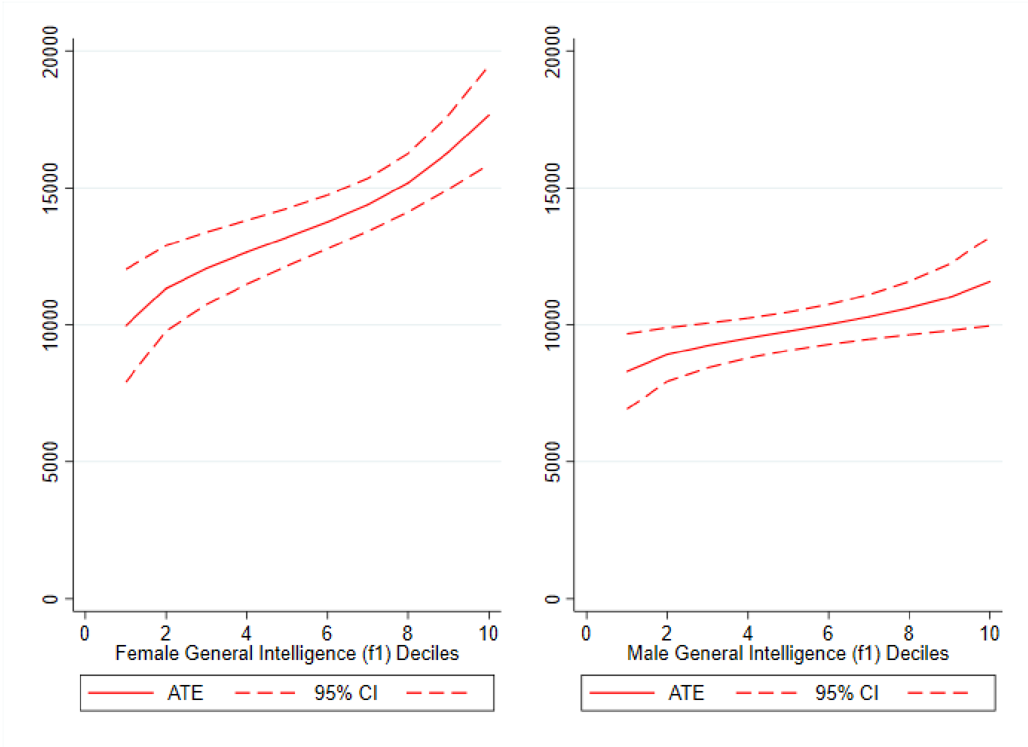

Figure 1.17.: ATE of Majoring and Working in STEM, on General Intelligence

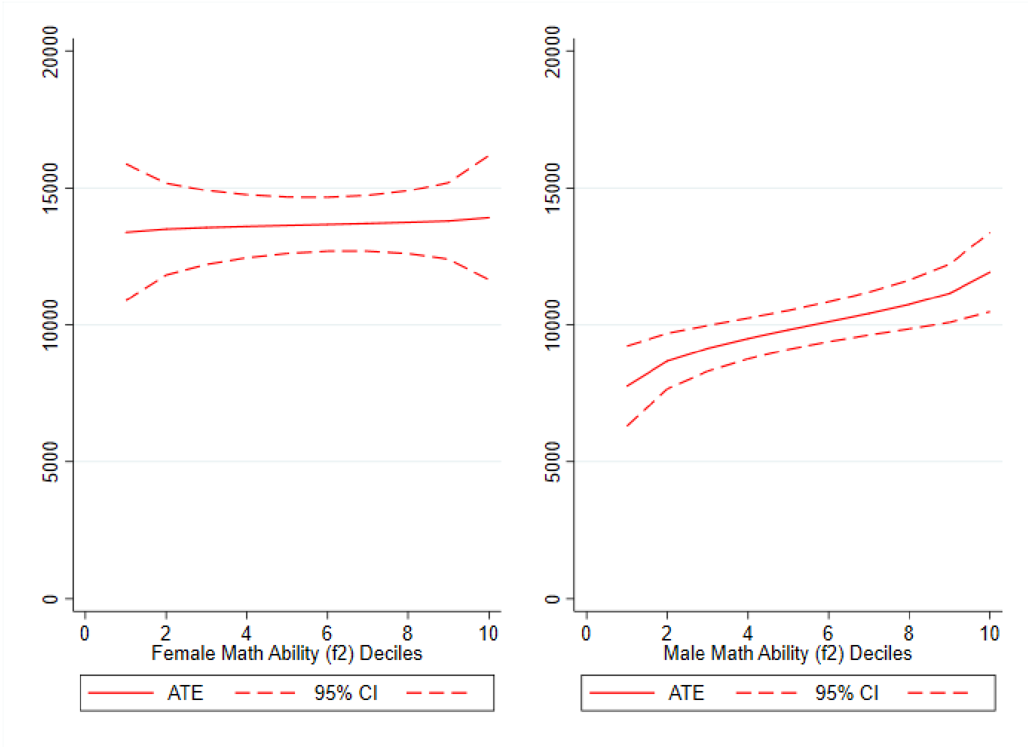

Figure 1.18.: ATE of Majoring and Working in STEM, on Mathematical Ability

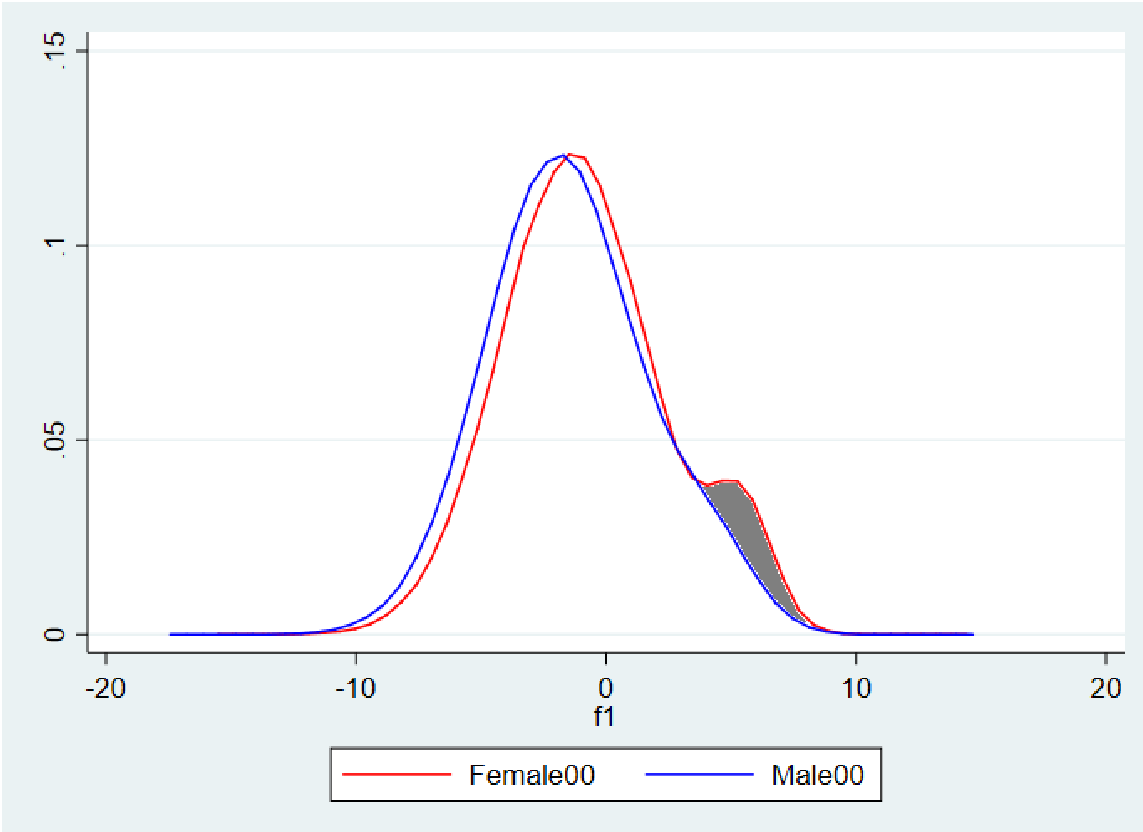

Figure 1.19.: Poor-Sorted High-Ability Women

Note: Overlap the simulated Female00 and Male00 distributions‘

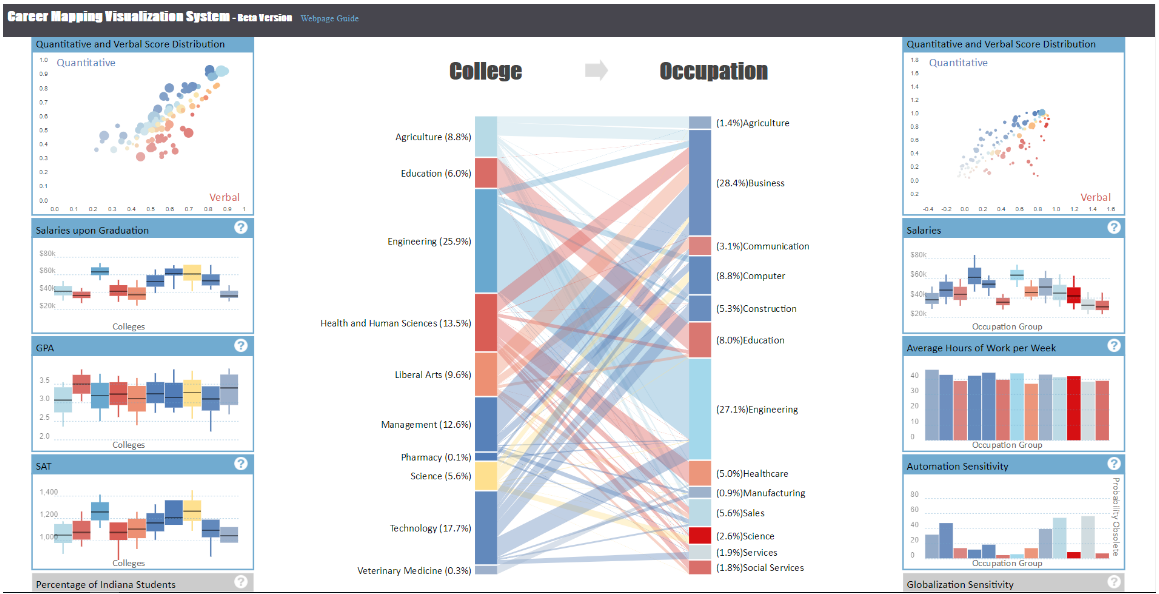

Figure 1.20.: Career Mapping Visualization System

Note: This is a career mapping visualization system developed by Purdue University to show the quantitative and verbal score distributions of each Purdue major and that of each occupation of Purdue graduates.

2. FERTILITY EXPECTATIONS AND EDUCATIONAL ATTAINMENT: EVIDENCE FROM THE MOTHERS OF CHINA'S SIBLING-LESS GENERATION

2.1 Introduction

In the late 20^{th} century, women's educational attainment increased remarkably relative to men's in China. Figure 2.1 shows that the gender gap in years of schooling started narrowing down among cohorts born in 1960, and fully closed within 20 years. I exploit China's One-Child Policy (OCP), a population planning policy enforced between 1979–2015, as an exogenous negative shock to fertility to estimate the causal effect of birth control policy on educational attainment of the mothers of the sibling-less generation, the generation born after the OCP.

Why should we expect mothers of the sibling-less generation to have increased their human capital investment in response to the birth control policy? It is well documented that changes in women's educational attainment are correlated with trends in fertility and marriage. Women who become mothers at an early age tend to have accumulated fewer years of schooling compared to those who delay their entry to motherhood (Waite & Moore, 1978). Goldin (2006) argues that "marriage delay enabled women to take formal education more seriously and led to changes in their relationship to work." There is also a large literature that examines the effect of fertility and childbearing on women's labor market attachment and human capital investments (Waldfogel, 1997; Budig & England, 2001; Goldin & Katz, 2002; Bailey, 2006; Buckles, 2008). Upon observing the OCP implementation, Chinese women would expect their future childbearing responsibility to be exogenously reduced. Their expected labor force participation and option value for their future career would be increased, which together lead to an increase in return to schooling. Furthermore, women may delay their entry to motherhood or even to marriage considering the more relaxed timetable for fertility. These forces would lead women to pursue more education. Thus, this paper asks whether women who observed the OCP before dropping out of school changed their educational choices, and how?

I use two difference-in-differences (DD) approaches to identify the impact of the OCP on mothers of the sibling-less generation. My first DD model estimates the differences in educational attainment between the Han (the ethnic majority) women and the Han men, for both the birth cohorts affected by the policy (the post-policy group) and the birth cohorts unaffected by the policy (the pre-policy group). Unlike women, men are less likely to change their dropout decisions in response to exogenously negative shock of their future fertility, because the opportunity cost of fatherhood is much lower than that of motherhood (Budig & England, 2001; Budig, 2014; Adda et al., 2015). Therefore, it is reasonable to assume that men's dropout decisions at schooling ages are less likely to be affected by the OCP. I find that, compared to Han men, the OCP significantly increased Han women's years of schooling by 1.28 years, which explains 53.6% of the 2.38 years increase in educational attainment of women born between 1950-1980. This estimate might be bias towards zero since Han men's educational attainment could also be positively affected by the OCP.

One concern of this approach is that the OCP might overlap with other economic reforms that might be in favor of women's educational attainment. Over this same time period, many developed and developing countries have experienced rapid convergence and even reversal in the gender gap in educational attainment. Potential reasons for these changes include declining prejudice in educational institutions, improvements in women's opportunities in the labor market, and changes in women's social status (Becker et al., 2010). One may argue that, even if without the OCP, China would have experienced the same convergence in gender gap. With this concern in mind, I explore alternative identifications for the researh question. Since the OCP is a national policy announced to the whole country by the end of 1979, geographical variation in implementation time is not available for the identification[1].

I consider a second DD approach that is free of gender-specific policy impact. This approach takes advantage of the fact that the OCP restricted Han (the ethnic majority) to have only one child per family while allowed non-Han to have two or more children per family. I exploit the difference in birth quota between Han and non-Han to construct the treated group, Han women, and the untreated group, non-Han women, by assuming that Han women's fertility expectation was strongly affected by the OCP while non-Han women's was slightly affected. This approach estimates the differences in the educational attainment between Han women and non-Han women, for both the post-policy group and the pre-policy group. I expect the OCP also had a positive effect on non-Han women's educational attainment. Therefore, my estimate should be considered as a lower bound of the OCP's true effect on Han women's educational attainment. I find that the OCP significantly increased Han women's years of schooling by 1.36 years compared to non-Han women. This approach provides close estimates to the first approach and more importantly, suggests that comfounding effects on gender differences is not a major concern.

There is an extensive literature on the effects of China's family planning policies, including the OCP, on China's fertility decline (Lavely & Freedman, 1990; McElroy & Yang, 2000; Wang et al., 2012; H. Li et al., 2005). The OCP's effects on human capital accumulation of the children—the sibling-less generation—has been attracting a lot of attention as well (Angrist et al., 2005; Black et al., 2005; H. Li et al., 2008; Rosenzweig & Zhang, 2009; Lee, 2012). However, the OCP's effect on educational attainment of mothers of the sibling-less generation has been overlooked by economists. The only study that investigates the OCP's effect on educational attainment of girls at schooling ages is the paper by Huang et al. (2015 working paper). They adopt

[1]The central government announced the OCP by the end of 1979. The local implementations of the OCP vary by fines for above-quota births, one-child subsidies, and the provision of contraceptives. It is unclear when the laws began being enforced at each local level. Literature often takes 1979 as the unique time of the OCP being implemented nationally (H. Li et al., 2011).

the ratio of the monetary penalty for one unauthorized birth to the local averaged household income as a measure of the OCP intensity[2] to estimate the policy's effect on girls' high school completion rates. They find a 2 percentage points increase in high school completion among Han girls when the fine rate doubled. Using variation in monetary penalty across provinces as a measure of the OCP, however, could be problematic because local governments may set the amount of fines according to local financial situations and local fertility demand (Zhang, 2017). Furthermore, monetary penalty is neither the only or the harshest enforcement of the OCP. Losing track of the other enforcements, like excluding unauthorized children from public education, discharging parents from social services, compulsory use of abortion and sterilization, etc. (Banister, 1991) may overestimate the increase in women's educational attainment in response to the increase in fine rates.

My paper uses a more straightforward measure of the OCP, the policy itself, by using a policy dummy to estimate its impact on women's educational attainment. It captures the whole effect of the OCP on education, and it is easy to interpret the point estimates in this paper as they link directly to policy implications. I investigate the differences of educational attainment among young and old cohorts to rule out the potential confounding effects from contemporaneous policy changes, such as the nine-year compulsory schooling law and college reopening. This analysis confirms the OCP's positive and significant effect on women's education. I find there is no gender differential or ethnicity differential effects on college entry or college completion, suggesting that college reopening did not confound the OCP‘s effect on education. I also find that both Han women's middle school completion rate and their high school completion rate are significantly increased among the young cohorts. I cannot rule out compulsory schooling law's effect on the increase in Han women's middle school completion; however, the increase in high school completion cannot be attributed to the compulsory schooling. Literature find that there is no positive effect of com-

[2]The same measure has been used in McElroy & Yang (2000).

pulsory schooling laws on educational attainment beyond the minimum equirement (Oreopoulos, 2006).

Analysis on the OCP's effect on women's post-school outcomes shows that the OCP led to delayed first marriages and motherhood, decreased number of births, and increased labor force participation for school-aged women. These findings provide evidence, though not direct, for potential mechanisms through which the OCP increased women's educational attainment. This paper contributes to literature addressing the shrinking educational attainment gap between women and men in China. It also shed light on literature that examines the effect of fertility and childbearing on women's labor market attachment and human capital investments.

The paper proceeds as follows. Section 2.2 provides some historical background of the OCP. Then, Section 2.3 describes the study data while Section 2.4 lays out the estimation strategy. Section 2.5 presents the main empirical results of the OCP's effect on educational attainment, and Section 2.6 provides additional results for later outcomes and discusses possible mechanisms. Finally, Section 2.7 concludes by addressing the policy implications and suggesting direction for future research.

2.2 Historical Background of One-Child Policy

Since China is such a populous country, controlling the population size has been a fundamental policy since the early 1960s. There are three periods in the history of the Chinese family planning policies Period 1 (1963–1971): the central government first announced a position advocating "birth planning in urban areas and densely populated rural areas." Although family planning commissions were established during Period 1, this early family planning operation was halted by the Cultural Revolution. Period 2 (1971–1979): A widely spread family planning campaign was successfully carried out, and Chinese people voluntarily[3] delayed marriage, lengthened the period during first and second birth, and had fewer children. Period 3 (1979–2015): The

[3]The campaign was technically voluntary, but it had some coercive elements, although they were significantly less coercive than the One-Child Policy (Zhang, 2017).

One-Child Policy was formally conceived in 1979 and rapidly established across the country in 1980 (Banister, 1991; H. Li et al., 2005; Wang et al., 2012; Huang et al., 2015 working paper). This paper identifies 1980 as the OCP implementation year for the whole country.

The OCP was the strictest family planning policy as it restricted each couple to having only one child, but this strict requirement only applied to the Han, the ethnic majority[4]. The policy allowed many exceptions for ethnic minorities[5]. An urban non-Han couple could have two children, and a rural non-Han couple could have three, or even more, children depending on the population size of the ethnic group (Wang et al., 2012). There are also some exceptions for rural Han couples, considering that most rural families make a living through labor-intensive agricultural activities. For example, a rural Han couple could apply for a permit to have a second child four years after their first birth if the only child is female or disabled. Thus, the intensity of the OCP could be roughly ordered from high to low from urban Han, rural Han, urban non-Han, and rural non-Han.

The provincial governments gradually issued detailed regulations to guarantee the enforcement. Population and Family Planning Commissions were set up at every level (province, city, county, etc.) to ensure the enforcement of the policy. The OCP was enforced through monetary penalties on above-quota birth, denial of public service, required abortion of subsequent pregnancy, sterilization etc. (Banister, 1991; McElroy & Yang, 2000; H. Li & Zhang, 2007). The government also encouraged people to comply with the policy by rewarding couples who had only one child with a "one child certificate," which entitled them to a variety of benefits (Arnold & Zhaoxiang, 1986). Meanwhile, the local governments tightened the *hukou* registration and inspection and raised awareness of the policy with campaigns and posters.

Note that this paper does not intend to capture the total effect of Chinese family planning policies on women's education. As mentioned above, there are several stages

[4]The 1982 Census of China indicated that 93.3% of Chinese were Hans.

[5]There is only one ethnic majority in China, Han. The other 55 ethnic groups count as minorities, non-Han

of the policies representing different levels of birth control restrictions before the OCP. Those policies likely already have effects on women's education. I only study the OCP's effect, which can be interpreted as the extra effect that the OCP added to the previous policy.

2.3 Data

The micro-data used for the analysis come from the ongoing CFPS[6]), a nationally representative, annual longitudinal survey of Chinese communities, families, and individuals. The CFPS is designed to collect individual-, family-, and community-level longitudinal data in contemporary China, which reflect the social and economic transformation of Chinese society and how that affects the economic activities, education outcomes, family relationships, migration, and health status of China's population. All members over age nine in a sampled household are interviewed. This study uses the cross-sectional CFPS 2010 baseline survey in its analysis. In the 2010 baseline survey, the CFPS successfully interviewed around 15,000 families and about 30,000 individuals within these families, with an approximate response rate of 79%.

The data contain a rich set of individual, household, and community information, including demographic, economic, and educational information. The survey covers most of the administrative regions[7] in China: all four municipalities[8] and 21 provinces[9]. The darker shaded regions in Figure 2.2 are the provinces and municipalities in which the survey has been conducted. Note that the ones left out[10] except the Hainan province (the island in the south), are very distinct from the others in terms of ethnic composition, language, and lifestyles; therefore, it would be hard to compare the policy's effect in these regions anyways, had the survey covered them.

[6]CFPS was launched in 2010 by the Institute of Social Science Survey (ISSS) of Peking University, China. It is funded by the Chinese government through Peking University.

[7]There are four municipalities, 28 provinces (including five autonomous regions) and two special administrative regions (Hongkong and Mocau) in China.

[8]Beijing, Tianjin, Shanghai, and Chongqing.

[9]Hebei, Shanxi, Liaoning, Jilin, Heilongjiang, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, Sichuan, Guizhou, Yunnan, Shaanxi, and Gansu.

[10]Inner Mongolia, Xinjiang, Tibet, Qinghai, Ningxia

The sample used in the estimation includes cohorts born between 1950 and 1980. Table 2.3 presents summary statistics of the sample. Women account for 52.12 percent of the population and Han account for 91.89 percent of the population. 83.83 percent of the population is rural. The primary variable used to represent educational attainment is years of schooling, constructed by the CFPS. It ranges from 0 to 22. All individuals in this analysis have completed their schooling.

On average, cohorts born between 1950-1980 have completed 7.37 years of schooling. Men have more years of schooling than women, and Han have more years of schooling compared to non-Han. Figure 2.3 shows most dropouts happen after completing junior high school (9th years schooling). Figure 2.1 shows the increasing trend of years of schooling across cohorts by gender. The graph shows women's average years of schooling has been catching up with men's among the younger cohorts. The gender gap among the 1980 cohorts has narrowed compared to the older cohorts.[11]

There are many benefits to using these survey data. First, they provide detailed information on family background that is essential to one's education outcome, namely, number of siblings, both parents' level of education and both parents' political status[12]. Second, the survey provides birth province, which helps to rule out the potential problem of inter-province migration. Third, the survey is nationally representative.

2.4 Method

This section introduces the empirical strategy to identify the effect of the OCP at different schooling ages on the educational attainment of women in the treated group. I use two standard difference-in-differences (DD) approaches to do this. Specifically,

[11] There is an obvious downturn between the mid 1960s to the early 1970s. This phenomenon has been noticed by Hannum (1999).

[12] The answers for father/mother's level of education include: "Illiterate," "Primary school," "Junior high school," "Senior high school," "2- or 3-year college," "4-year college/Bachelor's degree," " Master's degree," and "Doctoral degree." The answers for father/mother's political status include: "Member of Communist Party," "Member of Democratic Party," "Member of Communist Youth League," and "General public".

the first DD approach compares Han women relative to Han men, and the second one compares Han women relative to non-Han women.

2.4.1 Pre-Policy and Post-Policy Groups

There are two cohorts compared in this data. The "old generation," who were old enough when the policy was implemented that they had already made the decision between dropping-out of school and staying in school when the policy came into play. Thus, the policy should not have affected their educational outcome. This "old generation" is the pre-policy group. The "young generation was still in school when the policy was implemented. Considering that the policy lowered the expected fertility, the lifetime childcare cost was contemporaneously reduced. Therefore, they could be expected to devote more time to their own education and career in the future. Thus, the "young generation" is the post-policy group.

My sample includes cohorts born between 1950-1980. I define the 1950-1959 birth cohorts (age 21-30 when the policy was implemented) as my pre-policy group because people older than 20 may have already made dropout decisions or most likely finished schooling. Including even older cohorts may overestimate the policy's effect by attributing the contribution of domestic and international social and economic development to the overall education improvement. The 1960-1980 birth cohorts (age 0-20 when the policy was implemented) are defined as the post-policy cohorts for the main specification. Although this cut-off age is rather arbitrarily chosen, I do change the pre- and post-policy group by narrowing the post-policy group to contain younger cohorts while fixing the pre-policy group, as robustness checks in my subsequent specifications. I also conduct dynamic difference-in-differences analysis to show the policy's effect on each birth cohort. Figure 2.3 shows that age 12 was the earliest dropout age, age 15 is the next early dropout age, and most of people drop-out before entering college[13].

[13]Generally speaking, a normal Chinese primary school takes six years to finish, a junior high school and a senior high school each takes three years. Students usually start school at age six.

2.4.2 Han Women VS. Han Men

The first approach uses men as the control. Compared to women, men are much less likely to change their education decisions due to changes in the expected fertility of their future partners. The opportunity cost of motherhood is also much higher than that of fatherhood (Budig & England, 2001; Budig, 2014; Adda et al., 2015), because it is women who give birth, take of maternity leave, and bear most of the lifelong childcare burden. In this sense, men are appropriate controls for women. The regression can be written as follows:

$$Edu_{isc} = \alpha + \sum_{j=1}^{C} \gamma_j I_j + \lambda Women_{isc} + \eta Post_{sc} + \beta_1 Women_{isc} \times Post_{sc} + \Omega X_{isc} + \epsilon_{isc} \tag{2.1}$$

where i indexes individuals, s indexes provinces, and c indexes birth cohorts. The dependent variable Edu is the years of schooling. I_j is a set of birth cohort dummies, $Women$ is a dummy for Han women (relative to Han men), $Post$ is the dummy for the post policy group, $Women \times Post$ is a interaction of Han women and post-policy cohorts. X is a vector of observable characteristics. ϵ is the error term.

The set of demographic characteristics X_{isc} includes a dummy indicating rural residence, a $women \times rural$ interaction term, province fixed effects, parents' educational attainment, number of siblings, and parents' political status. Controlling for rural factors is important to the estimation, because around 84% of the population were rural residents in the 1960s. Education outcomes of rural residents are significantly lower than their urban counterparts. Also, the traditions of having a big family and son preference have been more deep-rooted in rural areas relative to urban areas. Thus, the policy's effect on rural women could be different compared to urban women. Additionally, number of siblings reflects one's educational resources. Women and men may face different education opportunities based on the number of siblings in their household, again because of son preferences in some areas. Controlling for parents' education might further control for the gender bias. Lastly, based on China's political environment, being a Communist Party member means having responsibility for insuring the policy's implementation. Therefore, if parents are members of the Communist Party, girls are more likely to be well informed of the OCP.

Regression (1) is run on a sample including only Han people. The interpretation of regression (1) is straightforward. The coefficient on the interaction term, β_1, is the coefficient of interest, capturing all variation in education specific to Han women (relative to Han men) who were younger than a certain cut-off age when the policy was implemented. The vector γ_j is the set of the cohort fixed effects that represent the policy's nationwide effects on birth cohorts. λ is the time-invariant gap between Han women and Han men. One thing worth to note is that β_1 may be bias towards zero. With fewer children in the future, men's expected financial support from children will decrease. We shouldn't overlook this channel, considering men were the primary providers of the families during this time. Thus, men's educational attainment could be positively affected by the implementation of the OCP, and my estimate might be biased towards zero. The estimate should be the lower bound of the true effect.

Considering that there might be some contemporaneous factors that influenced the education of post-policy men and women differently—which violates the parallel trend assumption of the DD method—I take another approach to estimate the OCP's effect on women's education.

2.4.3 Han Women VS. non-Han Women

The second DD approach is free of gender-specific policy impact. As discussed above, the "one child" quota constraint is only against Han couples. Non-Han couples had more relaxed family planning restrictions compared to Han. An urban non-Han couple could have two children, and a rural non-Han couple could have three or even more children depending on population size of that ethnic group. For some minority groups with a small population size, the OCP was further relaxed (Wang et al., 2012). The identification is straightforward: Han women's fertility expectation was largely reduced while non-Han women's fertility expectation was slightly reduced by the OCP. Thus this approach estimates the differences in the educational attainment between Han women and non-Han women, for both the post-policy group and the pre-policy group. In other words, I estimate the difference of OCP's effects between Han women and non-Han women. I expect the OCP also had a positive effect on non-Han women's educational attainment because it restricted non-Han's fertility to some extent. Therefore, the estimate should show a lower bound of OCP's true effect on Han women's educational attainment. Note that this study does not distinguish among minority groups and only compares Han to non-Han.

Regression for this DD approach can be written as regression (2). The notations are the same as in regression (1). Here, β_2 is the coefficient of interest, which indicates the educational improvements in the post-policy Han women relative to non-Han women. I run the following regression on a sample of only women.

$$Edu_{isc} = \alpha + \sum_{j=1}^{C} \gamma_j I_j + \lambda Han_{isc} + \eta Post_{sc} + \beta_2 Han_{isc} \times Post_{sc} + \Omega X_{isc} + \epsilon_{isc} \tag{2.2}$$

2.4.4 Why Not Difference-in-Difference-in-Differences?

One may suggest an alternative approach, a difference-in-difference-in-differences (triple differences) identification, by taking the difference between the *difference between Han women and non-Han women* and the *difference between Han men and non-Han men*. This approach would compare gender differences in schooling between Han and non-Han for cohorts that were differentially affected by the OCP. Unfortunately, non-Han men's educational attainment is distinctly different from the other three groups. Figure 2.4 shows that Han men, Han women and non-Han women all have a clear pattern of trending up, although the line of non-Han women is more scattered due to a much smaller sample size. There is no clear pattern for the educational attainment of non-Han men and no particular change compared the pre and post policy cohorts. Thus, applying a triple differences approach would clearly violate parallel trend assumption.

2.5 OCP's Effect on Educational Attainment

2.5.1 OCP's Effect on Years of Schooling

Table 2.4 summarizes my first set of results, OLS point estimates of β_1 in different specifications of Regression (1). In Column (1), I report the baseline specification including the women dummy, post-policy dummy, interaction of women and post-policy dummy, rural dummy, interaction of women and rural dummy, birth year fixed effects, and province fixed effects. Overall, as expected, women had less education, and rural women had even less. The estimate of interest in column (1) indicates that Han women obtained 1.269 more years of schooling relative to Han men, when exposed to the shock of the OCP. The standard errors in parentheses are clustered at the province-cohort level. The estimate is statistically significant at 1% level.

For column (2) and later, I add in controls for family characteristics. Column (2) shows that more siblings in a household leads to less education. Having a father with senior high school increases Han women's years of schooling. Having a mother with senior high school has the opposite effect. These two effects basically off-set each other. Having either a father or a mother who is a Communist Party member increases Han women's years of schooling. Estimates in column (1)–column(4) are highly consistent in magnitude and significance. After controlling for all the above family characteristics, the estimate of interest shows the average effect of the OCP on Han women at schooling ages relative to Han men is an increase in years of schooling by 1.281 years. This accounts for 53.6% of education improvement of women born between 1960-1980 relative to women born between 1950-1959.

The main threat to this approach is that some other potential factors may affect the post-policy men and women's educational attainment differently. For instance, contemporaneous feminism movements might encourage women to increase their educational attainment. Such potential factors would violate the assumption of the DD method: difference between the treated and untreated group is constant in absence of treatment. With this concern, I take a second approach which avoids gender-specific issues.

Table 2.5 presents the results from the second DD approach, which is used to address concerns related to the first approach. Similarly, the estimate in column (1) is from the baseline specification including the Han dummy, policy dummy, the interaction term of the Han and policy dummies, a rural dummy, a rural and Han interaction, birth cohort fixed effects, and province fixed effects. Column (1) shows the OCP increased Han women's years of schooling by 1.415 years, compared to non-Han women. The estimate is statistically significant at 1% level. By adding controls for family characteristics, the point estimate trends down a little. After controlling for all family characteristics, the average effect of the OCP at schooling ages on Han women relative to non-Han women is an increase in years of schooling by 1.302 years. Considering that non-Han women might be disproportionately represented in rural areas and to the extent that women's opportunities in the labor market or schooling have increased disproportionately for women in non-rural areas for the younger cohorts, I include rural by birth cohort fixed effects for the regression in column (5). The result indicates that the OCP increased Han women's years of schooling by 1.364, relative to non-Han women.

Although the comparison between Han women and non-Han women avoids gender-specific trends, it does not rule out the concern of the differential trends between the two ethnic groups. One may argue that some contemporaneous policies might offer more opportunities to the non-Han, resulting in different trends in educational attainment compared to Han. First, this is quite unlikely during the 1960–1980 time frame, as most of China's policies to boost ethnic minority regions happened after

1980. Second, compared the estimates to the ones from the first approach—which is free of ethnicity specific policy impact—they are not statistically different from each other. Thus, we should be confident about the positive effect of the OCP on Han women's education. Last, as mentioned earlier, the OCP may positively affect the non-Han women as well. In this sense, the estimate I provide here is the lower bound of the OCP's true effect on Han women.

Table 2.4 and Table 2.5 show the policy's average effects on all birth cohorts younger than 20 in 1980. As discussed in Section 2.4.1, the post-policy cohorts are the ones who were still in school and had not made dropout decisions when the policy was implemented. The cut-off age, 20, is rather arbitrarily chosen. Are the policy's effects robust across birth cohorts? Which cohorts were impacted the most? Table 2.1 shows how policy's effects vary across different post-policy cohorts. Column (1) to (9) present results from regression with different post-policy groups. The pre-policy group was fixed to the 1950-1959 birth cohorts, and the post-policy group was changed by dropping the cohorts in between. For example, the post-policy groups in column (1)[14] are the 1960-1980 birth cohorts and the post-policy groups in column (9) are cohorts 1968-1980.

In Panel A of Table 2.1, estimates across columns consistently show the positive effect of the OCP on women's education. All estimates are strongly significant at 1% level. The OCP's effect trends up for younger cohorts, but not statistically significantly. Similarly, Panel B in Table 2.1 shows the same pattern as Panel A. The dynamic DD results presented in Figure 2.5 and Figure 2.6 illustrate the OCP's effect on each birth cohort in another way and mirrors the results in Table 2.1.

To sum up, these estimates show that the OCP had a positive and significant effect on Han women's years of schooling. By constraining the quota of birth per couple, the OCP reduced the number of births for women who were exposed to the policy. Among those women, cohorts at schooling ages saw the opportunity of pursuing higher education and ended up getting about one more year of schooling on average.

[14]The estimates in column (1) are the same as the ones in the last column of Table 2.4 and Table 2.5.

2.5.2 Compulsory Education and College Reopening

China experienced rapid modernization in the 1980s, together with many policy changes. This fact raises concerns on the identification of the OCP's effect in this paper. One specific policy change that might confound the effects of the OCP is the nine-year compulsory education law, which took affect on July 1, 1986. The law established deadlines and requirements in an effort to attain a universal education for all school aged children. It requires that all children attend school for a minimum of nine years, equivalent to a junior high school completion. In order to take a closer look at the OCP's effect on years of schooling, I run linear probability models replacing the dependent variables of Equation (2.1) and (2.2) as dummy variables of completion of n years of schooling (i.e. $\mathbb{1}[\text{years of schooling} \geq n]$).

Panel A in Table 2.2 shows that a treated Han women increased her likelihood of completing 8 years of schooling by 7.48 percentage points and completing 9 years of schooling by 7.38 percentage points. The increase in the probability of finishing years of schooling from 10 to 12 is 2.48–2.63 percentage points. This implies that the cohorts affected by the OCP experienced both higher rate of finishing junior high school and senior high school[15]. If the gender convergence was only a result from the nine-year compulsory schooling law, we should only expect column (1)–(2) to be statistically different from zero; and column (3)–(8) to be no different than zero[16]. But results in column (3)–(8) clearly show that Han women experienced an increase in high school completion. The gender convergence in 10 to 12 years of schooling is evident that the OCP had a positive effect on women's educational attainment. Results in Panel B Table 2.2 are consistent with the results in Panel A. The OCP had a positive and significant effect on Han women's high school completion relative to non-Han women. If the differential improvement in education between Han women and non-Han women

[15] Junior high school is equivalent to 9 years of schooling; senior high school is equivalent to 12 years of schooling.

[16] Literature on compulsory schooling laws find that there is no positive effect of compulsory schooling law on educational attainment beyond the minimum requirement (Oreopoulos, 2006).

only came from the nine-year compulsory schooling law, we shouldn't observe any effect on years of schooling beyond junior high (estimates shown in column (3)–(8)).

Another policy change might arguably affect women and men differently in educational attainment is college reopening in late October 1977. In acknowledgment of more than a decade of missed opportunity due to the cultural revolution, candidates ranging in age from 13 to 37 were allowed to take the National Entrance Examination (a.k.a. *Gaokao*). Let's assume that college reopening had differential treatment effect on each gender or differential treatment effect on each ethnic group. We should be able to see significant estimates with decent magnitude in column(6)–column(9)[17]. Instead, we don't observe any increase in Han women's college enrollment or completion relative to Han men or non-Han women, indicating that college reopening had no effect on Han women relative to Han men (or non-Han women).

Here, I cannot rule out all possible policy changes that might confound the effect of the OCP, but only discuss the most acknowledged and influential ones above. This analysis implies that the OCP did contribute to women's education improvement.

2.6 Hypothesized Mechanism

The OCP explains a large portion of education improvement of women born between 1960–1980 compared to women born between 1950–1959. This section estimates the policy's effect on women's later outcomes after finishing school and links the later outcomes to the potential mechanism of increase in educational attainment.

There are several channels that could increase Han women's educational attainment. The first one is through labor force participation (LFP). Anticipating higher labor force participation due to the exogenous reduction of child-rearing burden, women would invest more in human capital. Women may also expect less financial support from children, assuming no quantity-quality trade-off. This strengthens the LFP channel. The second channel is through timing of marriage and timing of fer-

[17] 13–16 years of schooling are equivalent to 1–4 years of college education.

tility. Anticipating having fewer children, women may delay entry to motherhood or even delay entry to the first marriage (Buckles, 2008). Ideally, I would examine the OCP's effect on changes of women's expectation on career, marriage and fertility. Unfortunately, there is no measure of expectation on those aspects in any survey within the same time frame. Instead, I estimate the OCP's effect on later outcomes such as age at first marriage, age at first birth, and labor force participation. If the channel of the OCP affecting women's educational attainment is through changes in expectation of these later outcomes, we should be able to observe the changes in later outcomes reacting to the OCP.

Panel A in Table 2.6 presents the gender differences within Han. Assuming that men were much less impacted by the OCP due to their small share of child-bearing burden, we should expect Han men had little change in labor force participation (LFP). Column (1) shows that relative to Han men, the OCP significantly increased Han women's likelihood of having a formal job by 8.4 percentage points. We shouldn't assume that men's LFP was not affected by the OCP. But if men's labor force participation could be affected by a decline in expected financial support from children, we should expect an increase in men's LFP as well. In that case, the estimate here is the lower bound. However, column (1) in Panel B shows that the difference between Han women and non-Han women's LFP do not differ before and after the OCP. This means LFP is not the main channel that differentially affects Han women and non-Han women's investment in education. Column (2) in Panel B shows that Han women and non-Han women are not different in marriage entry either. In contrast, under the OCP, Han women delay their entry into first marriage by 0.6 years compared to Han men. This supports the hypothesis of delayed entry into first marriage. Results in Column (3)—both Panel A and Panel B—stand out: Han women significantly delay their entry to motherhood, providing evidence that delaying entry to motherhood is a channel of increasing education investment. Specifically, Han women's age at the first birth increased by 0.46 compared to Han men and increased by 0.9s compared to non-Han women. I want to point out that Column (2) and Column (3) in Panel A are not statistically different, which makes sense. Because Han women and Han men would be identically affected when further delay their entry to the first birth after marriage. Compared to non-Han women, Han women delay their entry to the first birth by 0.9 year. This implies the delay in entry to motherhood primarily explains the Han and non-Han gap.

Analysis in this section presents labor force participation, marriage, and fertility consequences caused by the OCP. More importantly, it supports the hypothesized mechanism that women increased their education due to the increase in labor force participation, delayed entry to marriage, and delayed entry to motherhood.

2.7 Conclusion

Women's educational attainment has been increasing tremendously compared to men's all over the world. This paper exploits China's One-Child Policy, as an exogenous shock to fertility to estimate its effect on educational attainment of the women who are the mothers of the sibling-less generation. Expected fertility was reduced by the OCP for women at schooling ages. Then the reduced expected fertility increased women's return to schooling, which led to higher educational attainment. This study uses two difference-in-differences approaches to estimate this effect. The first DD uses men as the untreated group because men are much less likely to change their educational decision due to the changes in the expected fertility of their partners. The second DD uses non-Han women as the untreated group. As non-Han women have much more relaxed OCP restrictions compared to Han in terms of birth quota, non-Han women's expected fertility was less reduced due to the policy.

I find that the OCP significantly increased Han women's years of schooling by 1.281 years relative to Han men, which explains 53.6% of the increase in women's educational attainment in birth cohorts between 1950–1980. By investigating the OCP's effect on each level of schooling, I rule out the arguable confound effects of the nine-year compulsory schooling law and the college reopening policy, which both also happened in the 1980s. By analyzing post-school outcomes, I provide evidence of the OCP's effect on women's delayed entry to first marriage and motherhood and increased labor force participation, which helps explain the mechanism of the OCP's effect on educational attainment.

This paper exploits China's OCP to explain the shrinking education gap between women and men, highlighted in the literature on links between fertility and human capital accumulation. More generally, it contributes to the literature on women's empowerment all over the world. Last, but not least, it fills in a gap of underexplored issues in the rich literature of China's Family Planning Policies.

Table 2.1.: OCP's Effects on Each Bunching of Cohort

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treated Cohorts	$Age \leq 20$	$Age \leq 19$	$Age \leq 18$	$Age \leq 17$	$Age \leq 16$	$Age \leq 15$	$Age \leq 14$	$Age \leq 13$	$Age \leq 12$
Panel A. Han Women VS. Han Men									
$Women \times Policy$	1.281***	1.319***	1.359***	1.435***	1.458***	1.513***	1.498***	1.488***	1.520***
	(0.153)	(0.154)	(0.154)	(0.153)	(0.155)	(0.156)	(0.156)	(0.159)	(0.161)
Panel B. Han Women VS. non-Han Women									
$Han \times Policy$	1.364***	1.329***	1.345***	1.348***	1.371***	1.421***	1.509***	1.497***	1.540***
	(0.357)	(0.358)	(0.362)	(0.366)	(0.368)	(0.373)	(0.379)	(0.386)	(0.393)
N	10593	10339	10137	9693	9191	8758	8371	7954	7587

Note: Data is from CFPS. The sample includes Han cohorts from 1950-1980. The dependent variable is years of schooling. Independent variables include women dummy, interaction of women and post-policy dummy, birth year fixed effects, and province fixed effects. Again, there is no post-policy dummy in the regression, because it would be perfectly collinear with the birth cohort fixed effects. Interaction of women and policy dummy equals one for Han women born between 1960-1980, and equals zero for everyone else. Other controls include rural dummy, interaction term of rural and women dummy, number of siblings, dummy of father completing high school, dummy of mother completing high school, dummy of father being a communist party member and dummy of mother being a communist party member. Each column presents results from a regression with a different specification.

Standard errors in parentheses are clustered at province-cohort level.

Table 2.2.: OCP's Effect on Each Level of Schooling

	(1) $Edu \geq 8$	(2) $Edu \geq 9$	(3) $Edu \geq 10$	(4) $Edu \geq 11$	(5) $Edu \geq 12$	(6) $Edu \geq 13$	(7) $Edu \geq 14$	(8) $Edu \geq 15$	(9) $Edu \geq 16$
Panel A. Han Women VS. Han Men									
$Women \times Policy$	0.0748***	0.0738***	0.0263**	0.0253**	0.0248**	-0.000183	-0.000354	-0.000175	-0.00631
	(0.0160)	(0.0158)	(0.0131)	(0.0129)	(0.0127)	(0.00649)	(0.00642)	(0.00643)	(0.00371)
N	18692	18692	18692	18692	18692	18692	18692	18692	18692
Panel B. Han Women VS. non-Han Women									
$Han \times Policy$	0.0979***	0.0945***	0.0467*	0.0438*	0.0470*	0.0165	0.0153	0.0165	0.00637
	(0.0323)	(0.0324)	(0.0249)	(0.0248)	(0.0244)	(0.0105)	(0.0104)	(0.0105)	(0.00826)
N	10593	10593	10593	10593	10593	10593	10593	10593	10593

Note: Data is from CFPS. The sample includes Han cohorts from 1950-1980. The dependent variable is years of schooling. Independent variables include women dummy, interaction of women and post-policy dummy, birth year fixed effects, and province fixed effects. Again, there is no post-policy dummy in the regression, because it would be perfectly collinear with the birth cohort fixed effects. Interaction of women and policy dummy equals one for Han women born between 1960-1980, and equals zero for everyone else. Other controls include rural dummy, interaction term of rural and women dummy, number of siblings, dummy of father completing high school, dummy of mother completing high school, dummy of father being a communist party member and dummy of mother being a communist party member. Each column presents results from a regression with a different specification.

Standard errors in parentheses are clustered at province-cohort level.

Table 2.3.: Descriptive Statistics of CFPS, by Demographic Groups

Variable	**Han**		**non-Han**		**All**
	Men	**Women**	**Men**	**Women**	
Observations	8597	9334	747	836	19514
Education					
Year of Schooling	8.156 (4.081)	6.331 (4.683)	6.226 (4.628)	4.444 (4.745)	7.373 (4.552)
≥Junior High Completed	62.04% (0.485)	45.35% (0.498)	42.84% (0.495)	29.67% (0.457)	51.88%(0.500)
≥Senior High Completed	25.11%(0.434)	17.61%(0.381)	14.59%(0.353)	10.52%(0.307)	20.47%(0.403)
≥4-yr College Completed	2.90%(0.168)	1.80%(0.133)	1.87%(0.136)	1.675%(0.128)	2.28%(0.149)
Family					
# of Siblings	3.09(1.908)	3.256(1.939)	3.325(1.842)	3.459(1.856)	3.195(1.921)
Father's Edu					
≥Junior high school	32.5%(0.469)	34.52%(0.475)	32.13%(0.467)	33.97%(0.474)	33.53%(0.472)
Mother's Edu					
≥Junior high school	18.06%(0.385)	18.63%(0.389)	17.40%(0.379)	20.45%(0.404)	18.42%(0.388)
Father: Member of Communist	0.169(0.375)	0.174(0.379)	0.146(0.353)	0.141(0.349)	0.169(0.375)
Mother: Member of Communist	0.022(0.147)	0.025(0.157)	0.030(0.170)	0.014(0.119)	0.024(0.152)
Rural	0.827(0.378)	0.834(0.372)	0.923(0.266)	0.921(0.270)	0.838(0.368)
Later Outcome					
Labor Force Participation	0.682(0.466)	0.511(0.500)	0.707(0.456)	0.590(0.492)	0.600 (0.490)
# of Birth	1.688(0.919)	1.810(0.908)	1.963(1.037)	2.138(1.000)	1.776(0.927)
Age at First Marriage	1988.8(8.582)	1987.4(8.470)	1989.6(8.853)	1988.7(9.062)	1988.1(8.593)
Age at First Birth	1990.5(8.214)	1989.2(8.196)	1991.6(8.206)	1990.9(8.301)	1989.9(8.242)

Notes: Data is from CFPS. Sample includes cohorts born between 1950-1980.
Standard deviations are in the parentheses.

Table 2.4.: Han Women v.s. Han Men

Dependent Var.	Years of Schooling			
	(1)	(2)	(3)	(4)
Women × Policy	1.269***	1.277***	1.287***	1.281***
	(0.153)	(0.153)	(0.153)	(0.153)
Women	-1.055***	-1.047***	-1.059***	-1.068***
	(0.152)	(0.152)	(0.152)	(0.153)
Policy	4.330***	4.094***	4.083***	4.035***
	(0.250)	(0.254)	(0.258)	(0.259)
Rural	-2.927***	-2.854***	-2.857***	-2.719***
	(0.107)	(0.107)	(0.108)	(0.110)
Women × Rural	-1.969***	-1.964***	-1.964***	-1.954***
	(0.133)	(0.133)	(0.133)	(0.133)
#Siblings		-0.110***	-0.113***	-0.113***
		(0.0171)	(0.0171)	(0.0168)
FatherSeniorHigh			0.346***	0.353***
			(0.0814)	(0.0803)
MotherSeniorHigh			-0.490***	-0.421***
			(0.0963)	(0.0956)
FatherCommunist				0.844***
				(0.0767)
MotherCommunist				1.307***
				(0.201)
Constant	9.626***	9.829***	9.843***	9.460***
	(0.263)	(0.264)	(0.260)	(0.259)
State FE	YES	YES	YES	YES
Birth Year FE	YES	YES	YES	YES
Number of Siblings	NO	YES	YES	YES
Father/Mother Edu ≥ Senior High	NO	NO	YES	YES
Father/Mother Being Communist	NO	NO	NO	YES
N	18692	18692	18692	18692

Note: Data is from CFPS. The sample includes Han cohorts from 1950-1980. The dependent variable is years of schooling. Independent variables include women dummy, policy dummy, interaction of women and policy dummy, birth year fixed effects, and province fixed effects. Again, there is no post-policy dummy in the regression, because it would be perfectly collinear with the birth cohort fixed effects. Interaction of women and policy dummy equals one for Han women born between 1960-1980, and equals zero for everyone else. Other controls include rural dummy, interaction term of rural and women dummy, number of siblings, dummy of father completing high school, dummy of mother completing high school, dummy of father being a communist party member and dummy of mother being a communist party member. Each column presents results from a regression with a different specification.

Standard errors in parentheses are clustered at province-cohort level.

Table 2.5.: Han Women v.s. nonHan Women

Dependent Var.	Years of Schooling				
	(1)	(2)	(3)	(4)	(5)
Han × *Policy*	1.415***	1.297***	1.294***	1.302***	1.364***
	(0.358)	(0.355)	(0.356)	(0.353)	(0.357)
Han	-0.856	-0.756	-0.765	-0.847	-0.963*
	(0.526)	(0.528)	(0.531)	(0.516)	(0.515)
Policy	4.542***	4.406***	4.408***	4.403***	3.535***
	(0.466)	(0.465)	(0.468)	(0.471)	(1.029)
Rural	-5.401***	-5.270***	-5.272***	-5.161***	-5.225***
	(0.479)	(0.480)	(0.485)	(0.474)	(0.889)
Han × *Rural*	0.804*	0.770	0.761	0.811*	0.900*
	(0.482)	(0.482)	(0.487)	(0.477)	(0.473)
#Siblings		-0.136***	-0.140***	-0.140***	-0.143***
		(0.0246)	(0.0245)	(0.0244)	(0.0246)
FatherSeniorHigh			0.339***	0.338***	0.334***
			(0.102)	(0.101)	(0.101)
MotherSeniorHigh			-0.581***	-0.489***	-0.487***
			(0.127)	(0.126)	(0.127)
FatherCommunist				0.950***	0.953***
				(0.106)	(0.106)
MotherCommunist				1.421***	1.463***
				(0.272)	(0.271)
Constant	9.351***	9.505***	9.549***	9.195***	9.261***
	(0.654)	(0.647)	(0.648)	(0.638)	(0.938)
State FE	YES	YES	YES	YES	YES
Birth Year FE	YES	YES	YES	YES	YES
Number of Siblings	NO	YES	YES	YES	YES
Father/Mother Edu $\geq$ Senior High	NO	NO	YES	YES	YES
Father/Mother Being Communist	NO	NO	NO	YES	YES
Dummy of Rural × Birth Year	NO	NO	NO	NO	YES
N	10593	10593	10593	10593	10593

Note: Data is from CFPS. The sample includes female cohorts from 1950-1980. The dependent variable is years of schooling. Independent variables include Han dummy, interaction of Han and post-policy, birth year fixed effects, and province fixed effects. Again, there is no post-policy dummy in the regression, because it would be perfectly collinear with the birth cohort fixed effects. Interaction of Han and policy dummy equals one for Han women born between 1960-1980, and equals zero for everyone else. Other controls include rural dummy, interaction term of rural and Han dummy, rural specific cohort fixed effects, number of siblings, dummy of father completing high school, dummy of mother completing high school, dummy of father being a communist party member and dummy of mother being a communist party member. Each column presents results from a regression with a different specification.

Standard errors in parentheses are clustered at province-cohort level.

Table 2.6.: OCP's Effects on Women's Post-School Outcomes

Dependent Variable	(1) (LFP)	(2) (Age at 1st Marr)	(3) (Age at 1st Birth)
Panel A. Han Women vs. Han Men			
Policy's Effect	0.084***	0.592***	0.456***
	(0.017)	(0.188)	(0.143)
N	18687	16452	17024
Panel B. Han Women vs. non-Han Women			
Policy's Effect	0.022	0.033	0.911**
	(0.043)	(0.317)	(0.431)
N	10589	9290	9787

Note: The sample includes birth cohorts from 1950-1980. The dependent variable in column (1)–(3) are labor force participation (i.e. dummy of whether one has ever had a formal job), and age at the first marriage, and age at the first birth. Independent variables include women dummy (Han dummy in Panel B), policy dummy, interaction of women and policy (interaction of Han and policy in Panel B), province fixed effects, birth year fixed effects, rural dummy, interaction term of rural and Han dummy, number of siblings, father and mother's level of education and father, and mother's political status. Policy dummy equals 1 for post-policy cohorts born between 1960-1980, and equals 0 for everyone else.

Standard errors in parentheses are clustered at province-cohort level.

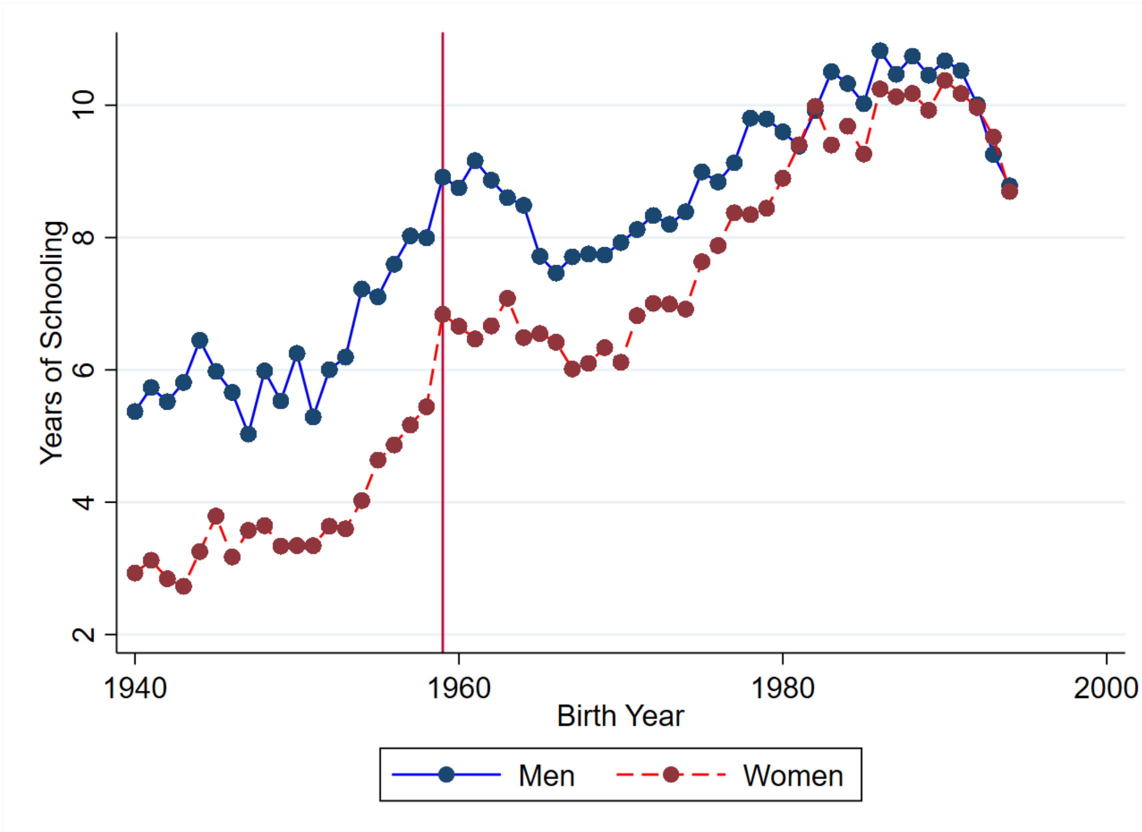

Figure 2.1.: Averaged Years of Schooling by Gender

Notes: Individual sample weights provided by CFPS were used in the construction of this figure.

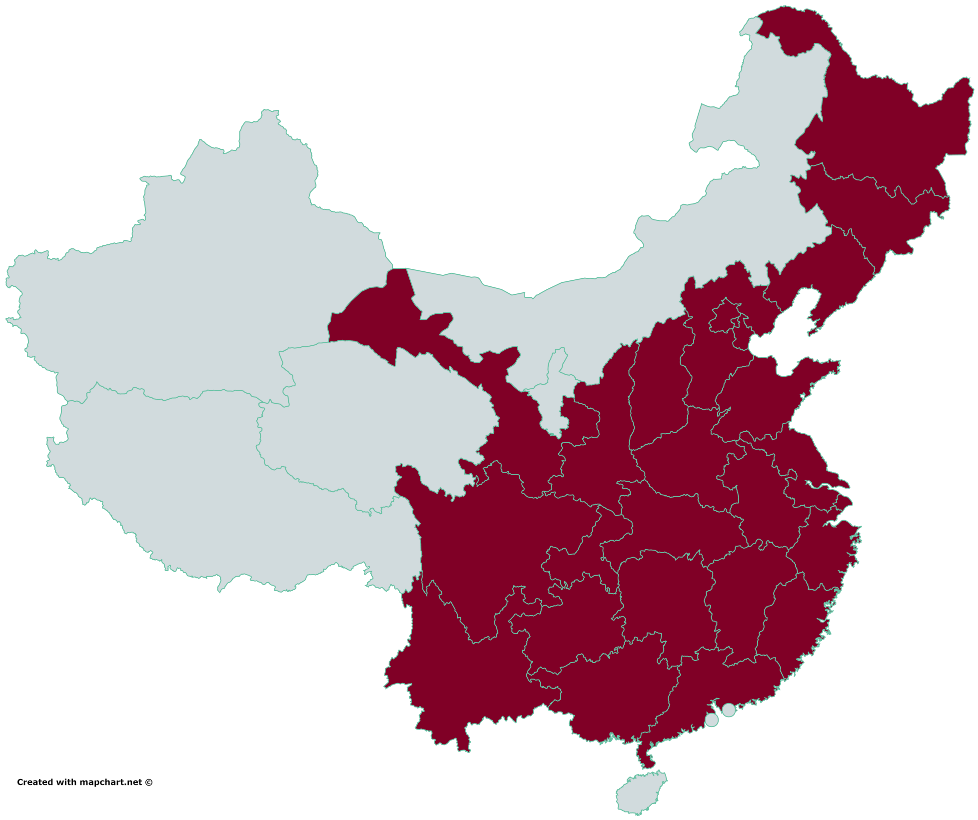

Figure 2.2.: CFPS Covers 21 Provinces and 4 Municipalities

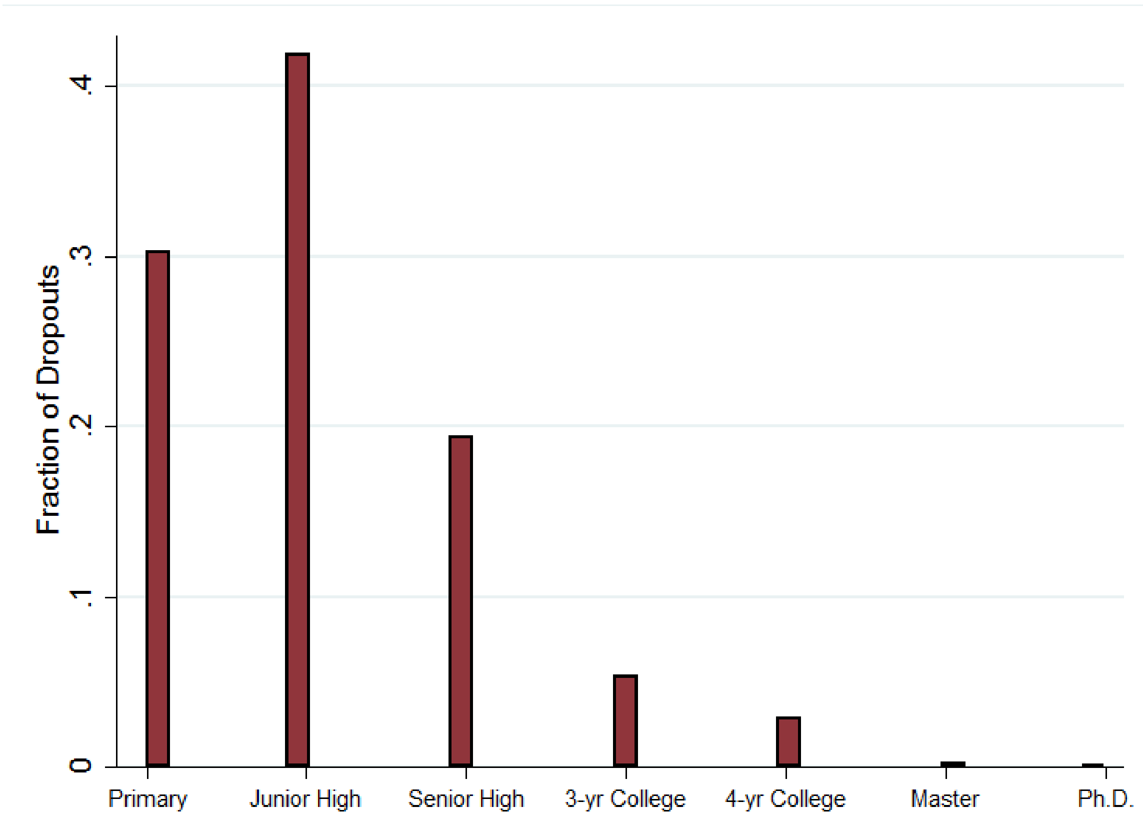

Figure 2.3.: Distribution of Highest Level of Education

Notes: The sample includes birth cohorts from 1950-1980

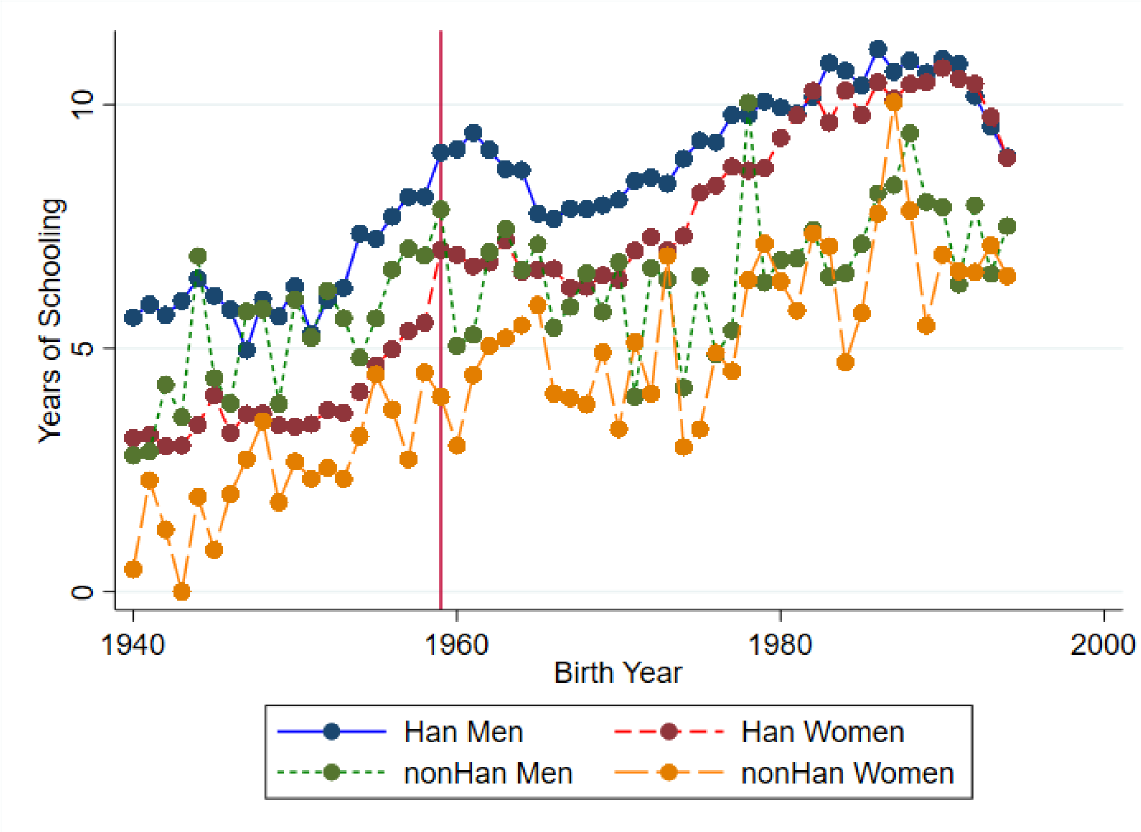

Figure 2.4.: Averaged Years of Schooling by Gender by Ethnicity

Notes: Individual sample weights provided by CFPS were used in the construction of this figure.

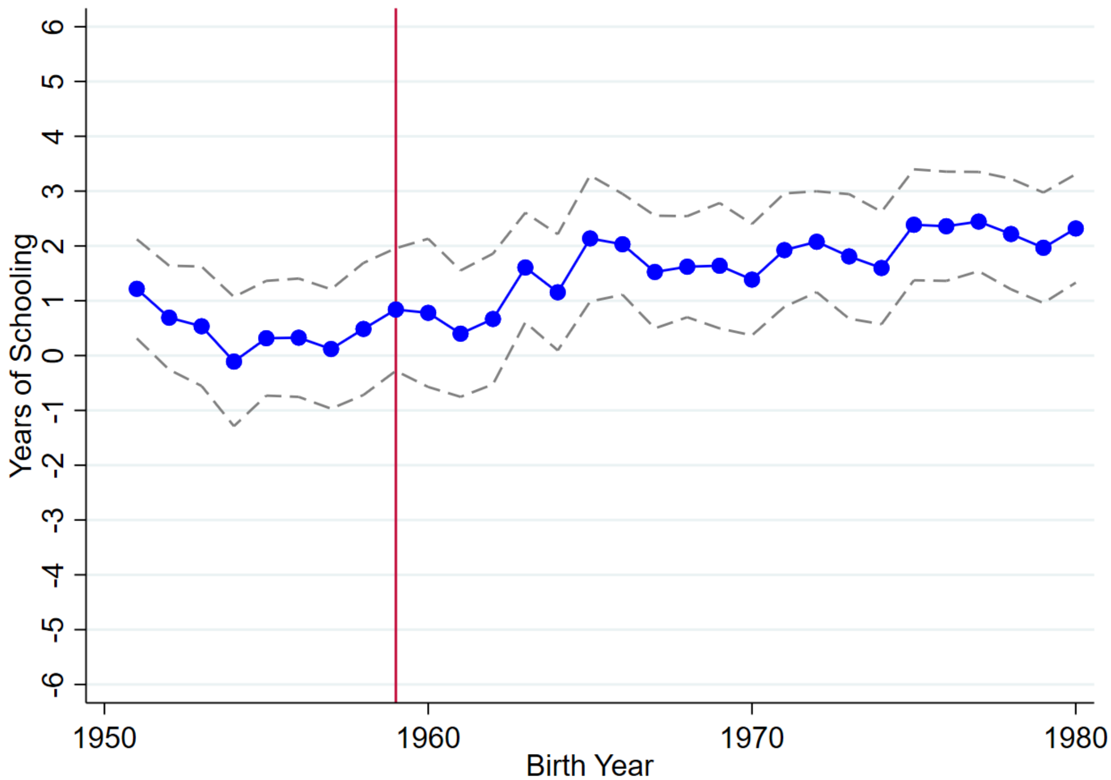

Figure 2.5.: Dynamic DD between Han Women & Han Men

Notes: The sample includes birth cohorts from 1950-1980

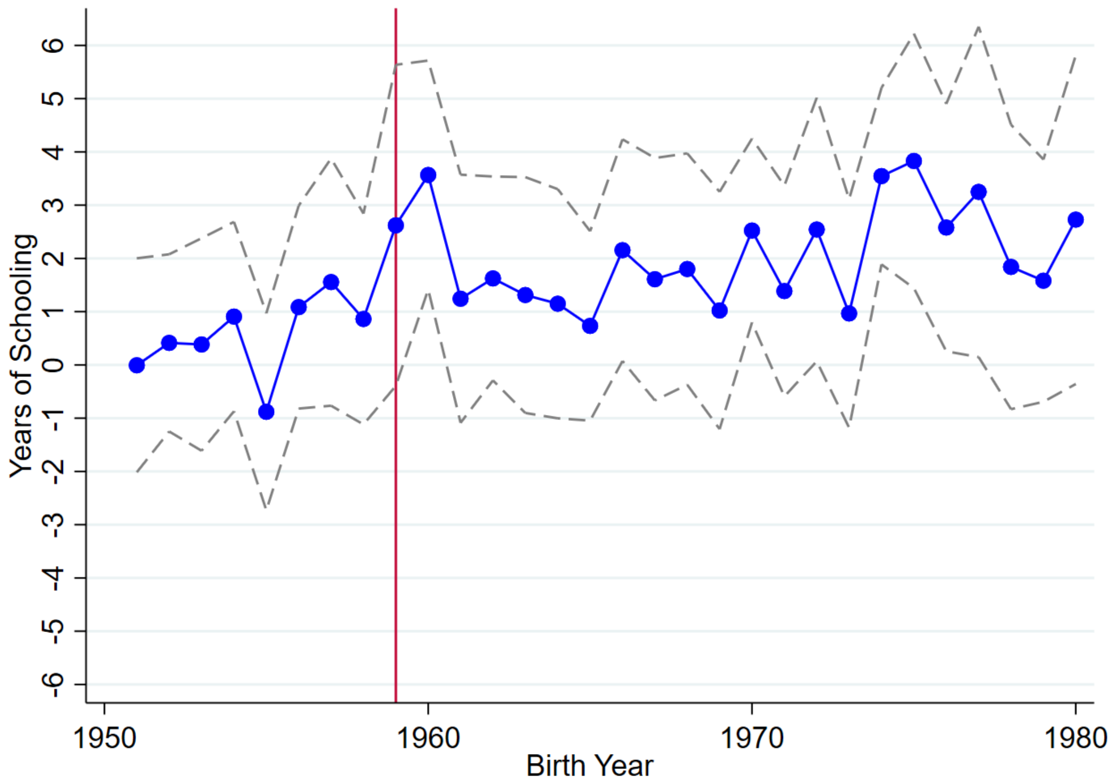

Figure 2.6.: Dynamic DD between Han Women & non-Han Women

Notes: The sample includes birth cohorts from 1950-1980

3. WHEN OPPORTUNITY KNOCKS: CHINA'S OPEN DOOR POLICY AND DECLINING EDUCATIONAL ATTAINMENT

3.1 Introduction

There is a growing literature exploring the links between trade and educational choice. New job opportunities brought by growth in exports shift the relationship between education and earnings. However, the direction of this change is ambiguous ex ante. Initial export growth in developing countries typically is driven by low-skill, labor intensive goods (Amiti & Freund, 2010). This should suggest a decrease in the returns to education and a decline in educational attainment, as less educated workers face greater wages and job availability after exposure to export growth. Alternatively, exports to industrialized, high-income countries have been shown to increase the skill premium (Brambilla et al., 2012; Pissarides, 1997), suggesting that the returns to education and educational attainment should increase in response to export growth. In this study, we examine the initial period of export growth in China following the Open Door Policy in 1978, investigating how the educational choices of teenagers changed in response to export exposure.

National trends in Chinese educational attainment suggest that the implementation of the Open Door Policy caused students to leave school and enter the workforce. Figure 3.1 shows that high school and middle school completion rates decline sharply for cohorts born in the early 1960s, only reversing in the late 1960s and 1970s. Compared to the cohort born in 1960, the cohort born in 1967 was 60 percent less likely to finish high school (16.7 percentage points), and was 16 percent less likely to finish middle school (10.2 percentage point). This is surprising, as the 1960s cohorts' primary and middle school education occurred during the Cultural Revolution. During the Cultural Revolution (1966-1976), all universities in China were closed; the national college entrance exam was not resumed until October 1977. Cohorts born in the late 1960s were in primary school at the end of the Cultural Revolution, however. Given nationwide improvements in education quality and the renewed possibility of college attendance, we would typically expect educational attainment to be higher for these younger cohorts than for those born in the early 1960s, but the opposite is true. It took over a decade for the middle school completion rate to return to its 1960 level and over twenty years for the high school completion rate to return to its 1960 level. Although the sociology literature has briefly mentioned this education trend (Hannum, 1999), ours is the first in economics to explore the causes of this decline and its long-run implications on Chinese labor markets.

We find that exposure to export growth in the late 1970s causes a substantial decline in high school completion. A $1000 increase in exports per worker in a prefecture[1] causes a 4.76 percentage point decline in high school completion from 1960 to 1970. Overall, between-prefecture differences in exposure to export growth caused by the Open Door Policy decrease the high school completion rate by 1.7 percentage point at the mean for cohorts born in the late 1960s. Though this only explains about 10.4% of the national decline in high school completion for 1960s birth cohorts, exposure to export growth induces substantial geographical variation in educational choice.[2] In this time period, high school graduates were the primary source of high-skilled labor in China, so our results demonstrate a decline in high-skilled labor and a corresponding increase in low-skilled labor occurred in the most highly trade-exposed areas of China for those born in the 1960s.

This paper contributes to the literature studying how educational choices are affected by trade flow changes. Atkin (2016) studies the education choices of Mexican teenagers after Mexican trade liberalization from 1986 to 2000, finding that the ex-

[1] The mean export exposure per worker in Table 3.1 is $402.

[2] We also find no substantial impact on the middle school completion rate; i.e., our results suggest a rise in dropping out of school after middle school, but not a rise in dropouts before middle school completion.

pansion of job opportunities in the manufacturing sector leads to students dropping out at grade 9 instead of continuing through grade 12. The main mechanism we investigate and our findings are similar to Atkin's, although the methods we use differ. Atkin's main specification is an instrumental variables regression, with a large single-firm expansion (e.g. a plant opening) as an instrument for new export-related jobs, and his independent variable is local cohort-average schooling. Our specification is useful for studies of countries and periods where firm-level microdata are not available and provides a measure for export-induced local job openings without relying on the counts of new openings.

The closest study to our paper is B. Li (2016 working paper). She studies the effects of export growth on educational attainment in China from 1990 to 2005 and finds that high-skill export shocks increase high school and college enrollment while low-skill export shocks depress both. We look at an older generation than Li because we aim to explain the puzzling decline in educational attainment in the 1960s, while Li examines a period of greater trade growth in China.

The paper proceeds as follows. Section 3.2 provides a historical background of China's Open Door Policy reforms in 1978, as well as an overview of major educational policy changes in the 1970s. Section 3.3 describes the data, and Section 3.4 explains the estimation strategies used. Section 3.5 presents the empirical results of the Open Door Policy's effects on educational attainment. Finally, Section 3.6 provides concluding remarks.

3.2 Historical Background

3.2.1 The Open-Door Policy

Before 1978, China had a rigid centrally planned economy. Individuals and private corporations were not allowed to trade without intermediation with state-owned corporations. Domestic commodity prices were not linked to international prices, and foreign currency exchanges were highly restricted. These policy barrier resulted in almost no trade. From the data reported by all trade partners of China in the UN Commodity Trade database, the total value of all Chinese exports in 1962 was 616,785,000 USD, 1.3% of the national GDP.

In December 1978, China enacted a series of reforms to loosen its trade policy. The government decentralized decision making regarding exports and imports, granting local governments and foreign trade corporations decision-making power. Meanwhile, the government replaced the administrative restrictions on exports and imports with tariffs, quotas, and licensing. Controls on foreign exchange were loosened, particularly for foreign-invested or foreign-managed firms. The government first designated 4 special economic zones (SEZ) in 1980, where foreign and domestic investment decisions could be made without authorization from the central government in Beijing.[3] Later, 14 cities spread along the entire Pacific coast were designated "open coastal cities" for a similar purpose to the original 4 SEZ (Wei, 1995).[4]

During the same period, China restructured the administration of the agriculture sector. Under the new household responsibility system, local rural households were held responsible for the profits and losses of the land assigned to them. It was first adopted in 1979, and expanded nationwide in 1981. Unlike the former agricultural system, this household responsibility system stimulated farmers' enthusiasm and substantially increased agricultural productivity (Lin, 1987, 1988).

3.2.2 Educational History

Figure 3.1 shows that educational attainment declined for cohorts born in the 1960s. We aim to link this decline to the implementation of the Open Door Policy, but this was a tumultuous time period in China with many reforms and shocks that affected education. Perhaps the most well known of these is the Cultural Revolution. However, the Cultural Revolution is unlikely to be the cause of declining education

[3]The 4 SEZ were Shenzhen, Zhuhai, Shantou, and Xiamen.
[4]The "open coastal cities" differed from the SEZ by their well-established industry facilities and educated labor force.

among the 1960s birth cohorts because it occurred from 1966-1976, long before the younger cohorts with the lowest educational attainment entered middle school. The most well-known impact of the Cultural Revolution on education is the closure of all colleges from 1966 to the early 1970s. The national university entrance exam was reinstated in 1977. Middle school education and high school education were affected to a lesser degree as well. The Down to the Countryside Movement started in 1968, by sending urban middle school and high school graduates to rural areas. The main group of "sent-down youth" were birth cohorts 1948-1953 (aged 13-18 in 1966). During the same time period, the government expanded primary schools and middle schools, especially in rural areas. As a result, according to the Chinese National Statistics Yearbook 1980, enrollment in primary and middle school increased throughout the 1970s nationwide.

3.3 Data

Our primary data source is the 1990 Chinese Population Census 1% subsample, providing educational attainment, prefecture and province of residence, migration status and other individual characteristics. We then link the Census with a prefecture-level export exposure factor. The export exposure factor is a measure for how changes in exports influence a prefecture. Export flows are measured as the changes in China's total export value for commodities from 1975 to 1982. The commodity export values come from the United Nations Commodity Trade (UN ComTrade) database, measured in US dollars. We aggregate the import flows from China reported by all countries and use that as China's total value of exports. China did not begin reporting its export flows to the United Nations until 1984, despite China exporting goods for decades before that. We need trade flows from the 1970s to observe changes in exports from the late 1970s to the 1980s, thus it is not feasible to use export flows reported by China. Additionally, import flows are generally more reliable than export flows because countries have incentives to track import shipments carefully for tariff purposes (Hummels & Lugovskyy, 2006).

It is commonly believed that export growth in China primarily occurred during the 1990s and 2000s, especially after China joined the World Trade Organization in 2001. The 1990s and 2000s are when China's exports became substantial relative to the rest of the world. However, if we focus on export growth within the country, as industrialization spread and China's productivity increased after a series of political reforms, exports grew exponentially starting in the mid-1970s. According to the World Bank, the total value of Chinese exports grew five-fold from 1970 to 1980, quintupling again from 1980 to 1990. Figure 3.2 shows the changes in export value for the four highest value industries before 1990 in China. We can see that for the manufacturing of small goods, clothing, and textiles, export value increased rapidly.

In addition to export changes, we need information on the local labor market conditions Chinese teens faced in the 1970s, yet poor employment statistics in China at that time make direct measurement of local labor market conditions impossible. We instead use the 1982 Chinese Population Census to infer employment by industry by prefecture in the mid-1970s. We cannot use the whole labor force in 1982 to calculate this directly, as we expect some of the changes in job opportunities brought by exports have started to appear in the labor market, particularly for younger workers. We instead used older cohorts, aged 40-50 in the 1982 census (born 1922-1942), to estimate the employment shares in 1975.

There are concerns that some of these workers may have switched industries between 1975 and 1982. However, given that most workers worked in state-owned enterprises at that time, the labor market was rigid and moving occupations was not common. In addition, we choose a cohort that is in a stable stage in their career; they are less likely to move than their younger, less experienced counterparts. Another potential concern is workers migrating across regions, so we restrict our sample to only individuals who have not migrated between prefectures in the last five years. We lose less than 5% of the sample from this restriction.

As shown in table 3.1, prefecutre-leve export exposure per worker from 1975 to 1982 increases in the median prefecture by about \$123. The bottom 10% of the prefectures saw a negative impact. Those are exclusively inland prefectures, mostly in Tibet. The province-evel export exposure per worker is less disperse. Table 3.2 presents the province-level export exposure per worker by quintiles. The top quintile includes three municipalities, Beijing, Shanghai and Tianjin, and two oil producing provinces, Xinjiang and Liaoning.

3.4 Methods

We aim to estimate the effect of trade on the educational choices of Chinese students in the 1970s and 1980s, around the implementation of China's Open Door Policy in late 1978. To begin, we modify the local labor market exposure measure used by Autor et al. (2013) to be applicable to the rise in exports in China, rather than in import competition from a single trading partner:

$$\Delta XPW_{ck} = \sum_j \frac{L_{jk}}{L_{ck}} \frac{\Delta X_{wcj}}{L_k} \tag{3.1}$$

In equation (3.1), L_{jk} is the total employment in prefecture k and industry j in China in 1975, ΔX_{wcj} is the change in Chinese exports to the world (w) in industry j from 1975 to 1982 (in \$1000s). The term ΔXPW_{ck}, then, is the average export change per worker in prefecture k, weighted by the prefecture's pre-Open Door Policy share of total employment nationwide in industry j.

Ideally, we would observe employment by industry and by prefecture in China in 1975, and use this to construct our local export exposure variable. However, these data are not available, likely due to the political turmoil in China in the mid-1970s. Instead, we observe employment using China's 1982 National Population Census, and restrict our sample to older workers who are unlikely to change industries between 1975 and 1982. Our sample for constructing these labor share variables includes only workers ages 40 to 50 in 1982 (33 to 43 in 1975), and requires the assumption that any movement of these older workers between industries or between prefectures from 1975 to 1982 is not endogenous with the education decisions of teenagers in this time period. Constructing ΔXPW_{ck} provides us with a single export exposure measure per prefecture, used as the primary variable of interest in our regressions.

We wish to observe the final education decisions of teens who are in school when China implements its Open Door Policy in 1978; to do this, we use China's 1990 National Population Census. Treatment is assigned based on prefecture of residence in 1990, restricting our sample to only individuals who have not moved across prefectures in the past 5 years ($> 95\%$ of the sample). Additionally, we exploit heterogeneity across different age groups, as older teens when the Open Door Policy begins are likely to respond to the trade shock differently than younger teens. Our primary regression model is:

$$Ed_i = \alpha + \sum_y \beta_y \Delta XPW_{ck} \times \delta_y + \gamma X_i + \varepsilon_i \tag{3.2}$$

In (3.2), our coefficients of interest are β_y – the different effects of the export exposure ΔXPW_{ckt} on each birth cohort y born between 1960 and 1970, aged 8 to 18 when the Open Door policy begins in 1978. Importantly, the export exposure does not change between cohorts, it only varies across prefectures. We also include fixed effects for birth cohort, province, sex, and ethnicity in X. The coefficients β_y identify between-prefecture, within-province, within-birth cohort differences in the educational response to a prefecture's export exposure change. Our outcome variable, Ed_i, is a middle school completion dummy variable or a high school completion dummy variable. In our regressions in Section 3.5, we set birth cohort 1960 as our baseline, as 18 year olds in 1978 would have already completed middle school and high school by the time China implemented its' Open Door policy. This allows us to make direct comparisons between an unaffected cohort (1960), partially affected cohorts (1961-66)[5], and fully affected cohorts (1967-70).

[5]The cohort born in 1966 would be in middle school when the Open Door policy began

Our paper is closely related to the literature using trade flow changes in the form of a Bartik instrument (Bartik, 1991) to study labor market responses. Autor, Dorn and Hanson's influential paper used Chinese import flow changes to study the impact of import competition on labor market outcomes in the United States (Autor et al., 2013). Our methodology is similar, with one key difference: ΔXPW is constructed using changes in aggregate export flows from China to the rest of the world. This sidesteps the simultaneity issue that Autor, Dorn, and Hanson use IV estimation to circumvent, as we are interested in Chinese trade with all partners, not with one particular trading partner. As a result, we estimate equation 3.2 as is, without implementing a 2SLS framework.

3.5 Results

3.5.1 High School Completion

To begin, we estimate the average effect of prefecture-level export exposure changes on treated cohorts' likelihood of completing high school.

Table 3.4 presents the OLS point estimates of the effect of export exposure changes on high school completion. Column (1) shows the estimate from a naïve regression including only export exposure, and gender and ethnicity dummies. The estimate indicates that a \$1000 increase in exports per worker increases the likelihood of completing high school by 10.4 percentage points. Adding province fixed effects and birth year fixed effects, column (2) shows that a \$1000 increase in exports per worker increases high school completion by 4.76 percentage points. Both regressions in column (1) and (2) show a positive correlation between export growth and high school completion in this era in China. However, a more interesting question is how this effect differs between younger and older students. In other words, does export growth explain that high school completion rates of those born in the late 1960s are significantly lower than those of ones born in 1960.

Column (3) includes export exposure per worker interacted with birth cohort fixed effects, in addition to the covariates in column (2). This specification identifies how the effects of export growth differ across birth cohorts. With the 1960 birth cohort set as the baseline, cohorts born in 1961, 1962, and 1963 experienced increased high school completion, while the cohorts born after 1964 decreased their high school completion, relative to the 1960 cohort. Column (4) adds interaction terms of province fixed effects and birth cohort fixed effects, capturing any potential province-year specific effects on education. Column (5) adds prefecture-level controls, including population, fraction of minority, education level[6] before the Open-Door Policy and is our preferred specification. The estimates in column (5) show that the rise in exports has a significant, negative effect on cohorts born in and after 1965. Specifically, compared to the cohort born in 1960, a $1000 increase in exports per worker leads to a 3.62 percentage point decrease in the high school completion rate for one born in 1965. Moreover, this negative effect is greater for younger cohorts. On average, those born in 1970 have a 4.76 percentage point lower probability of completing high school compared to the 1960 cohort, when experiencing the same trade shock.

It is hard to interpret the effects shown in Table 3.4, since there is substantial between-prefecture heterogeneity in export growth from 1975 to 1982. The mean export exposure per worker is $402, but the 25th percentile experienced only $35 of export exposure, the 50th percentile experienced $123, and the 90th percentile experienced over $650. Figure 3.3 plots the point estimates from Table 3.4, evaluated at the mean export exposure per worker for each birth cohort, with the 1960 birth cohort as the baseline. One born in 1966 with a mean export exposure has a 1.7 percentage point lower probability of finishing high school compared to one born in 1960 with the same exposure. Overall, our relatively coarse export exposure measure

[6]Education level is represented by three variables, middle school completion rate, high school completion rate and college completion rate.

explains 10.4% of the high school completion decline among cohorts born in the 1960s.[7]

Figure 3.4 includes three curves showing the estimated effects at the 25th, 50th, and 90th percentile of export exposure per worker. The high school completion rate for cohorts born between 1964-1970 with the 90th percentile export exposure[8] is reduced by 1.3 to 3 percentage points compared to the 1960 birth cohort.

Overall, the results shown above indicate that China's Open Door Policy had a negative and significant effect on the high school completion rates of the 1964-1970 birth cohorts, compared to the cohort born in 1960.

3.5.2 Middle School Completion

The previous results suggest that high schoolers dropped out of school due to job opportunities brought by the Open Door Policy. It is important to also investigate if this trade shock had a similar effect on middle school completion. In Figure 3.1, both middle school and high school completion rates declined for the 1960s birth cohorts, although the reduction in high school completion rate was greater and affected older cohorts compared to the decrease in middle school completion. We run the same regressions as in Table 3.4, with the dependent variable as middle school completion.

Table 3.5 presents OLS point estimates of the effect of export exposure on middle school completion. Surprisingly, the trade shock has a positive effect on the middle school completion rate of all the 1960s birth cohorts compared to the baseline cohort in 1960. The estimates are statistically significant for cohorts from 1963 to 1970 in column (3) and (4), and the effects are stronger for younger cohorts. After controlling for prefecture level controls, we can still see the positive effects for cohorts 1963 and

[7]The high school completion rate decreased from 30.02% in the 1960 birth cohort to 13.67% in the 1966 birth cohort.

[8]Jinzhou city, Chaoyang city, Huludao city, Taiyuan city, Anshan city, Dandong city, Tongling city, Shanghai municipality, Beijing municipality, Tianjin municipality, Dalian city, Huainan city, Qiqihar city, Suihua city, Daqing city, Liaoyang city, Urumuqi city, Baicheng city, Songyuan city, Yingkou city, Panjin city, Lanzhou city, Benxi city, Wuhai city, Jiuquan prefecture, Fushun city and Karamay city.

1970. These education variables are cumulative: a high school graduate counts as both a high school and a middle school completer. Thus these findings are not explained by teens dropping out of high school and only completing middle school. This presents a puzzle – why would export growth increase middle school completion, yet decrease high school completion for cohorts born in the 1960s?

Farmer Heterogeneity

During the same period as the Open-Door Policy, China experienced a series of fundamental changes to the agricultural sector, where rural households gained responsibility for the profits and losses of the land assigned to them. These policies were first adopted in 1979, and expanded nationwide in 1981 by Deng Xiaoping. Unlike the previous agricultural system under Mao Zedong, this more privatized system stimulated farmers' enthusiasm and increased agricultural productivity. As a result, labor demand in the agricultural sector increased under this new system. Our export exposure measure is larger in highly industrialized, non-agrarian prefectures. Given that export exposure is positively associated with the middle school completion rate in Table 3.5, it is likely that this effect can be explained by a reduction in middle school completion in rural provinces, rather than by a positive causal effect of export growth on middle school completion. To investigate this, we construct a farmer dummy variable and a series of interaction terms of this variable and birth cohort and include them in the primary regression model.[9]

Column 1 in Table 3.6 shows the estimates of export exposure's effect on middle school completion, accounting for farmer heterogeneity. The coefficients shown are only for non-farmers; coefficients for farmers are shown in Table D.1 in the appendix. We can see that after accounting for farmer differences, the coefficients of interest for non-farmers become small and insignificant. Figure 3.5 also plots the point estimates

[9] We use the occupation reported in the 1990 Census to identify farmers, as we do not have their *hukou* information for their official urban/rural designation. Occupation codes we consider farmers are detailed in the data appendix.

with confidence intervals from this regression, and Figure 3.6 shows the effects at different percentiles of export exposure per worker on middle school completion. These results show that the Open Door Policy had no effect on the middle school completion rates of the 1960s cohorts, and suggest that agricultural reform is the cause of the decline in primary and middle school completion among these cohorts.

As a robustness check, we add the same set of farmer dummies to the high school completion regression and show the results in Column 2 of Table 3.6. The effect on high school completion becomes smaller after controlling for farmer heterogeneity, but the effects are still significant and comparable in magnitude to those in Table 3.4. In Figure 3.7 we can still see obvious negative effects, although the effects are not statistically significant for several birth cohorts. Compared to Figure 3.4, Figure 3.8 shows that the trade shock's effect on high school completion is weaker at all levels of export exposure per worker after accounting for farmer heterogeneity.

3.5.3 Falsification Tests

One potential concern with our identification is that the local export exposure per worker could change in conjunction with human capital accumulation so that this trade shock is not exogenous to education. We test this concern by running the same regression on older cohorts, born from 1940-1960, who had already finished their education when the Open Door Policy started. Figure 3.9 presents the coefficients of interest of the regression on birth cohorts 1940-1970. Although noisy, the trade shock's effect on earlier cohorts (1940-1960) are not significantly different from zero, and are generally smaller than the primary effects shown from 1964-1970.

3.6 Conclusion

We investigate how China's Open-Door Policy can explain the decline in educational attainment among China's 1960s birth cohorts. There are clear drops in both high school and middle school completion for nearly a decade, and we are the first to examine the underlying causes of these nationwide trends. We find that export growth driven by the Open Door Policy decreased high school completion by 4.76 p.p. for the cohorts born in 1970, compared to the baseline cohort born in 1960. This suggests a tradeoff between education and labor market opportunities in China. The negative effect of export exposure are more prominent for cohorts who were younger when China's Open-Door Policy began, even though these teenagers also faced a stronger education system compared to the earlier cohorts. We find no effect of the export exposure on middle school completion rates.

This paper is the first study that links the educational attainmetn of the 1960s cohort in China to the Open-Door Policy. It contributes to the literature on international trade's effect on low-skill worker in the developing country and the broader literature on tradeoff between labor participation and human capital accumulation. The findings in this paper also encourages investigation of further evidence from other countries.

Table 3.1.: Summary Statistics of Export Exposure per prefecture, in 1000 USD

Percentile	Export Exposure	Statistics	
10%	-0.074	Mean	0.402
25%	0.035	Std Dev	2.527
50%	0.123	Minimum	-1.467
75%	0.303	Maximum	34.898
90%	0.664	Median	0.123
N	198		

Table 3.2.: Summary Statistics of Export Exposure per province, in 1000 USD

Quintiles	Provinces	Mean	SD	Min	Max
20%	Zhejiang, Hunan, Guangxi, Guizhou, Yunnan, Tibet	-0.023	0.026	-0.065	0.001
40%	Inner Mongolia, Anhui, Fujian, Jiangxi, Henan, Sichuan	0.015	0.006	0.005	0.022
60%	Hebei, Jiangsu, Hubei, Guangdong, Shaanxi, Qinghai	0.039	0.0131	0.023	0.053
80%	Shanxi, Jilin, Heilongjiang, Shandong, Gansu, Ningxia	0.140	0.068	0.073	0.255
100%	Beijing, Shanghai, Tianjin, Liaoning, Xinjiang	0.395	0.083	0.258	0.465

Table 3.3.: Descriptive Statistics

	1960		1970	
1990 Census	**Mean**	**SD**	**Mean**	**SD**
Education				
Complete primary school	0.847	0.36	0.863	0.344
Complete middle school	0.631	0.483	0.524	0.499
Complete high school	0.281	0.449	0.096	0.294
Some high school	0.289	0.454	0.142	0.349
Some College	0.024	0.154	0.028	0.164
Demographic Characteristics				
Female	0.486	0.5	0.489	0.5
Ethnic Minority	0.078	0.268	0.08	0.272
Agriculture	0.574	0.494	0.627	0.484
N	142270		277357	

Source: IPUMS 1990 China Population Census.

Table 3.4.: High School Completion

	(1)	(2)	(3)	(4)	(5)
	1	2	3	4	5
ΔXPW	0.104**	0.0476**	0.0595*	0.0710**	0.0458**
	(0.0363)	(0.0175)	(0.0299)	(0.0257)	(0.0130)
1961.birthyr$\times\Delta XPW$			0.0217*	0.00183	-0.000448
			(0.0119)	(0.00893)	(0.00844)
1962.birthyr$\times\Delta XPW$			0.0107	-0.00274	-0.00595
			(0.00855)	(0.00680)	(0.00698)
1963.birthyr$\times\Delta XPW$			0.0103	0.00302	-0.0000967
			(0.00886)	(0.00916)	(0.00890)
1964.birthyr$\times\Delta XPW$			-0.00222	-0.0176	-0.0203
			(0.0123)	(0.0123)	(0.0127)
1965.birthyr$\times\Delta XPW$			-0.0212	-0.0332**	-0.0362**
			(0.0185)	(0.0143)	(0.0139)
1966.birthyr$\times\Delta XPW$			-0.0265	-0.0392**	-0.0423**
			(0.0223)	(0.0145)	(0.0144)
1967.birthyr$\times\Delta XPW$			-0.0305	-0.0389*	-0.0411**
			(0.0252)	(0.0192)	(0.0179)
1968.birthyr$\times\Delta XPW$			-0.0194	-0.0365**	-0.0399**
			(0.0267)	(0.0176)	(0.0171)
1969.birthyr$\times\Delta XPW$			-0.0265	-0.0385*	-0.0400**
			(0.0262)	(0.0198)	(0.0187)
1970.birthyr$\times\Delta XPW$			-0.0407	-0.0449**	-0.0476**
			(0.0293)	(0.0181)	(0.0177)
Province FE		Y	Y	Y	Y
Birth FE		Y	Y	Y	Y
Province $\times$ Birth FE				Y	Y
Prefecture Controls					Y
N	2450185	2450185	2450185	2450185	2450185

Standard errors in parentheses are clustered at province level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Table 3.5.: Middle School Completion

	(1)	(2)	(3)	(4)	(5)
	1	2	3	4	5
ΔXPW	0.173***	0.0803**	0.0578	0.0588	0.0156
	(0.0418)	(0.0339)	(0.0345)	(0.0350)	(0.0166)
1961.birthyr×ΔXPW			0.00984	0.0125	0.00328
			(0.00652)	(0.00744)	(0.00497)
1962.birthyr×ΔXPW			0.00228	0.0132	0.00382
			(0.00885)	(0.00817)	(0.00647)
1963.birthyr×ΔXPW			-0.000103	0.0225**	0.0135*
			(0.00988)	(0.00986)	(0.00767)
1964.birthyr×ΔXPW			0.0107	0.0211**	0.0113
			(0.0105)	(0.00965)	(0.00901)
1965.birthyr×ΔXPW			0.0186	0.0230**	0.0129
			(0.0124)	(0.0112)	(0.00901)
1966.birthyr×ΔXPW			0.0279**	0.0245**	0.0127
			(0.0130)	(0.0115)	(0.00880)
1967.birthyr×ΔXPW			0.0321**	0.0209	0.0110
			(0.0148)	(0.0136)	(0.0108)
1968.birthyr×ΔXPW			0.0463**	0.0280*	0.0145
			(0.0170)	(0.0147)	(0.0120)
1969.birthyr×ΔXPW			0.0450**	0.0261*	0.0161
			(0.0180)	(0.0139)	(0.0113)
1970.birthyr×ΔXPW			0.0545**	0.0380**	0.0263**
			(0.0184)	(0.0142)	(0.0123)
Province FE		Y	Y	Y	Y
Birth FE		Y	Y	Y	Y
Province × Birth FE				Y	Y
Prefecture Controls					Y
N	2450185	2450185	2450185	2450185	2406219

Standard errors in parentheses are clustered at province levvel.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Table 3.6.: Trade Effects on Non-Farmers

	(1) Middle School Completion	(2) High School Completion
ΔXPW	-0.0109	0.0171
	(0.0165)	(0.0166)
1961.birthyr$\times\Delta XPW$	-0.00905	-0.0118
	(0.00560)	(0.00825)
1962.birthyr$\times\Delta XPW$	-0.00518	-0.00359
	(0.00810)	(0.0103)
1963.birthyr$\times\Delta XPW$	0.00160	0.000129
	(0.00725)	(0.0101)
1964.birthyr$\times\Delta XPW$	-0.00787	-0.0193
	(0.00862)	(0.0144)
1965.birthyr$\times\Delta XPW$	-0.00351	-0.0302**
	(0.00960)	(0.0133)
1966.birthyr$\times\Delta XPW$	-0.00646	-0.0324**
	(0.0110)	(0.0149)
1967.birthyr$\times\Delta XPW$	-0.0122	-0.0331
	(0.0122)	(0.0203)
1968.birthyr$\times\Delta XPW$	-0.0109	-0.0215
	(0.0122)	(0.0191)
1969.birthyr$\times\Delta XPW$	-0.0167	-0.0214
	(0.0126)	(0.0218)
1970.birthyr$\times\Delta XPW$	0.00834	-0.0157
	(0.0141)	(0.0197)
N	2286998	2286998

Standard errors in parentheses are clustered at province level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

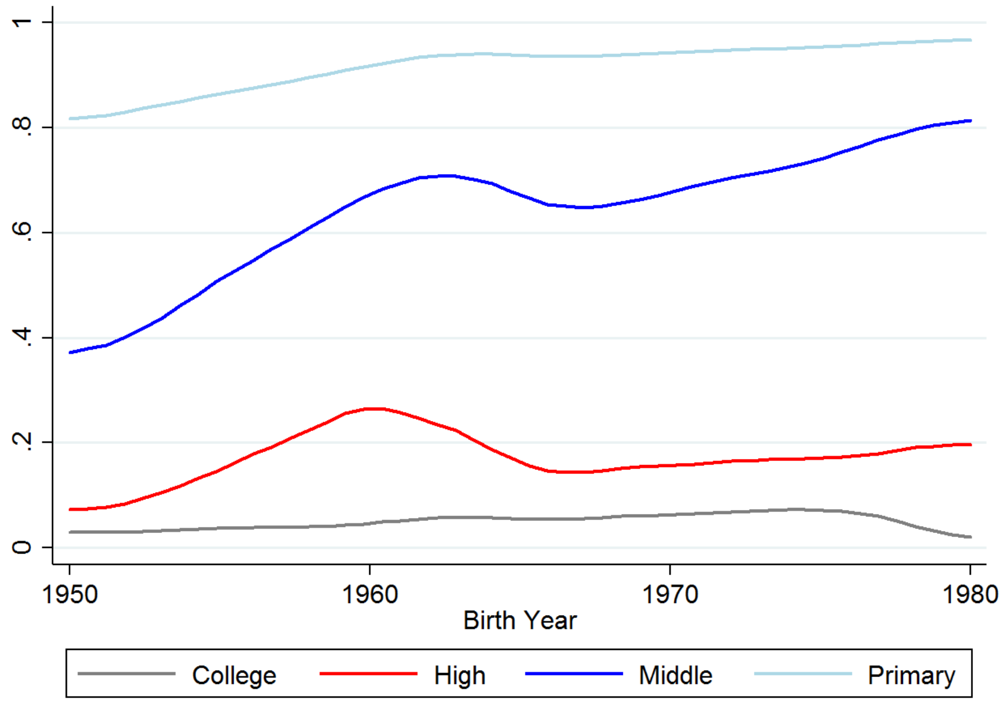

Figure 3.1.: School Completion Rates across Cohorts

Notes: Data is from China's 2000 Census.

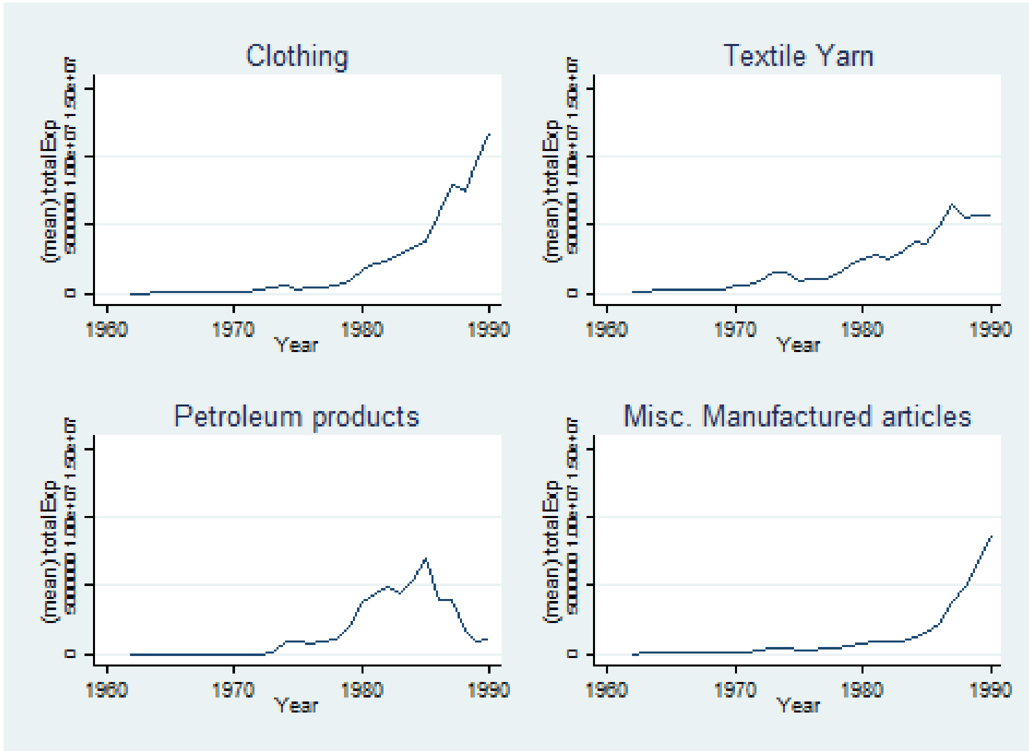

Figure 3.2.: Highest Export Value Industries, 1960-1990

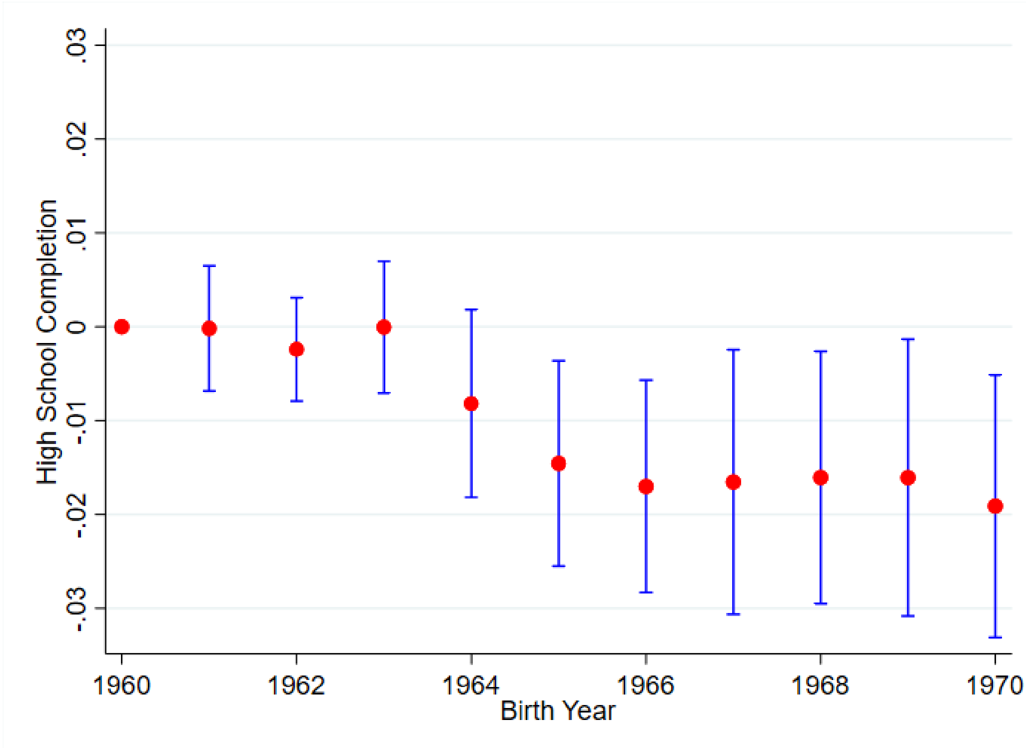

Figure 3.3.: Export Exposure Mean Effects on High School Completion

Notes: The y-axis shows the estimates of the decreases in high school completion rates in response to a $402 (mean) increase in export exposure.

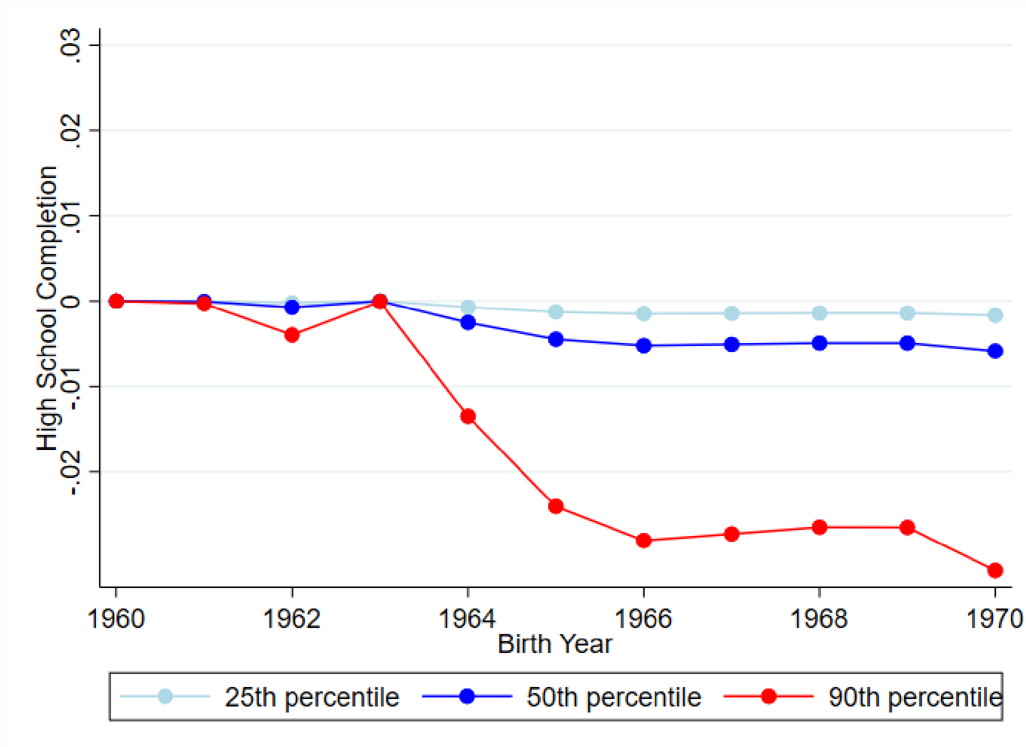

Figure 3.4.: Percentile Effects on High School Completion

Notes: The y-axis shows the estimates of the decreases in high school completion rates in response to a certain level of increase in export exposure. From the top to the bottom, the export exposure are at the 25th percentile, the 50th percentile and the 90th percentile.

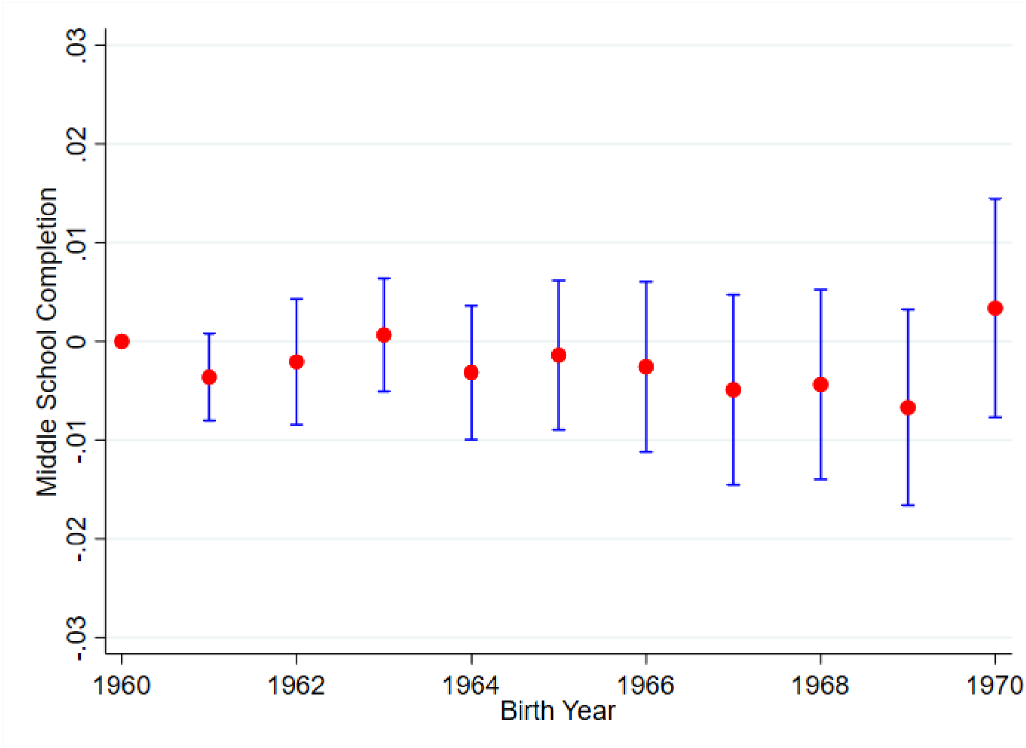

Figure 3.5.: Export Exposure Mean Effects on Middle School Completion (Non-Farmers)

Notes: The y-axis shows the estimates of the decreases in middle school completion rates of non-farmers in response to a $402 (mean) increase in export exposure.

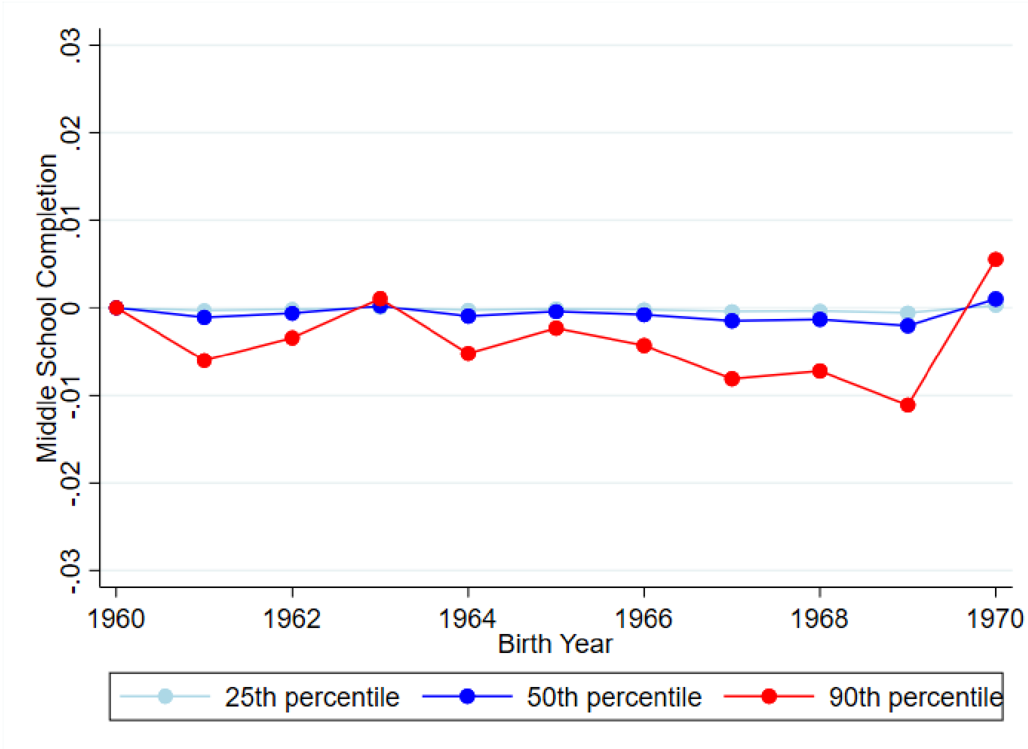

Figure 3.6.: Percentile Effects on Middle School Completion (Non-Farmers)

Notes: The y-axis shows the estimates of the decreases in middle school completion rates of non-farmers in response to a certain level of increase in export exposure. From the top curve to the bottom, the export exposure are at the 25th percentile, the 50th percentile and the 90th percentile.

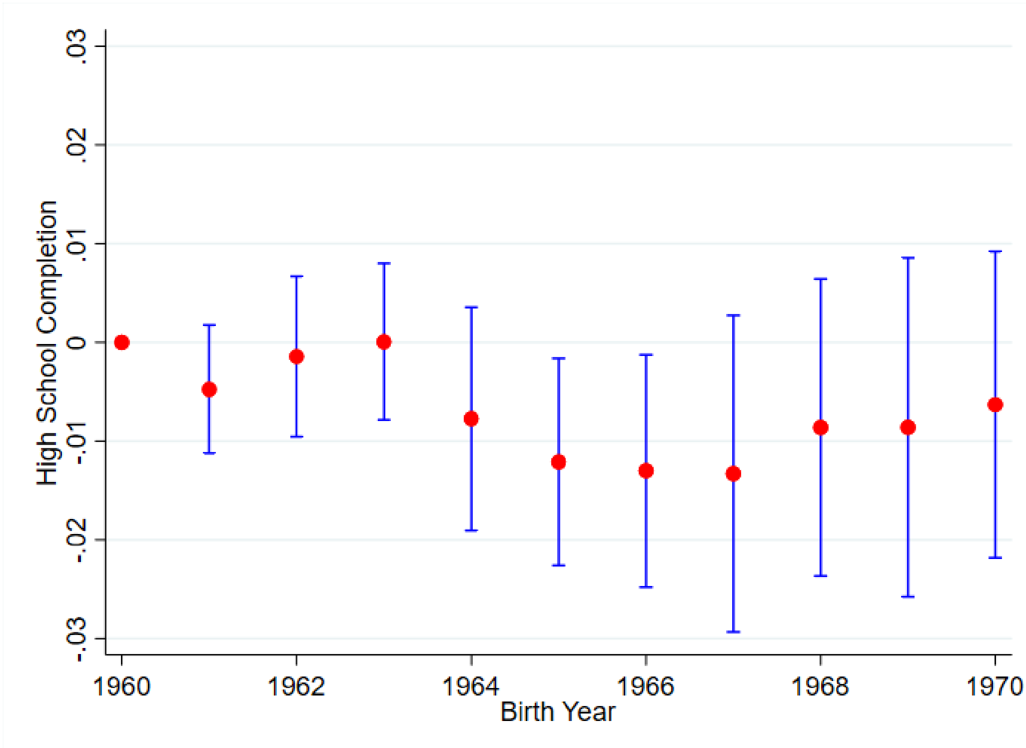

Figure 3.7.: Export Exposure Mean Effects on High School Completion (Non-Farmers)

Notes: The y-axis shows the estimates of the decreases in high school completion rates of non-farmers in response to a $402 (mean) increase in export exposure.

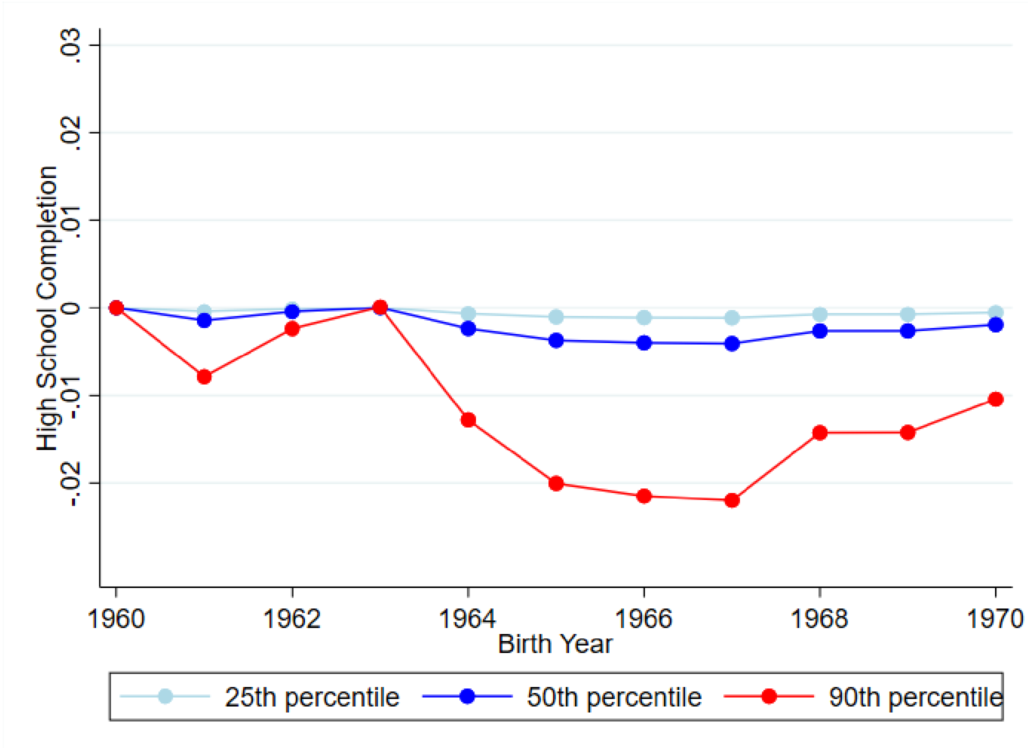

Figure 3.8.: Percentile Effects on High School Completion (Non-Farmers)

Notes: The y-axis shows the estimates of the decreases in high school completion rates of non-farmers in response to a certain level of increase in export exposure. From the top curve to the bottom, the export exposure are at the 25th percentile, the 50th percentile and the 90th percentile.

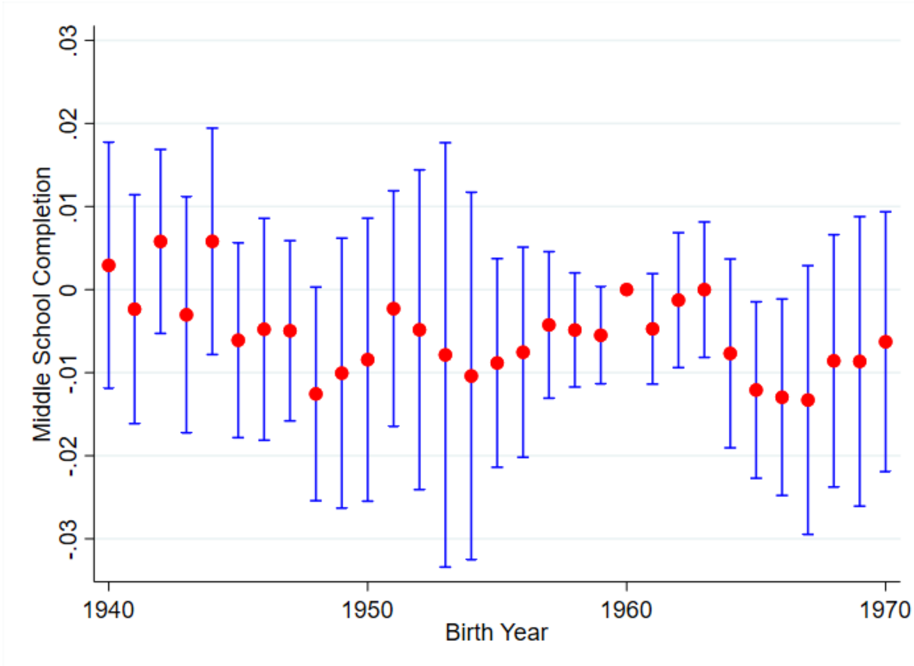

Figure 3.9.: Export Exposure Effects on High School Completion, 1940-1970

Notes: The y-axis shows the estimates of the changes in high school completion rates of non-farmers born 1940-1970 in response to a $402 (mean) increase in export exposure.

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APPENDICES

A: Alternative Setting for The Factors 1

An alternative restriction to the factor loadings is non-triangular, as follows.

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

where the first factor is identified only from the covariances of $ACT_{English}$, $COM114$, and $ACT_{Reading}$. The second factor is identified from the covariances of $ACT_{Science}$, $HSGPA$ and ACT_{Math}. Therefore, an increase in the first factor will only affect the first three scores and an increase in the second factor will only affect the other three scores. Intuitively, I name the first factor as verbal ability and the second as math ability. Compared to the main specification of the factors in Section 1.4.1, the alternative sacrifices part of the covariances of the test scores by assuming the first factor does not affect the second set of test scores at all. It might, however, makes it easier to interpret the factors and more importantly, show more variation on the second factor.

Table A.1 and A.2 shows the estimates of this alternative measurement system. Coefficients of controls are not much different from the main specification. The loadings of verbal skill on the first set of test scores are significantly positive, indicating that an increase in verbal skill will significantly increase $ACT_{English}$, $COM114$ and $ACT_{Reading}$, as expected. Similarly, an increase in math skill will significantly increase $ACT_{Science}$, $HSGPA$ and ACT_{Math}. Specifically, for example, one standard deviation[1] increase in an average woman's verbal skill will increase her $ACT_{English}$ by 3.92 points. One standard deviation increase in an average woman's math skill

[1]Standard deviation of female's verbal skill is 3.448, female's math skill is 3.770, male's verbal skill is 3.572, male's math skill is 3.937.

will increase her ACT_{Math} by 3.77 points. Compared to the main specification of the factors, the loadings of the new second factor have bigger magnitudes due to more variations it takes from the test scores.

Figure A.1 and A.2 show the alternative ability distributions. Compared to Figure 1.1 and 1.2, it is obvious that distributions of the second factor (blue curves) in both gender's are more off from normality. Specifically, female's second factor is bimodal with a hump on the left tail and male's second factor is left-skewed.

I then estimate the same model to analyze the sorting effects in major choice and job choice. Table A.3 show the estimates in major choice given the alternative factors. Individuals sort positively on both abilities. Specifically, one standard deviation increase in an average woman's verbal ability will increase her likelihood of graduating in STEM by 5.23% percentage points; and that number for an average man is 6.42%. One standard deviation increase in an average woman's math ability will increase her likelihood of graduating in STEM by 15.83% percentage points; and that number for an average man is 25.98%. Both genders sort more on math ability than on verbal ability. This is not surprising: the second factor now takes all common variations form $ACT_{Science}$, $HSGPA$ and ACT_{Math}, not the "left-over" variations of these scores after the first factor has been identified. Additionally, it is intuitive that math ability is more essential to STEM majors than verbal. Similar to the estimates in the main specification, we see here men sort more on both abilities as well. Men's coefficients are statistically larger than women's. In job choice (Table A.4), no sorting on verbal ability for both gender. Although there is positive sorting on math ability, however, the gender difference is zero. Overall, the estimates from the two specifications are telling a consistent story: men sort more on both latent abilities in major choice; there is no gender difference in sorting on abilities in job choice.

Table A.1.: Non-triangular Abilities at College Entrance, Female

Dependent Var→	ACT_E	COM114	ACT_R	ACT_S	HSGPA	ACT_M
Home Region: Indiana	-0.754	-0.103	-0.911	-1.710***	0.270	-1.519**
	(0.749)	0.092	(0.804)	(0.585)	(1.995)	(0.653)
Home Region: Midwest	0.981	-0.128*	0.107	-0.322	-4.285**	-0.044
	(0.752)	(0.097)	(0.824)	(0.628)	(2.129)	(0.705)
Home Region: Northeast	-1.273	-0.194*	-0.793	-1.453*	-3.334	-0.814
	(1.218)	(0.146)	(1.298)	(0.883)	(3.071)	(0.949)
Home Region: South	2.323**	-0.049	1.659	0.336	0.472	0.992
	(1.129)	(0.119)	(1.149)	(0.773)	(2.594)	(0.883)
AFGR	0.117***	0.012**	0.097**	0.103***	0.579***	0.109**
	(0.039)	(0.005)	(0.043)	(0.034)	(0.113)	(0.038)
First Term Semester: Fall	1.862*	-0.034	2.574*	1.526	8.516**	2.423
	(1.052)	(0.170)	(1.275)	(1.315)	(4.201)	(1.599)
First Term Semester: Spring	-1.521	0.037	0.752	-0.251	-2.37	-0.100
	(1.607)	(0.254)	(1.915)	(1.966)	(6.270)	(2.398)
General Intelligence	1.138***	0.042***	1			
	(0.049)	(0.005)	X			
Math Ability				0.697***	1.811***	1
				(0.027)	(0.095)	X
Constant	14.669***	2.770***	16.279***	16.168***	-14.099	15.597 ***
	(3.054)	(0.418)	(3.425)	(2.957)	(9.701)	(3.484)
Observations	1,145					

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

Note: Each column is a separate regression specified in Equation 1.11. All columns have the same observations: 1145. The loading of Verbal Skill is normalized to one in regression of $ACT_{Reading}$, so that Verbal Skill takes the metrics of $ACT_{Reading}$. The loading of Math Skill is normalized to one in regression of ACT_{Math}, so that Math Skill takes the metrics of ACT_{Math}. I control for annual state-averaged freshmen graduation rate (AFGR) on the year of each student graduated from high school, home census region fixed effects and first enrollment semester fix effects.

Table A.2.: Non-triangular Abilities at College Entrance, Male

	ACT_E	COM114	ACT_R	ACT_S	HSGPA	ACT_M
Home Region: Indiana	-1.788***	-0.066	-1.707***	-1.726***	0.335	-1.206***
	(0.692)	(0.079)	(0.698)	(0.548)	(1.595)	(0.544)
Home Region: Midwest	-0.590	-0.199**	-0.799	-0.276	-4.919**	-0.160
	(0.714)	(0.083)	(0.726)	(0.571)	(1.673)	(0.563)
Home Region: Northeast	-1.039	-0.195*	-0.941	-0.335	-3.523	-0.406
	(1.019)	(0.118)	(1.035)	(0.758)	(2.300)	(0.712)
Home Region: South	0.476	-0.007	0.296	0.244	0.064	0.776
	(0.757)	(0.091)	(.7799)	(0.626)	(1.844)	(0.613)
AFGR	0.168***	0.018***	0.090**	0.115***	0.664***	0.131***
	(0.029)	(0.004)	(0.033)	(0.029)	(0.086)	(0.027)
First Term Semester: Fall	4.837***	-0.212	3.515**	5.558***	13.106***	5.817***
	(1.076)	(0.180)	(1.276)	(1.152)	(3.545)	(1.063)
First Term Semester: Spring	2.705***	-0.236	1.210	4.589***	10.850**	4.744***
	(1.354)	(0.225)	(1.601)	(1.417)	(4.403)	(1.289)
General Intelligence	1.180***	0.043***	1			
	(0.049)	(0.004)	X			
Math Ability				0.808***	1.684***	1
				(0.027)	(0.079)	X
Constant	8.7869***	2.2636***	16.952***	13.233***	-26.697***	12.888***
	(2.5743)	(0.379)	(2.8526)	(2.437)	(7.402)	(2.296)
Observations	1,910					

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

Note: Each column is a separate regression specified in Equation 1.11. All columns have the same observations: 1910. The loading of Verbal Skill is normalized to one in regression of $ACT_{Reading}$, so that Verbal Ability takes the metrics of $ACT_{Reading}$. The loading of Math Skill is normalized to one in regression of ACT_{Math}, so that Math Skill takes the metrics of ACT_{Math}. I control for annual state-averaged freshmen graduation rate (AFGR) on the year of each student graduated from high school, home census region fixed effects and first enrollment semester fix effects.

Table A.3.: Likelihood of Graduating with A STEM Major (nontriangular)

	(1) Female	(2) Male
	Marginal Effects at the Mean	
Verbal Ability	0.015**	0.018***
	(0.0071)	(0.0064)
Math Ability	0.042***	0.066***
	(0.0059)	(0.0052)
N	1145	1910

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

Note: This table is different with Table 1.6 in terms of the loadings structure of two factors. 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 verbal ability is 3.488 and 3.572; the standard deviation of female's and male's math ability is 3.770 and 3.937. 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, first enrollment year, first enrollment semester, degree year fixed effects are controlled but not shown in this table for short.

Table A.4.: Likelihood of STEM Graduates Work in STEM Occupations (nontriangular)

	(1) Female	(2) Male
	Marginal Effects at the Mean	
Verbal Ability	0.001	0.004
	(0.0119)	(0.0062)
Math Ability	0.023**	0.013***
	(0.0108)	(0.0050)
N	1145	1910

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

Note: This table is different with Table 1.7 in terms of the loadings structure of two factors. 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 verbal ability is 3.488 and 3.572; the standard deviation of female's and male's math ability is 3.770 and 3.937. The dependent variable in both column (1) and (2) is dummy of working 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.

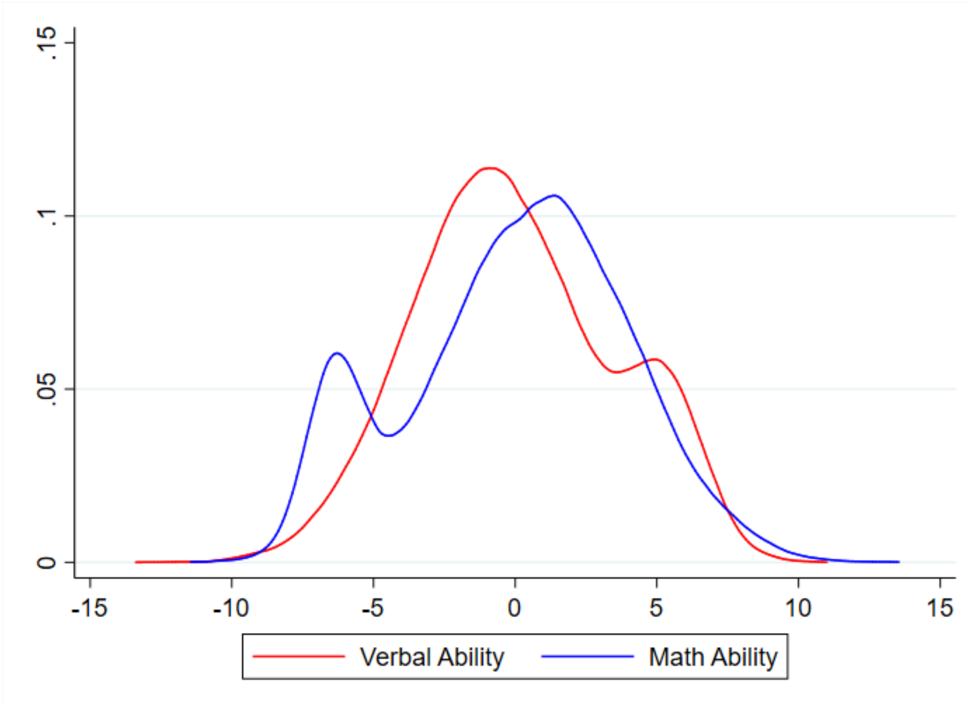

Figure A.1.: Distributions of Female's Two Abilities (nontriangular)

Distributions are centered at mean zero. $sd(f1) = 3.488$; $sd(f2) = 3.770$

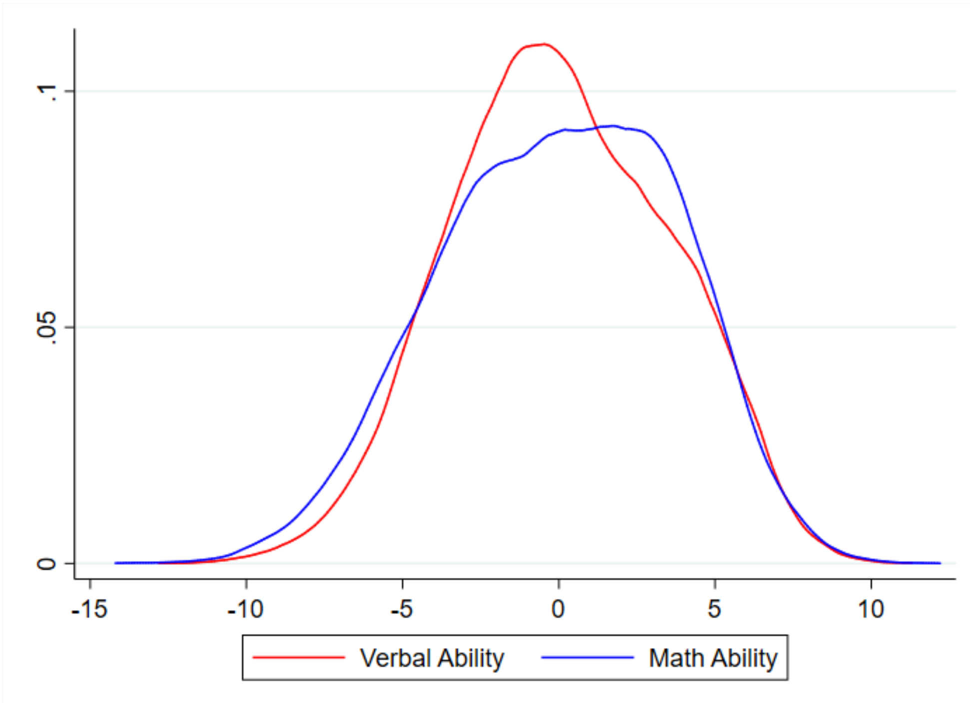

Figure A.2.: Distributions of Male's Two Abilities (nontriangular)

Distributions are centered at mean zero. $sd(f1) = 3.572$; $sd(f2) = 3.937$

B: Additional Tables and Figures for Chapter 1

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

	(1) Female	(2) Male
General Intelligence	0.0070428	-0.0057017
	(0.0083508)	(0.0077115)
Extra 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: 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. 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. The estimates show that women who reported to the survey do not differ on both abilities from women who did. Although there is a positive and significant effect on men's extra math ability, the magnitude is too small to have significant economic meaning. Using the loading to calculate the marginal effect, I get one standard deviation increase in extra math ability will increase the probability for an average man to report his first job information by 1.5 percentage points.

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

	(1) Female	(2) 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 B.3.: Likelihood of STEM Major Graduates Working in A STEM Occupation

	(1) Female	(2) Male
# 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 B.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: 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 B.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: 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 B.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: 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.

C: Parallel Trend Assumption Tests 1

I use a linear time trend test on the Han cohorts born between 1950-1959 to confirm that there is no pre-treatment trend in men's education compared to women.

$$Edu_{isc} = \theta + \sum_{j=1}^{C} \psi_j I_j + \tau Women_{isc} + \eta t + \delta_1 t \times Women_{isc} + \Lambda X_{isc} + \varepsilon_{isc}$$

where t is a linear time trend. Other notations are the same as the ones in the main regressions. The null hypothesis is that the coefficient of interaction term of women and linear time trend, δ_1, is not significantly different from zero. See Panel A in Table C.1 shows that δ_1 is small in terms of magnitude and not statistically significant different than zero.

Similarly, I test that if the parallel trend assumption holds for the DD between Han women and non-Han women. The estimates of δ_2 shows in Panel B of Table C.1. is no different trend between pre-treatment Han women and non-Han women.

Table C.1.: Pre-Trend Assumption Test

	(1) CFPS (1950-1957)	(2) CFPS (1950-1958)	(3) CFPS (1950-1959)
Panel A. Han Women VS. Han Men			
$t \times Women$	-.0779048	-.0488348	-.0220141
	(.0577179)	(.0499611)	(.0432983)
N	4303	4650	4900
Panel B. Han Women VS. non-Han Women			
$t \times Han$	.118145	.1092896	.1641309
	(.1263541)	(.1000051)	(.0936827)
N	2283	2470	2619

Note: The sample in column (1) includes birth cohorts from 1950-1957, the sample in column (2) includes birth cohorts from 1950-1958, and the sample in column (3) includes birth cohorts from 1950-1959. The dependent variable is years of schooling. Independent variables include women dummy/Han dummy, interaction of women and time/interaction of Han and time, province fixed effects, and birth year fixed effects. Other controls include rural dummy, interaction term of rural and women dummy/interaction term of rural and Han dummy, number of siblings, dummy of father completing high school, dummy of mother completing high school, dummy of father being a communist party member and dummy of mother being a communist party member.

Standard errors in parentheses are clustered at province-cohort level.

D: Additional Tables and Figures for Chapter 3

Table D.1.: Export Exposure Effects on Farmers' Education

	(1) High School Completion	(2) Middle School Completion
Farmer	-0.374***	-0.335***
	(0.0192)	(0.0167)
Farmer×ΔXPW	-0.00159	0.00184
	(0.0279)	(0.0290)
Farmer×1961.birthyr×ΔXPW	0.00310	-0.0101
	(0.0110)	(0.0102)
Farmer×1962.birthyr×ΔXPW	0.0130	-0.0137
	(0.0110)	(0.0127)
Farmer×1963.birthyr×ΔXPW	0.0102	-0.0162
	(0.0168)	(0.0148)
Farmer×1964.birthyr×ΔXPW	0.0234	-0.00690
	(0.0158)	(0.0149)
Farmer×1965.birthyr×ΔXPW	0.0160	-0.00166
	(0.0144)	(0.0158)
Farmer×1966.birthyr×ΔXPW	0.0193	-0.00285
	(0.0160)	(0.0172)
Farmer×1967.birthyr×ΔXPW	0.0237	0.00205
	(0.0168)	(0.0238)
Farmer×1968.birthyr×ΔXPW	0.0297	-0.00828
	(0.0208)	(0.0267)
Farmer×1969.birthyr×ΔXPW	0.0365*	-0.0112
	(0.0186)	(0.0287)
Farmer×1970.birthyr×ΔXPW	0.0203	-0.0174
	(0.0205)	(0.0306)
N	2244692	2244692

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

VITA

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Education

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May 2015	M.S., Economics, Purdue University
Dec 2012	M.S., Agricultural Economics, Purdue University
Jul 2011	B.S., Industrial Engineering, Beihang University

Fields of Research

Labor Economics, Economics of Education, Applied Econometrics

Working Papers

"Planting the Seeds for Success: Why Women in STEM Don't Stick in The Field" (Job Market Paper)

"Fertility Expectations and Educational Attainment: Evidence from the Mothers of China's Sibling-less Generation"
"When Opportunity Knocks: China's Open Door Policy and Declining Educational Attainment," with Kendall Kennedy and Jiatong Zhong.

Works in Progress

"Does the Risk of Divorce Increase Female College Education," with Kevin Mumford
"The Influence of One Child Policy on Inter-Generational Wealth Inequality: A Marriage Market Matching Approach," with Yiqian Lu

Presentations

Society of Labor Economists, Toronto, Canada	May 2018
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National STEM Education Research and Practice Summit, Purdue	October 2017
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Midwest Economics Association, Cincinnati OH	April 2017
Western Economics Association International, Portland OR	June 2016

Professional Memberships

American Economic Association, *Association for Public Policy and Management*, *Midwest Economics Association*, *Society of Labor Economists*, *Southern Economics Association*

Teaching Experience

Primary Course Instructor

Microeconomics	Spring 2016

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Econometrics (Masters)	Fall 2016
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Game Theory (MBA)	Fall 2014

Skills

Stata, Python, Matlab

References

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