Life-cycle Returns to Social and Math Skills: The Roles of Gender, Sorting and Employer Learning

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April 2019

Abstract

This paper documents gender differences in life-cycle returns to social skills and math skills in the labor market. Using the National Longitudinal Survey of Youth 1979 data, I test for whether women and men sort into occupations that match with their pre-market skills, and whether there are increasing returns to skills as employers learn about workers' abilities over time. Workers with higher social skills choose occupations that put higher emphasis on job interactions, but this sorting effect is stronger for men than for women and the gap is widening over the life-cycle. Math skills are also positively correlated with social characteristics of an occupation such as leadership activities, and there is a significant gender gap in sorting by math skills. I then follow the employer learning literature to estimate the returns to each skill and the growth of returns with experience. Returns to social skills and math skills grow at a faster rate for men than for women, suggesting differential speed of employer learning. However, the initial of return to a female worker's math skills is significantly higher such that on average women enjoy higher returns to math skills in the first 10-15 years of their career. These findings reflect gender differences in both workers' occupational sorting and employers' belief updating process, and suggest a higher return to investing in skills that counter beliefs about gender stereotypes.

1 Introduction

A growing literature documents the differential impacts of cognitive and noncognitive abilities on labor market outcomes (e.g., Cunha and Heckman 2008; Lindqvist and Vestman 2011; Kottelenberg and Lehrer 2018). Since skills are multidimensional in nature (e.g., Guvenen et al. 2018), the distinction between different types of skills is important for understanding which skill matters more and for whom, and thus providing guidance on skill investment decisions. Deming (2017) documents a rise in labor market returns to social skills from mid 1980s to 2000s by comparing the 1979 cohort with the 1997 cohort of the National Longitudinal Survey of Youth in the U.S. With more precise measures of abilities, Lindqvist and Vestman (2011) argue that both cognitive and noncognitive abilities (including social skills) are strong predictors for labor market earnings of Swedish men, and noncognitive abilities are particularly valuable to men at the lower end of the earnings distribution. Nevertheless, little is known about whether different types of skills are equally valuable to women versus men. On one hand, the rising share of interpersonal tasks can help explain a large fraction of the decrease in gender wage gap between 1970s and 1990s as women are believed to be typically better at dealing with people (e.g., Borghans, Weel and Weinberg 2014; Black and Spitz-Oener 2010). On the other hand, it is unclear how beliefs about gender stereotypes that associate women with social skills and men with math skills translate into labor market returns for each group, which may actually slow down the convergence in earnings and provide alternative implications on skill investments.

In this paper, I focus on two types of skills – social and math, and examine whether women and men sort into occupations that match with their pre-market skills, and whether there are increasing returns to skills as employers learn about workers' abilities over time. I use the 1979 cohort of the National Longitudinal Survey of Youth (NLSY) to follow about 8,500 people born between 1957 and 1964 over a span of 35 years. To measure an individual's pre-market social skill, I run a principal component analysis on a similar set of variables on personality and high-school extracurriculars to that in Borghans et al. (2006) and Deming

(2017), and use the first principal component that explains the highest fraction of variance across all variables as an aggregate measure of social skill. Math skill is measured by combining each person's scores in arithmetic reasoning and math knowledge, two subsections of the Armed Services Vocational Aptitude Battery (ASVAB) test conducted on all participants of NLSY in 1980. There is no significant gender difference in social skills, but women have 0.14-SD significantly lower math skills than men on average. At the top of the skill distributions, there is a slightly higher fraction of women with top social skills, and a higher fraction of men with top math skills, which may be sufficient to generate stereotypical beliefs that associate men with math and women with social characteristics (see Bordalo et al. 2016).

To motivate the empirical analysis, I develop a simple conceptual framework for understanding how employers compensate workers when they receive signals about their skills in each dimension. Assume employers set wages based on what they believe to be a worker's social and math skills. Employers may hold differential prior beliefs about the skills of women versus men, and they can update their beliefs as they receive private signals from a worker. The rate at which wage responses to a signal sent by a worker can be decomposed into two factors. First, it depends on whether one works in an occupation that emphasizes tasks matched with her skills and thus allows her to signal certain skills faster. Second, it depends on the speed at which employers update their beliefs. Under a Bayesian updating process with normal priors, the more uncertain an employer is initially about the skills of one group, the more weights the employer will put on signals rather than prior beliefs. This suggests that when women are believed to have lower math skills than men, the signals about their math abilities are actually more valuable and lead to higher returns for women than for men.

The first channel in the model points to the importance of evaluating the matching between a worker's skills and occupational characteristics, which influences the amount of opportunities workers have to signal their abilities at work and eventually translates into the returns to skills. Using O*Net 1998 data, I characterize an occupation by the importance of job interactions in work context and by the intensity of math requirements. I also look at whether an occupation is managerial, identified from the occupation titles directly. With a dataset at person-year level, I estimate the marginal effects of a 1-standard-deviation increase in social skill or math skill on each of the occupational characteristics within each age group. Workers with higher social skills choose occupations that put higher emphasis on job interactions. However, this sorting effect is stronger for men than for women and the gap is widening over the life-cycle.

Interestingly, math skills also turn out to be positively correlated with the importance of job interactions in an occupation. A closer look into the social aspects of occupations suggests that math skills are stronger predictors for sorting into leadership activities and managerial positions than pre-market social skills based on personality or high school extracurriculars. Male workers increasingly sort themselves into leadership by their math skills, whereas the sorting among female workers is flat. Similar gender differences appear in sorting into occupations with higher math requirements, suggesting a systematic tendency for women to sort less actively based on their skills into occupations.

In the second part of this paper I estimate the labor market returns to workers' social skills and math skills, and the growth of returns with experience. Following the public employer learning frameworks in Farber and Gibbons (1996) and Altonji and Pierret (2001), I run a series of regressions of log wages on pre-market skills and their interactions with experience and gender, along with controls for education and demographic characteristics, and occupation group, year and region fixed effects. Initially there is a higher return to females' social skills than to males', but the growth of return with experience for males is about 4-5 times larger than that for females, reversing the initial female lead in about 6-7 years into the labor market. The returns to social skills are attenuated when the regression controls for math skills simultaneously, but the gender gap in growth of return with experience remains significant.

As for math skills, the initial return is approximately 7 log-point higher wages per 1-SD increase in math skills for female workers, twice as large as the initial return for males.

Although the returns to math skills grow at a slower rate for women than for men with experience, the large initial lead implies women enjoy a higher return to math skills in the first 10-15 years of their careers. Under the conceptual framework, this finding suggests employers put relatively higher weights on signals about women's math skills, at least early in their career. If women sorted as actively as men by their math skills into occupations, the estimated returns to their math skills would be even higher.

The complementarity between social skills and math skills does not turn out to be significant for either gender. This finding may be driven by the limited predictive power of pre-market social skills on earnings. It remains unclear whether there would be much stronger complementarity between social skills and math skills developed on the job.

To explore whether the gender divergence in returns to skills later in the career is driven by family factors, I fit separate models for observations before vs. after people have their first kids. I find a 25-log-point direct wage penalty on mothers relative to fathers; the difference in returns to skills, in comparison, is second-order. The wage gap between women and men who never have kids is much smaller, and women in this group enjoy a significantly higher return to both social skills and math skills from the beginning.

Finally I fit the model separately for each education level and do not find statistically significant gender differences in returns to skills or growth of returns within each group. Education itself is often considered as a strong proxy for one's general ability, which can be a function of both social skills and math skills. It is possible that the gender differences in sorting by skills have been absorbed into their schooling decisions. It would be fruitful to conduct a first-stage analysis of how social skills and math skills affect education decisions as in Kottelenberg and Lehrer (2018).

In summary, the aggregate results (across education groups) show that women sort less based on their pre-market social skills and math skills than male workers. Women have an initial lead in returns to social skills, but since there is little growth of their returns with experience, this advantage is overturned in 6-7 years into the labor market. In contrast, women enjoy a higher return to math skills for about 10-15 years, an advantage that women do not appear to take advantage of as indicated by their lack of occupational sorting by skills. These findings suggest that workers can find a higher return to skills that are not typically associated with their gender identity and thus have some important implications on skill investment decisions.

The rest of the paper is structured as follows: Section 2 presents the conceptual framework for decomposing the returns to signals about skills into employer learning vs. occupational sorting. Section 3 discusses the datasets and presents a series of descriptive statistics. Section 4 focuses on occupational sorting by skills. Section 5 estimates the labor market returns to skills and the growth of such returns with experience. Section 6 concludes.

2 Conceptual Framework

In this section I present a simple conceptual framework for understanding how employers update their beliefs when they receive signals about workers' social and math skills over time, and how they compensate workers accordingly.

There are two groups of workers in the labor market: $g \in \{F, M\}$. Let (s_i, m_i) denote a worker i's true social and math abilities, which are not observed by the employer immediately.

Assume employers set wages based on their beliefs about a worker i's skill $(\tilde{s}_{it}, \tilde{m}_{it})$ at time t. That is, $w_{it} = f(\tilde{s}_{it}, \tilde{m}_{it})$ where f is a concave production function that satisfies $f_1 > 0$, $f_2 > 0$ and $f_{12} \geq 0$. I further assume employers are Bayesian. Specifically, given their prior beliefs $m_i|_{i \in g} \sim N(\mu_m^g, \sigma_m^g)$ about the distributions of math skills of workers in group g, an one-step belief updating according to signals θ_{it} would be:

$$\tilde{m}_{it} = \frac{\gamma_0^g}{\gamma_0^g + \gamma_1^g}\mu_m^g + \frac{\gamma_1^g}{\gamma_0^g + \gamma_1^g}\theta_{it} \tag{1}$$

where $\gamma_0^g = \frac{1}{(\sigma_m^g)^2}$ and γ_1^g is the inverse of the variance of signals. The less certain the employer is about a given group's math ability, the more weights he would put on the signals received over time. In sequential updating from $(t-1)$ to t, this implication still holds and the difference is that the weight on an employer's prior group-specific belief (at $t=0$) diminishes even more over time.

The value of the signal about i's math ability can be quantified as follows:

$$\frac{\partial w_i}{\partial \theta_{it}} = f_2(\tilde{s}_{it}, \tilde{m}_{it}) \times \frac{\partial \tilde{m}_{it}}{\partial \theta_{it}} = f_2 \times \frac{\gamma_1^g}{\gamma_0^g + \gamma_1^g} \tag{2}$$

Suppose the signal converges to her true math ability over time at rate λ_j (specific to occupation j that one belongs to): $\theta_{it} = (1 - exp(-\lambda_j t)) \times m_i$. Then we can quantify the rate at which wage responds to a worker's ability m_i:

$$\frac{\partial}{\partial t}\left(\frac{\partial w_i}{\partial m_i}\right) = \frac{\partial}{\partial t}\left(\frac{\partial w_i}{\partial \theta_{it}} \times \frac{\partial \theta_{it}}{\partial m_i}\right) = \underbrace{f_2 \times \frac{\gamma_1^g}{\gamma_0^g + \gamma_1^g}}_{(i)\text{ Employer Learning}} \times \underbrace{\lambda_j exp(-\lambda_j t)}_{(ii)\text{ Occupational Sorting}} \tag{3}$$

where (i) is driven by employer's belief updating process about workers' abilities, and (ii) is determined by how fast workers can signal their true ability in an occupation. In particular, consider the case where employers' prior beliefs are $\mu_m^F < \mu_m^M$ with $\gamma_0^F < \gamma_0^M$: there is an initial disadvantage to women if employers use gender to infer their ability (statistical discrimination); however, employers put higher weights on signals they receive rather than the prior beliefs about women, and this mechanism can boost the growth of wages in response to signals. In the meantime, the occupation a worker belongs to matters. If one works on a job that matches with her skills, she can presumably send signals about her true ability at a faster rate λ_j than on a job lack of such opportunities. Therefore, it is also important to test for any gender differences in occupational sorting by skills, which can lead to a gap in the growth of returns to skills over time through the term (ii).

3 Data and Descriptive Statistics

The National Longitudinal Survey of Youth (NLSY) 1979 surveys a nationally representative sample of young women and men in the United States annually from 1979 to 1994, and every two years since 1996. The original sample consists of 12,686 members in the U.S. born between 1957 and 1964. I exclude the military subsample (1,280 members) who were no longer eligible for interview after 1984, and the subsample of 1,643 economically disadvantaged, non-black/non-Hispanic members who were not eligible after 1990.

NLSY 1979 provides an employer roster that keeps up to 65 unique employment records for each person throughout the survey years. For each employment relationship, the data records the start and end dates of the employment, occupation and industry codes, hourly wage, number of hours per week, and cumulative tenure in each survey year. I define a worker's actual labor market experience to be the cumulative sum of tenure across different full-time, paid jobs (at least 30 hours per week and positive hourly wage). I also construct an alternative measure of potential experience by one's age minus 6 minus total years of schooling. If the actual experience exceeds the hypothetical measure by ≥ 3 years, I use the hypothetical one instead[1].

To address the concern that the empirical results would be driven by highly mobile individuals with multiple jobs in a given year, I focus on the current job of each individual at the time of the survey, and thus have a dataset at person-year level. Table 1 provides an overview of demographic and employment-related characteristics of female and male members, respectively. The five education levels are defined through the highest grade ever reported by each individual. Females concentrate significantly more at each education level above high school than males. Across all survey years, females hold about 2 less full-time paid jobs than males and earns 23 log points less in log real wage on average.

[1]In the data at person-year-job level, this adjustment affects 27,311 (7.88% observations)

3.1 Gender Differences in Occupational Characteristics

Given the 3-digit occupation codes, I identify whether an occupation is managerial (under the category "Executive, Administrative, and Managerial Occupations" or containing "supervisors"/"managers" in a title). On average about 9.9% of occupations a female member ever works in, versus about 12.6% of occupations a male member ever works in, are managerial.

I also merge my sample with O*Net 1998 data provided in replication files for Deming (2017). I define the importance of job interactions as an average of O*Net measures of interpersonal relationships in work context, including dealing with external customers and leading others. The rest are composite scores as defined in Deming (2017). Each occupational characteristic is normalized to have mean zero and unit variance.

Table 1 shows that on average women work in occupations that have significantly more interactions in work context, especially activities dealing with external customers. However, the gender difference in "Coordinate/Lead Others" that reflects leadership activities is insignificant. The occupations women work in require significantly higher levels of math skills, and contain less routine tasks on average.

Figure 1 provides a dynamic view by showing the mean of each occupational characteristic across full-time, paid jobs taken by women and men at each age between 16 and 57 (oldest as of 2014 survey). Both women and men work in occupations that have more interactive tasks as they get older, but the level of such activities flattens around age 40. (a) shows that women work in occupations with greater importance of job interactions at all ages, but the profile for men is steeper. A closer look at subcategories of job interactions reveals that there is a large gender gap in activities dealing with external customers over the life cycle. A few examples for occupations with high emphasis on external customers include: registered nurses, sales representatives, receptionists, which tend to have more female than male workers in the sample. Although there is a small increase in such activities for older men, the profile for women is flat. In contrast, there are steep increases in (c) leadership activities for both genders from 20s to late 30s, and the gender difference does not occur until early 30s, which may coincide with the time workers start to be promoted to managerial positions.

Figure 1 - (d) shows the average math requirements in occupations of women and men at each age. The growth in math requirements is much steeper for both genders, and the flattening occurs in workers' late 20s, much earlier than leadership activities. Young women work in occupations with more math requirements, which reflects their higher representation in occupations such as accountants and auditors, and teachers. However, women are largely underrepresented in occupations with the highest math requirements such as physicists, mathematicians or engineers.

Finally, Figure 2 reveals heterogeneity across education levels. In particular, I plot the average job interactions and average math requirements for two groups: High School (12 years of schooling) and College (16 years of schooling). The female lead in job interactions and math requirements is reversed among college graduates relative to high school graduates. This contrast suggests that interactive tasks and math intensity may characterize different occupations people at different education levels sort into. It is thus important to control for education in the following empirical analysis.

3.2 Measures of Pre-Market Social and Math Skills

Social Skills

Following Borghans, Weel and Weinberg (2014) and Deming (2017), I identify questions in early waves of NLSY surveys that represents a person's pre-market social skills: (1) self-reported personality in the 1985 survey, (2) participation in high school extracurriculars in the 1984 survey, and (3) attitude towards the statement "Friends can easily be made" in the 1979 survey. From these questions I construct a series of indicator variables. Table 2 displays the means of each variable for females and males, respectively. Female members are significantly more likely to report being shy at age 6, more likely to participate in student government, newspaper, arts and hobby-related clubs in high school, and significantly less likely to participate in athletics than male members.

I then run a principal component analysis (PCA) to construct an aggregate measure of social skills. Using all variables above, the first principal component explains about 23.3% of the total variance. Table 2 displays the weights this primary measure of social skills puts on each variable. It puts highly positive weights on variables indicating outgoing personality, and participation in high school extracurriculars such as athletics and student government. Female members in my sample have lower social skills than male members on average, but the difference is insignificant (see Table 1). Figure 3 - (a) shows the distribution of social skills, normalized to have zero mean and unit variance. Despite the difference on average, there are slightly more women at the top of the distribution of social skills than men.

To check whether the primary measure is driven by particular categories, I construct two alternative measures. Alternative 1 does not consider athletics in PCA. It puts comparable weights on other high school clubs, and higher weights on self-reported personality. There is a smaller gender gap in this measure as males are significantly more active in athletics than females during high school (see Table 1). Alternative 2 excludes questions on personality and focuses on high school extracurriculars only. The gender gap is also smaller than that in the primary measure as females are more likely to report being shy at age 6 than males. Throughout the text I will use the primary measure based on all information listed.

Math Skills

In 1980, 94% of the NLSY 1979 respondents participated in the Armed Services Vocational Aptitude Battery (ASVAB), which comprises 10 tests in areas ranging from word knowledge to mechanical comprehension. In particular, math skills are measured by combining scores in arithmetic reasoning and math knowledge, two subsections of ASVAB. Female members have significantly lower math skills than male members on average. Figure 3 - (b) shows the distribution of math skills, normalized to have zero mean and unit variance. There are more men at the top of the distribution than women. Women with math skills above mean also tend to have higher social skills on average, robust across different measures of social skills (see Appendix Figure 1).

In Section 3 and 4, I test whether both social and math skills matter for occupation sorting and wages and consider the complementarity between them.

4 Occupational Sorting by Pre-Market Skills

In this section I aim to quantify the extent to which pre-market social skills or math skills matter for sorting into occupations with different characteristics, and test for gender differences in sorting within each age group. I characterize occupations by the importance of job interactions in work context, and math requirements at work, both of which are composite scores constructed from O*Net data. I also look at sorting into managerial occupations, identified directly through 3-digit occupation codes.

Let i index an individual, j index an occupation i works in, and t index a calendar year in which a survey is conducted. κ_j denotes the characteristics of occupation j. I first estimate the model below separately for each age group in a panel data at person-year level, restricted to full-time and paid jobs only.

$$\kappa_{ij} = \beta_0 + \beta_1 skill_i + \beta_2 Female_i + \beta_3 Female_i \times skill_i + \Gamma X_{it} + \phi_t + \epsilon_{it} \tag{4}$$

where $skill_i \in \{Social_i\, Math_i\}$, and X_{it} includes indicators for education levels, race, region of residence and an indicator for urban vs. rural in each survey year, and ϕ_t's are year fixed effects. The coefficient β_1 measures the effect of a 1 standard deviation increase in a male worker's pre-market skill (social or math) on the increase in occupation characteristic κ_j, and β_3 measures the additional degree of such sorting behavior among female workers relative to male workers on average.

4.1 Occupational Characteristics and Social Skills

I first look at the relationship between occupational characteristics and workers' pre-market social skills. Figure 4 shows the estimates for the marginal effects of a one-standard-deviation (1-SD) increase in social skills on each occupation-level characteristic within each age group (i.e., β_1 for males and $\beta_1 + \beta_3$ for females). Figure 4 – (a) shows that on average both female and male workers with higher social skills sort into occupations with higher importance of job interactions, except for females above age 50. However, in each age group above age 24, male workers show significantly higher degree of sorting based on their social skills than female workers on average. For example, among those aged between 36 and 40, conditional on observable characteristics such as race and education, males with 1-SD higher social skills will work in occupations with 0.12 SD higher importance in job interactions, whereas females with 1-SD higher social skills will only see an 0.04 SD increase in job interactions on average.

As discussed in Section 3.1., there are some important distinctions between dealing with external customers, and coordinating/leading others, which are two components of the aggregate measure of job interactions. Figure 4 – (b) and (c) looks at the effects of social skills on these two different characteristics, respectively. The gender difference in sorting shows up early on for dealing with external customers and remains significant across different age groups, whereas the gap in sorting into "Coordinating / Leading Others" by social skills is not statistically significant in any age group. Appendix Figure 2 shows that there is no significant gender difference in sorting into managerial occupations by social skills until age groups above 36.

4.2 Occupational Characteristics and Math Skills

For each occupational characteristic, I re-estimate equation (4) to look at sorting by workers' math skills. Figure 5 displays the estimates for female and male workers within each age group. Interestingly, workers with higher math ability are also more likely to sort into occupations with higher job interactions. Male workers with 1-SD higher math skills are increasingly sorted into these occupations as they get older, a life-cycle pattern that is particularly strong in sorting into coordinating or leading others (see Figure 5 – (c)) and selection into managerial occupations (see Appendix Figure 1 – (b)). For women, however, there is no such upward trend in sorting over the life cycle, and as a result the gender gap in sorting by math skills is growing between age 20s and 40s. Figure 5 – (b) also reveals that women with higher math ability appear to have less interactions with external customers, although the estimates are not significantly negative at 95% level. It suggests that at least some of the customer-related activities are routine and female workers would move away from these jobs if they have high quantitative skills.

Finally, as a sanity check, Figure 5 – (d) shows that for both genders, math ability matters more for sorting into occupations with higher math requirements than for sorting into job interactions, which concern more about workers' social skills. However, there remains a gender gap in sorting by math skills into quantitative occupations.

There are two main channels that can drive these gender differences in occupational sorting. First, women are less inclined to change occupations in response to their own skills, potentially due to family factors such as child care. Second, employers may provide less opportunities for workers to reveal their true abilities. The findings above also reveal that social skills and math skills may have different implications for women and men, especially in the contrast between activities that deal with customers vs. those associated with leadership. In Section 5 I will estimate the returns to each skill and discuss the complementarity between them.

5 Labor Market Returns to Skills

Following the symmetric employer learning framework (Farber and Gibbons 1996; Altonji and Pierret 2001), I use a series of regressions of log wage on workers' skills interacted with actual labor market experience to test whether a worker's pre-market social and math skills are increasingly rewarded as the market learns about his or her ability over time.[2] I analyze the gender differences in returns to each skill, and the complementarity between social and math skills.

The baseline specification is as follows:

$$\begin{aligned} log(w_{it}) = {} & \gamma_0 + \gamma_1 skill_i + \gamma_2 skill_i \times E_{it} \\ & + \gamma_3 Female_i + \gamma_4 Female_i \times E_{it} + \gamma_5 Female_i \times skill_i \times E_{it} \\ & + H(E_{it}) + \Gamma X_{it} + \delta_{k(it)} + \phi_t + \epsilon_{ijt} \end{aligned} \tag{5}$$

which controls for a cubic polynomial in experience $H(E_{it})$, demographic characteristics X_{it} that includes pairwise interactions between education levels, race and gender, family characteristic – 1 if having a kid interacted with gender, region of residence and an indicator for urban vs. rural, and finally occupation group fixed effects $\delta_{k(it)}$ and year fixed effects ϕ_t.

Assuming the pre-market social skills and math skills are not directly observable to employers, γ_1 represents the return to a 1 standard deviation increase in each skill upon labor market entry. The coefficient γ_2 on the interaction between skill and labor market experience reflects employer learning about each skill over time for male workers, and the coefficient on γ_5 reflects the gender difference in employer learning.

5.1 Main Results

Column (1) in Table 3 displays the baseline estimates for returns to social skills. A worker's pre-market social skill is positively correlated with wages upon entry into the labor market, but the initial return is significantly higher for women than for men. This initial gap may reflect differential occupational sorting earlier in one's career as a female worker is more likely to start off from an occupation with high job interactions than a male (see

[2] A worker's actual labor market experience is defined as the sum of tenure (in weeks) across all full-time, paid jobs of each person, divided by 50 and rounded to an integer. I also construct a measure of potential experience by (age-6-years in school). When the measure actual experience is ≥ 3 years above the potential experience, I use potential experience instead.

Figure 1). Nevertheless, the return to a male worker's social skill grows by 0.31 log points per year of experience, 0.24 log points (t=3.82) higher than that to a female worker's, which suggests the initial female lead in return to social skill (about 1.6 log points) is overturned in about 6-7 years into the labor market on average.

Column (2) in Table 3 displays the baseline estimates for returns to math skills. Math skills appear to be more positively correlated with wages than social skills from the beginning, for both women and men. A male worker with 1-SD higher math skills earns 3.6 log points higher wages upon labor market entry, while for a female worker the initial return is almost twice as large. Given the estimated growth of return to math skill in experience (0.52 log points/year for males and 0.28 log points/year for females), holding all else constant, it will take about 13 years for the initial female lead in returns to math skills to vanish to 0. These estimates suggest that female workers are rewarded more than their male counterparts for math skills for a relatively long time from the beginning of their careers. Under the conceptual framework in Section 2, this pattern is consistent with the hypothesis that employers put higher weights on signals about females' math skills than on males' in a Bayesian updating process (see equation (3)). That is, a female worker showing high math ability is more likely to come as a surprise to employers who are initially less certain about women's math skills, and therefore induces them to react more to the signals. However, the model cannot explain why men would enjoy higher returns to math skills later in their career, which may be driven by other factors such as family concerns that I will discuss in Section 5.3.

To further look into the different roles of social versus math skills, I estimate the returns to both skills simultaneously in (3), and in addition estimate the complementarity between social and math skills through the interaction term in (4). With controls for math skills, there is no longer a significant female lead in return to social skills initially; the growth of return with experience for males is attenuated but remains significantly positive, whereas for females there is little growth. In contrast, for both genders the returns to math skills are not attenuated as much. The key finding that female workers enjoy a higher return to math skills in the first 10-15 years of their career still holds. This contrast suggests that the pre-market social skills based on personality and high school activities has less predictive power on labor market earnings. This limitation may also affect the estimates for the complementarity between skills in column (4), which manifest no significant gender differences in returns to complementarity.

To check the robustness of the findings above, I replicate the regressions on workers who hold at least one full-time, paid job in their 20's, 30's and 40's, respectively. The results are displayed in Appendix Table 1, and show that the findings above are not driven by a dynamic selection of workers over the life-cycle and thus provide more confidence.

Although the baseline specification includes flexible pairwise interactions between a worker's education, race and gender, under this panel structure if there were any unobserved person-specific factor that influences one's growth of returns with experience, the estimates on the dynamic terms would be biased. To address this concern, I control for worker fixed effects in each model and re-estimate the growth of returns. Table 4 shows that the growth of returns to social skills are comparable to those in Table 3. The within-person estimates for growth of returns to math skills are slightly higher for both female and male workers, but the gender gap remains significant. Another small difference from previous estimates is that there is a small but statistically significant growing return to complementarity for males but little growth for females. In summary, the gender gaps in growth of returns to each skill with experience are robust to model specifications, and suggest employers learn about female workers' abilities at a slower rate than about male workers'.

5.2 Comparisons across Age Groups

Given the concave earning profiles for both women and men (see Appendix Figure 3), the assumption in the baseline specification that returns to skills grow linearly in experience may not hold. I re-run the model by controlling for indicators for age group, interacted with gender and skills rather than assuming a linear growth in return over the life cycle. All other controls remain unchanged. I control for social skills, math skills and their interaction in a single regression as in column (4) of Table 3.

Figure 6 shows the returns to social skills, math skills, and complementarity between them across age groups. Consistent with the regressions using experience, the returns to social skills are largely attenuated when the model controls for math skills, which are more predictive about earnings than the pre-market social skills. There is no significant gender difference in returns to social skills, but female workers enjoy significantly higher returns to math skills from their 20s to mid 30s, confirming the prediction based on the estimates in Table 3. It is also worth pointing out that the returns to math skills flatten across age groups above 35 for both genders, which suggest quantitative abilities may play a less important role in boosting earnings later in one's career. This pattern is consistent with workers' occupational sorting that those above age 30, regardless of education level, do not select occupations with higher math requirements when they get older (see Figure 1 (d) and 2 (d)).

5.3 Heterogeneity Analysis

Family Factors

A large literature documents the role of family factors such as children and household responsibilities in driving the widening of the gender wage gap over the life cycle (e.g., Waldfogel 1998; Goldin et al. 2010; Kleven et al. 2018). To examine the role of family factors and in particular the presence of children, I estimate the regression for returns across age groups as in Section 5.2. separately for person-year observations before the first kid is born (including people who never have kids over the sample period) versus after. Figure 7 shows the estimated gender difference in returns (female's relative to male's). The two samples – before vs. after first kid do not manifest notable differences among younger age groups. For example, among workers between their 20s and mid 30s, both women who have given birth to their first kids and those who have not, enjoy a higher return to math skills than their male counterparts. However, the return to math skills for women with kids above age 40 is significantly lower than men with kids, whereas for those who haven't given birth the gender difference is insignificant. A small divergence also occurs among older workers for social skills.

It is important to point out that workers in either the "Before 1st Kid" or "After 1st Kid" sample are positively selected in the sense that they hold a full-time, paid job at a given age. That is, these estimates apply to women and men who remain in the labor market. It is plausible that some women have already exited the labor force after giving birth, and therefore the estimated gender differences in returns to skills are relatively conservative.

Despite the relatively small differences in returns, there is a direct penalty to women who have kids. Table 5 displays the estimates for the regression of log wage on skills interacted with experience, along with other covariates as in equation (4). I further separate people who never from kids from the "Before 1st Kid" sample, and the estimates for them are in column (3). There are 8 log point significant gap in wages between women and men who never have kids, but their wages grow roughly at the same rate with experience. Women without kids also enjoy a higher return to social skills and math skills from the beginning, and their growth rates of returns with experience are also similar to men's. In contrast, women who have given birth earn 25 log points significantly lower than men with kids on average (see column (2)), and there is a significant 15 log-point wage gap even among those who are yet to have kids (see column (1)). These results suggest that childbearing decision imposes a first-order direct penalty to mothers, whereas its influence on returns to social or math skills are second order in comparison.

Education

Education has been widely used as a proxy for a worker's skill level in the labor literature. Although I control for education levels (interacted with gender) in regressions presented in this section, it's not clear whether the returns to social and math skills are heterogeneous across education levels. On the other hand, if education is a function of one's skills along different dimensions, it may not be possible to identify returns to a specific skill within an education group.

?? shows the estimates for returns to skills and the growth of returns with experience within each of the five education levels: less than high school ($<$ 12 years of schooling), high school ($=$ 12), some college (13-15), college ($=$ 16) and postgrad $>$ 16. There is no significant growth in returns to social skills with experience, except for men at the high school level and women with less than high school education. Math skills continue to be more predictive about earnings than social skills within each education group. Although the estimated coefficient on female interacted with math skills is positive among those with $>$ 12 years of schooling and comparable in magnitude from the estimate in Table 3, the estimates are much noisier and a null hypothesis of no gender difference cannot be rejected. These findings suggest education itself as a measure of one's ability absorb a large fraction of the variations in social skills and math skills between women and men, and as a result, the gender difference in returns to skills within each education level is not salient as the aggregate estimate across education groups. It may be helpful to conduct a first-stage analysis on sorting into education by pre-market social and math skills, and check whether the gender differences in returns to skills across education levels can be fully absorbed by education decisions at that stage.

6 Conclusion

The key findings of this paper can be summarized as follows:

- Women sort less actively into occupations based on their social or math skills.
- Math skills have stronger predictive power on sorting into leadership activities and managerial occupations than social skills. The gender gap in sorting into leadership

by math skills is significant from late 20s.

- Women enjoy a higher return to social skills upon entry into the labor market, but this initial lead is reversed in about 6-7 years as the returns to social skills grow at a much faster rate with experience for men than for women.

- Women enjoy a return to math skills about twice as large as that for men initially. Although the return to men's math skills grow at a faster rate with experience, women have higher returns to math skills 10-15 years into the labor market.

- The returns to social skills are largely attenuated once controlling for math skills, suggesting limitations in the predictive power of pre-market social skills on earnings. On-the-job development of social skills may be more important and more complementary with math skills in practice.

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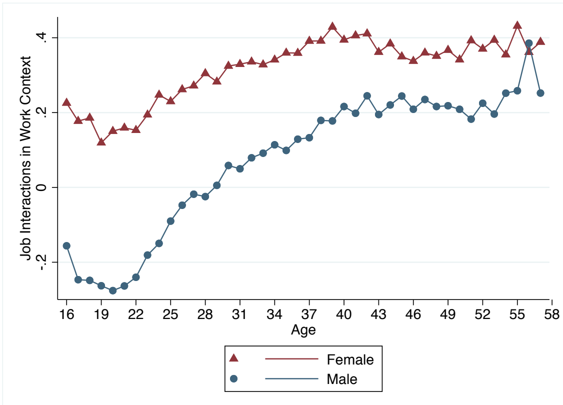
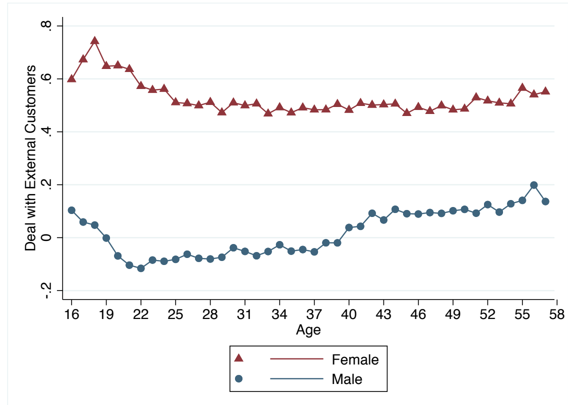
Figure 1: Occupational Characteristics by Workers' Age

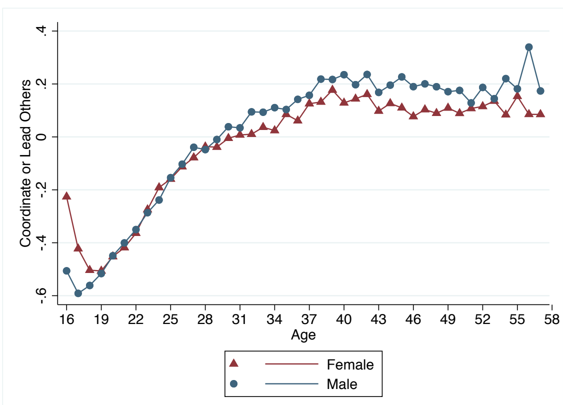
(a) Importance of Job Interactions



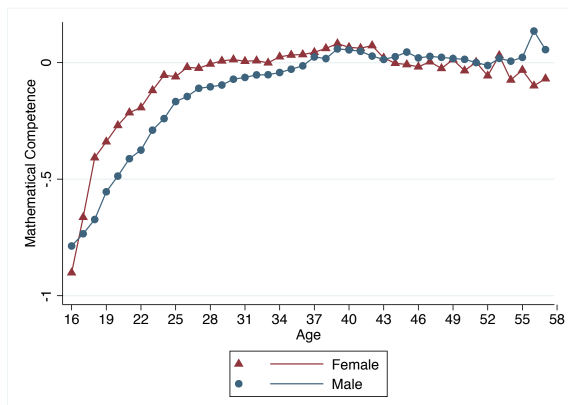
(b) Deal with External Customers



(c) Coordinate or Lead Others



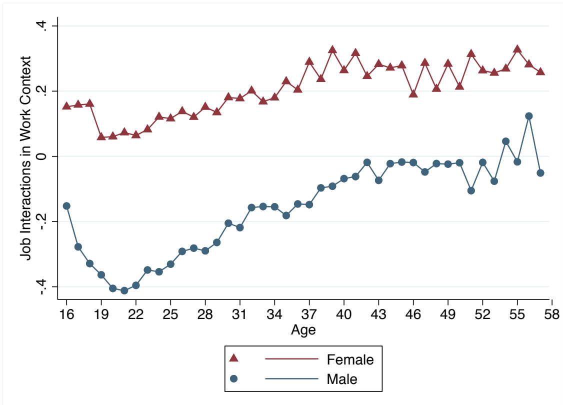
(d) Math Requirements



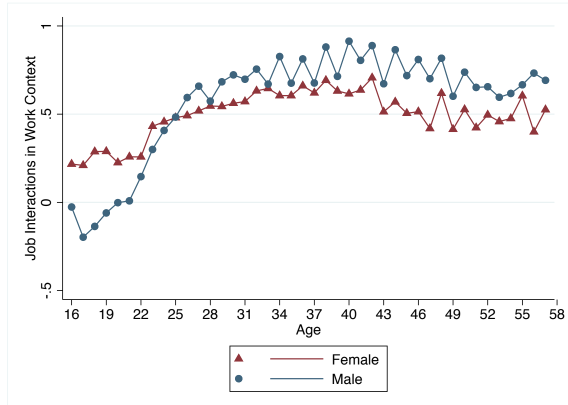
Each subfigure shows the mean characteristic of occupations females and males work in at each age, restricted to full-time ($\geq$ 30 hours per week) and paid (positive hourly wage) jobs only. The importance of job interactions in (a) is an average across measures of interactions in work context, including but not restricted to (b) and (c). "Math Requirements" is a composite score defined in Deming (2017). Each characteristic is normalized to have a zero mean and unit variance.

Figure 2: Gender Differences in Occupation Characteristics by Education

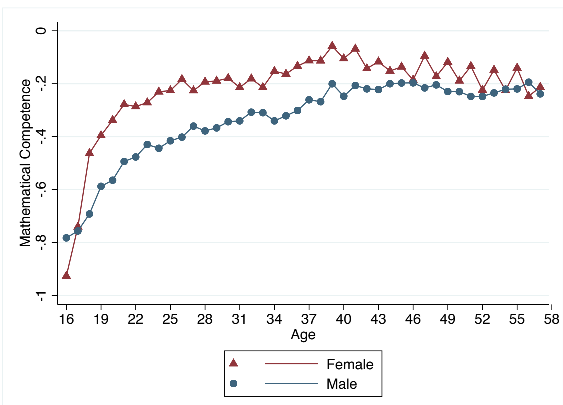
(a) Job Interactions - High School (12 yrs)



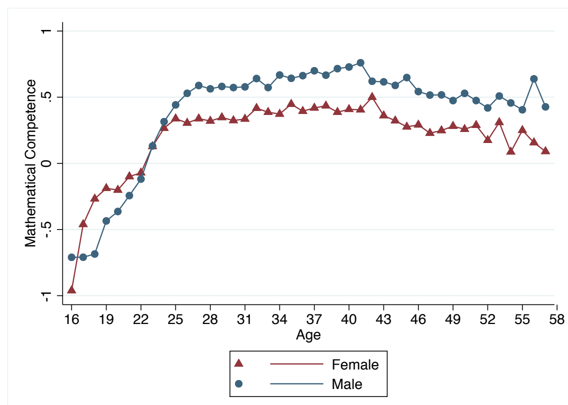
(b) Job Interactions - College (16 yrs)



(c) Math - High School (12 yrs)



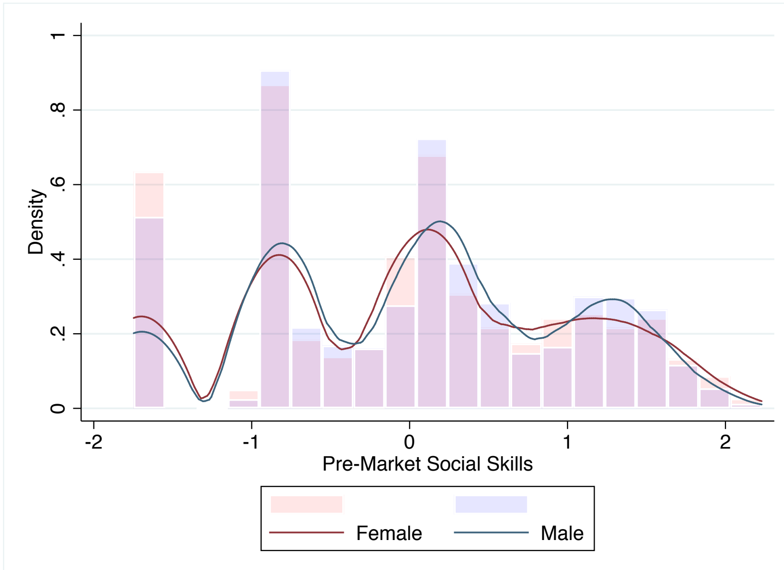
(d) Math - College (16 yrs)



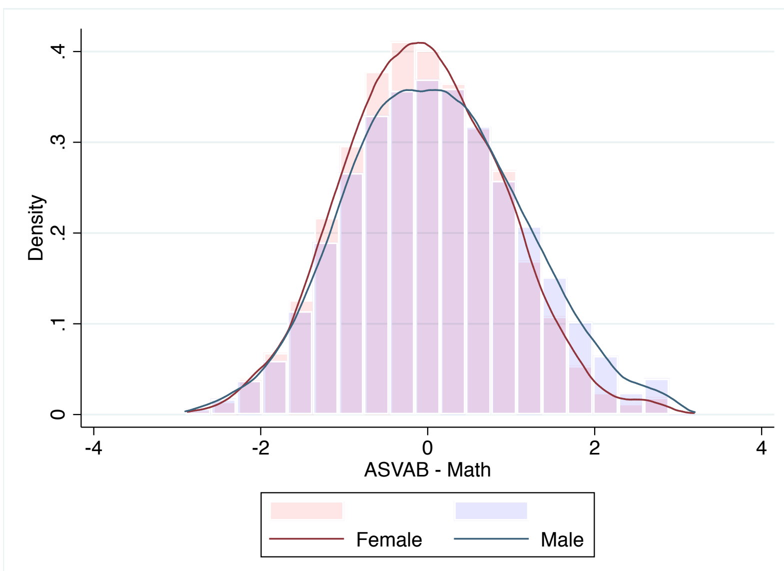
This figure displays the gender difference in the job interactions math requirements for two education levels: High School (exactly 12 years of schooling) and College (exactly 16 years of schooling).

Figure 3: Skill Distributions

(a) Pre-Market Social Skills



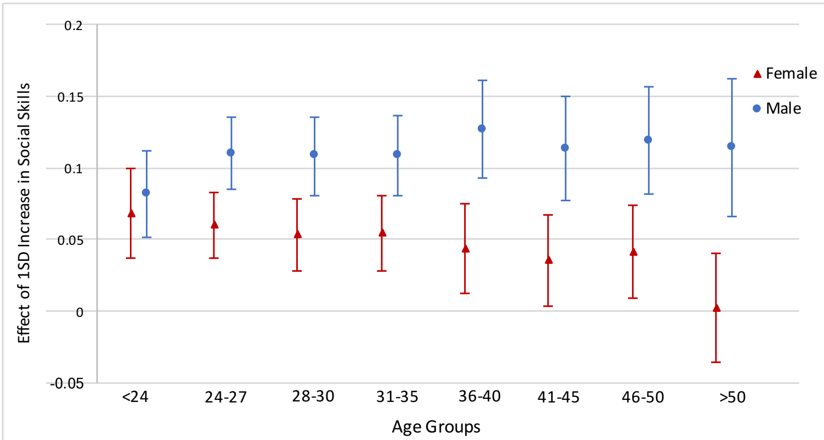
(b) ASVAB - Math Skills



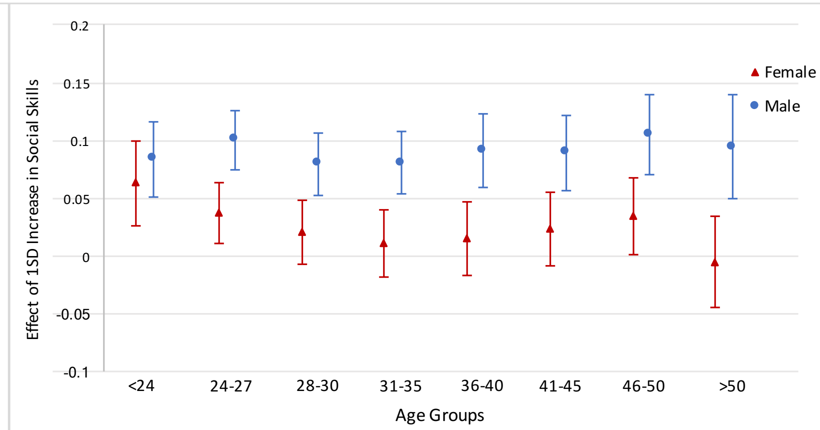
This figure shows the histogram and kernel density of pre-market social skills and math skills, respectively.

Figure 4: Occupational Sorting by Workers' Social Skills

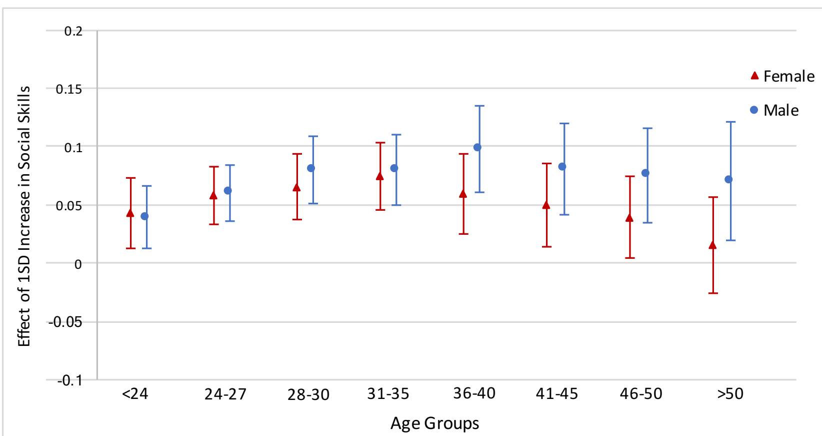
(a) Importance of Job Interactions



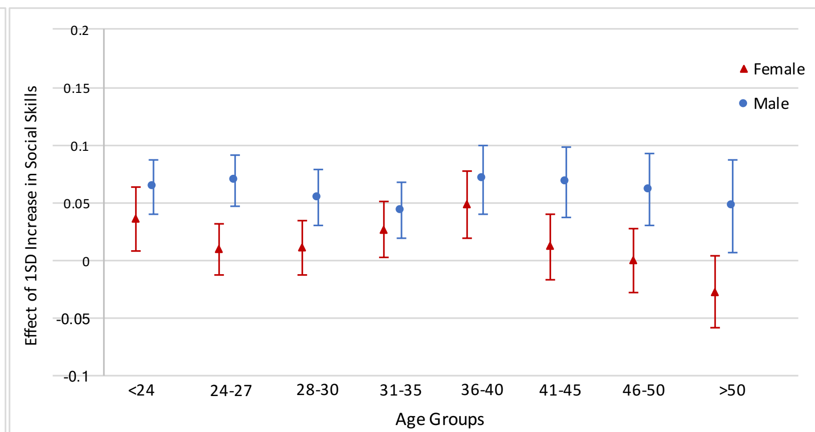
(b) Deal with External Customers



(c) Coordinating / Leading Others



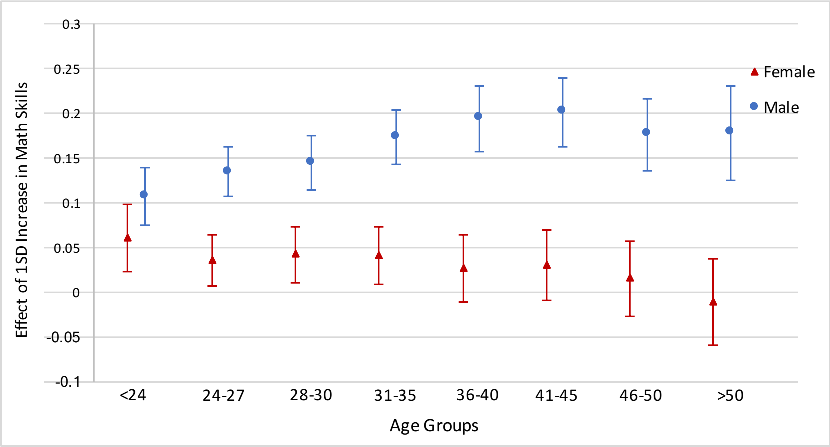
(d) Math Requirements at Work



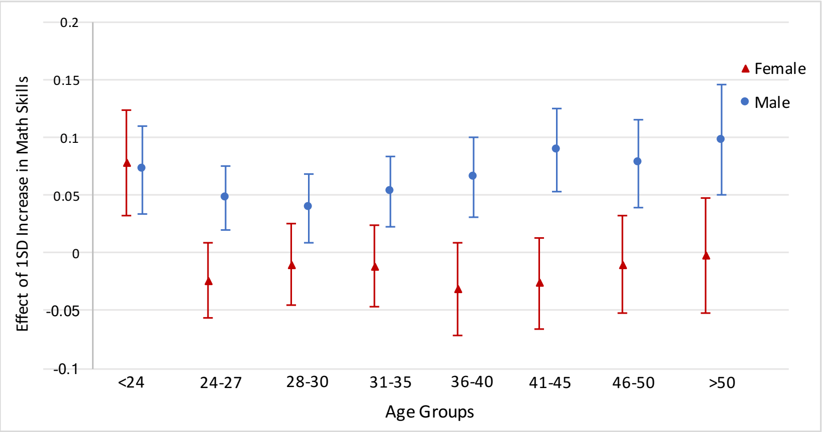
Each subfigure shows the estimated regression coefficients $\hat{\beta}_1$ for males and $\hat{\beta}_1 + \hat{\beta}_3$ for females in model (1), fitted separately for each age group. The data is at person-year level. Each regression also includes a constant,race and education levels, year fixed effects, region fixed effects, and an indicator for urban/rural. Standard errors are robust and clustered at person level.

Figure 5: Occupational Sorting by Workers' Math Skills

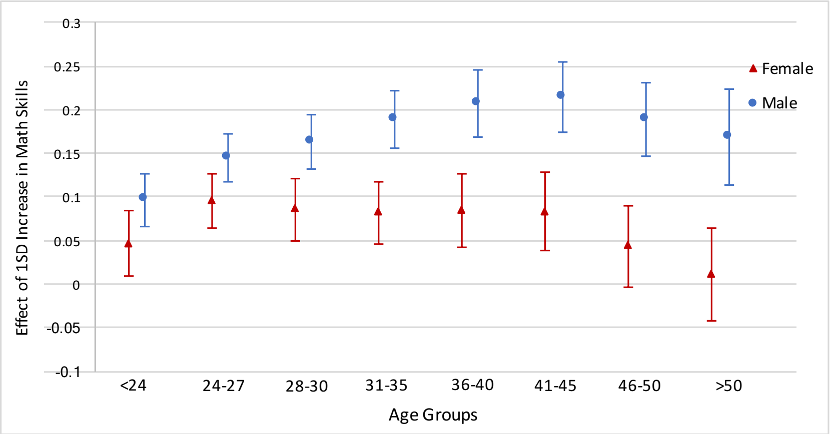
(a) Importance of Job Interactions



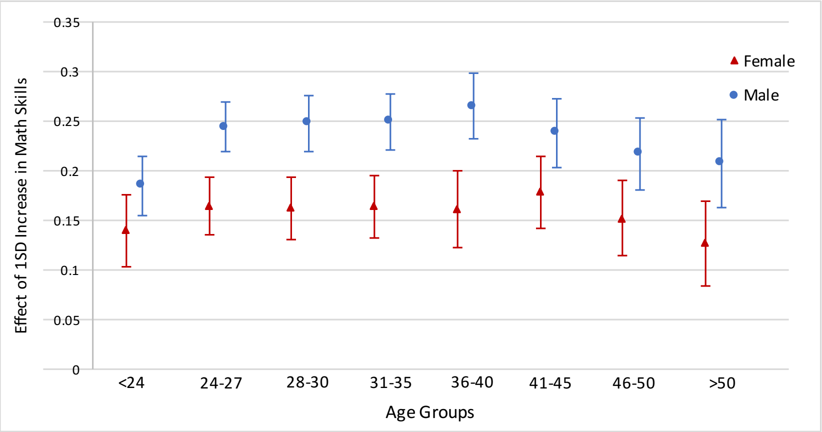
(b) Deal with External Customers



(c) Coordinating / Leading Others



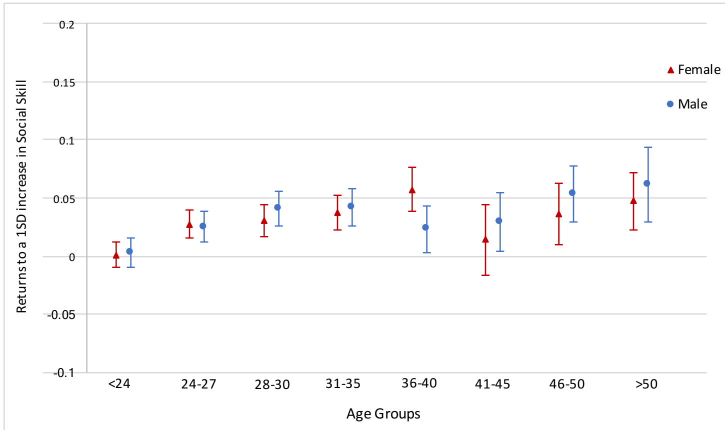
(d) Math Requirements at Work



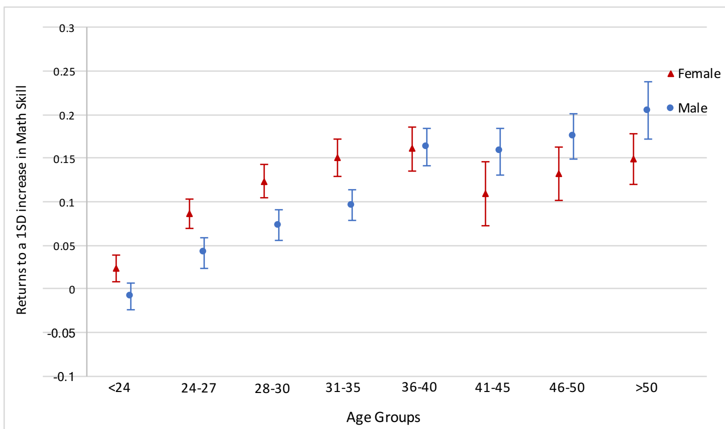
Each subfigure shows the estimated regression coefficients $\hat{\beta}_1$ for males and $\hat{\beta}_1 + \hat{\beta}_3$ for females in model (1), fitted separately for each age group. The data is at person-year level. Each regression also includes a constant,race and education levels, year fixed effects, region fixed effects, and an indicator for urban/rural. Standard errors are robust and clustered at person level.

Figure 6: Returns to Each Skill Across Age Groups

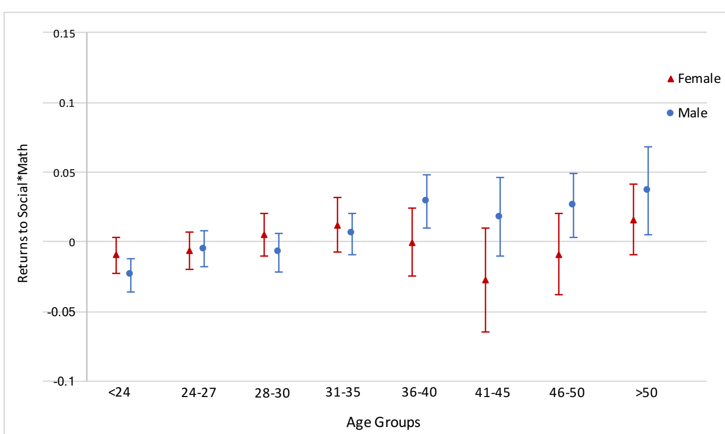
(a) Returns to Social Skills



(b) Returns to Math Skills



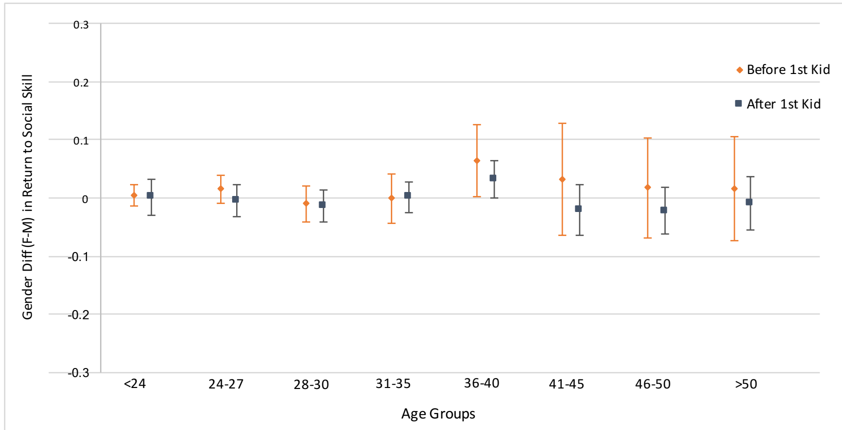
(c) Complemenatrity Social×Math



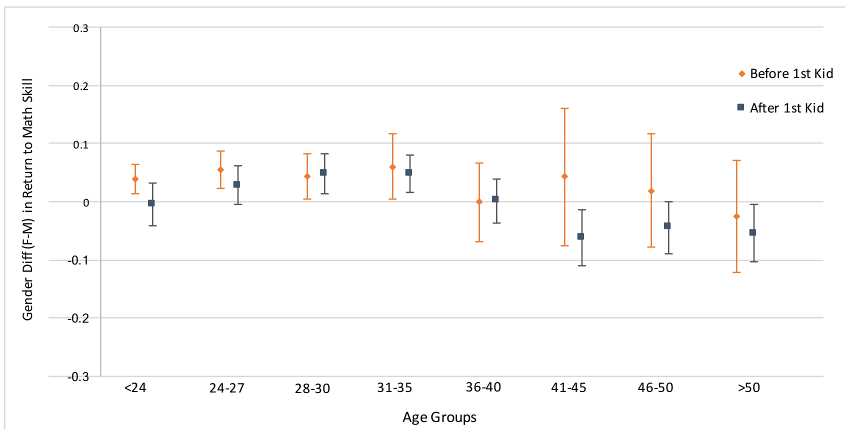
The data is at person-year level. I run a single regression of log real wage (in 2000 USD) on each of $\{social, math, social \times math\}$ interacted with gender and dummies for age groups.The regressions also control for pairwise interactions between education levels, race and gender, an indicator for after the first childbirth interacted with gender, occupation group fixed effects, calendar year fixed effects, an indicator for urban vs. rural and region fixed effects. The 95% confidence intervals are shown.

Figure 7: Gender Difference in Returns: Before vs. After Having First Kid

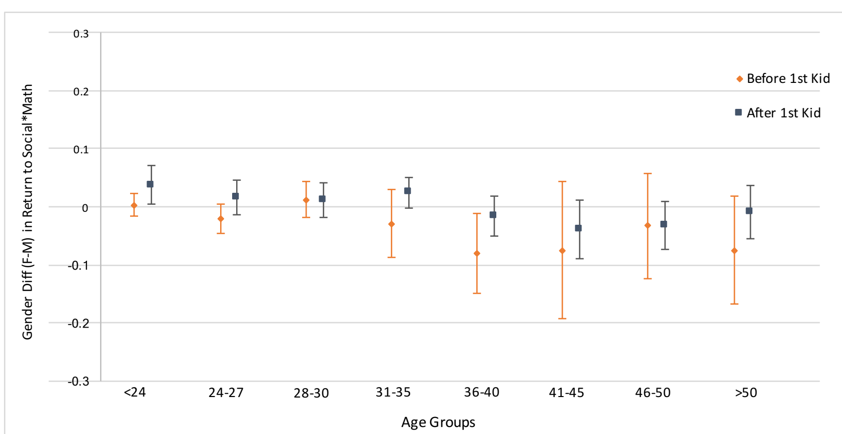
(a) F-M Difference in Returns to Social Skills



(b) F-M Difference in Returns to Math Skills



(c) F-M Difference in Returns to Social×Math



"Before 1st Kid" refers to person-year observations before the year in which the first kid is born. This sample also includes people who never have kids over the sample period. "After 1st Kid" refers to person-year observations since the year of first childbirth. Please see notes under Figure 6 for regression specifications. The 95% confidence intervals are shown.

Table 1: Summary Statistics

	Female	Male	Difference (F-M)	t-statistic
No. Individuals	4, 313	4, 171		
Education Levels				
Less than HS (<12 yrs)	0.0619	0.1050	-0.0431	-7.1836
High School (12 yrs)	0.3946	0.4572	-0.0626	-5.8381
Some College (13-15 yrs)	0.2799	0.2158	0.0641	6.8572
College (16 yrs)	0.1338	0.1230	0.0108	1.4857
Postgraduate (>16 yrs)	0.1298	0.0990	0.0308	4.4678
Skills				
Social	0.0060	0.0381	-0.0321	-1.4805
– Alternative: exclude athletics	0.0178	0.0192	-0.0013	-0.0613
– Alternative: HS clubs only	0.0204	0.0210	-0.0005	-0.0251
AFQT	0.0164	0.0388	-0.0224	-1.0372
ASVAB - Math	-0.0450	0.0962	-0.1412	-6.5623
Race				
Hispanic	0.1850	0.1839	0.0011	0.1345
Black	0.3081	0.3098	-0.0016	-0.1614
Non-Hispanic, Non-Black	0.5068	0.5064	0.0005	0.0448
Jobs				
# Jobs	11.6142	12.7502	-1.1360	-7.4718
# Full-time, Paid Jobs	7.3019	9.0925	-1.7907	-16.0092
Log Real Wage	2.1862	2.4121	-0.2259	-23.9781
Tenure (weeks)	216.5130	218.0937	-1.5807	-0.3054
Occupational Characteristics				
# Occupations	7.8187	9.2455	-1.4268	-17.4716
1 if Managerial Occupation	0.0989	0.1263	-0.0274	-9.1074
O*Net				
Importance of Job Interactions	0.2680	-0.0339	0.3019	27.6496
– Deal with External Customers	0.4790	-0.0534	0.5324	50.1535
– Coordinate/Lead Others	-0.0747	-0.0766	0.0020	0.1836
Math Requirements	-0.0525	-0.1646	0.1121	10.4807
Routine	-0.0435	0.0067	-0.0502	-5.2422

Notes: The means of log real wage, tenure in weeks, and occupational characteristics are calculated across full-time, paid jobs in the employer roster only. Measures of pre-market skills are normalized to have zero mean and unit variance. See text for details about the measures of social skills. “ASVAB - Math” is a subsection of AFQT composite score. Occupational characteristics from O*Net 1998 data are normalized to have zero mean and unit variance. “Deal with External Customers” and “Coordinate/Lead Others” are subcategories of the first composite score - “Importance of Job Interactions”.

Table 2: Measures of Pre-Market Social Skills

	Means			Loadings in Principal Components		
	Female	Male	t-stat (F-M)	Primary	Alt 1	Alt 2
PCA Results						
% Variance Explained				0.2330	0.2368	0.3580
Self-reported Personality (1985 survey)						
Shy as of 1985	0.2814	0.2684	-1.3938	-0.3246	-0.4000	
Outgoing as of 1985	0.6955	0.6944	-0.1121	0.3306	0.4055	
Shy at age 6	0.6160	0.5825	-3.2646	-0.3847	-0.4834	
Outgoing at age 6	0.3594	0.3783	1.8691	0.3913	0.4895	
Extracurriculars in High School (1984 survey)						
Community Service	0.1041	0.1063	0.3464	0.0981	0.0826	0.1548
Student Government	0.1533	0.1061	-6.7351	0.1482	0.1259	0.1842
Athletes	0.3449	0.4568	10.9586	0.3496		0.5025
Newspaper	0.1577	0.0856	-10.6094	0.1236	0.1035	0.1620
Hobby-related	0.1156	0.0943	-3.3150	0.0902	0.0712	0.1312
Art	0.2406	0.1574	-10.0164	0.1823	0.1548	0.2486
Others	0.0538	0.0281	-6.2167	0.0289	0.0243	0.0383
Very active member	0.2924	0.2878	-0.4897	0.2866	0.2260	0.3737
Not very active member	0.3151	0.3268	1.1937	0.1250	0.0566	0.2305
Participate in None	0.3911	0.3848	-0.6261	-0.4121	-0.2829	-0.6051
Belief regarding “Friends can easily be made” (1979 survey)						
Not very true	0.2559	0.2376	-2.0279	-0.0348	-0.0391	
Very true	0.2555	0.3326	8.0989	0.0643	0.0583	

Notes: This table displays the means of each variable included in the principal component analysis, and the loadings (weights) of each variable in the first principal component under each definition. The primary definition of social skills includes all variables listed. Alternative 1 excludes partcipation in athletics, and Alternative 2 uses high school extracurriculars only. All variables are indicators.

Table 3: Returns to Skills and Growth of Returns with Experience

	Log Real Wage			
	(1)	(2)	(3)	(4)
Female	-0.1073***	-0.0987***	-0.1037***	-0.1057***
	(0.0145)	(0.0142)	(0.0143)	(0.0144)
Experience	0.0661***	0.0628***	0.0629***	0.0626***
	(0.0020)	(0.0020)	(0.0020)	(0.0020)
Female × Experience	0.0009	0.0016**	0.0015**	0.0017**
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
<u>Social Skills</u>				
Social	0.0100*		0.0172***	0.0178***
	(0.0060)		(0.0060)	(0.0060)
Female × Social	0.0157**		0.0066	0.0062
	(0.0079)		(0.0079)	(0.0079)
Social × Experience	0.0031***		0.0016***	0.0014***
	(0.0005)		(0.0005)	(0.0005)
Female × Social × Experience	-0.0024***		-0.0013**	-0.0011*
	(0.0006)		(0.0006)	(0.0006)
<u>ASVAB Math Skills</u>				
Math		0.0356***	0.0331***	0.0334***
		(0.0070)	(0.0073)	(0.0073)
Female × Math		0.0317***	0.0344***	0.0340***
		(0.0100)	(0.0103)	(0.0103)
Math × Experience		0.0052***	0.0048***	0.0047***
		(0.0004)	(0.0005)	(0.0005)
Female × Math × Experience		-0.0024***	-0.0022***	-0.0021***
		(0.0007)	(0.0007)	(0.0007)
<u>Complementarity - Social × Math</u>				
Social × Math				-0.0011
				(0.0054)
Female × Social × Math				0.0042
				(0.0077)
Social × Math × Experience				0.0008
				(0.0005)
Female × Social × Math × Experience				-0.0007
				(0.0007)
Adjusted R^2	0.3256643	0.3334506	0.3354977	0.3355889
F	208.7693	222.4204	209.9597	202.5273
N	125,859	129,774	125,859	125,859

Notes: The unit of observation is a person-year. Each regression also controls for pairwise interactions between education levels, race (non-Hispanic, non-Black as base) and gender, an indicator for after having the first kid interacted with female, a cubic polynomial in experience, occupation group fixed effects, year and region fixed effects, and urban/rural. Standard errors are robust and clustered at person level. * for p<0.10, ** for p<0.05, *** for p<0.01

Table 4: Growth of Returns to Skills with Experience (with Worker Fixed Effects)

	Log Real Wage			
	(1)	(2)	(3)	(4)
Experience	0.0649***	0.0600***	0.0601***	0.0596***
	(0.0025)	(0.0024)	(0.0025)	(0.0025)
Female × Experience	0.0012*	0.0022***	0.0023***	0.0026***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Social Skills				
Social × Experience	0.0033***		0.0013***	0.0010**
	(0.0005)		(0.0005)	(0.0005)
Female × Sociall × Experience	-0.0024***		-0.0011	-0.0008
	(0.0006)		(0.0007)	(0.0006)
ASVAB Math Skills				
Math × Experience		0.0067***	0.0064***	0.0062***
		(0.0004)	(0.0005)	(0.0005)
Female × Math × Experience		-0.0035***	-0.0033***	-0.0032***
		(0.0007)	(0.0007)	(0.0007)
Complementarity - Social × Math				
Social × Math × Experience				0.0012**
				(0.0005)
Female × Social × Math × Experience				-0.0013*
				(0.0007)
Adjusted R^2	0.4868906	0.490561	0.4901932	0.4902916
F	148.3906	156.3525	150.7405	147.4216
N	125,859	129,774	125,859	125,859

Notes: The unit of observation is a person-year. Each regression includes person fixed effects, an indicator for after having the first kid interacted with female, a cubic polynomial in experience, occupation group fixed effects, year and region fixed effects, and urban/rural. Standard errors are robust and clustered at person level. * for p<0.10, ** for p<0.05, *** for p<0.01

Table 5: Returns to Skills and Growth of Returns with Experience

	Log Real Wage		
	(1) Before 1st Kid	(2) After 1st Kid	(3) No kid
Female	-0.1471***	-0.2478***	-0.0797**
	(0.0207)	(0.0186)	(0.0315)
Experience	0.0642***	0.0547***	0.0591***
	(0.0035)	(0.0030)	(0.0043)
Female × Experience	0.0038	0.0030***	-0.0016
	(0.0026)	(0.0008)	(0.0014)
Social Skills			
Social	0.0052	0.0088	0.0220*
	(0.0095)	(0.0097)	(0.0116)
Female × Social	0.0097	0.0113	0.0309*
	(0.0125)	(0.0125)	(0.0171)
Social × Experience	0.0065***	0.0015**	0.0013
	(0.0022)	(0.0006)	(0.0009)
Female × Social × Experience	-0.0051*	-0.0014*	-0.0004
	(0.0028)	(0.0008)	(0.0014)
ASVAB Math Skills			
Math	0.0429***	0.0624***	0.0070
	(0.0118)	(0.0109)	(0.0139)
Female × Math	0.0009	-0.0001	0.0843***
	(0.0158)	(0.0149)	(0.0243)
Math × Experience	0.0051**	0.0031***	0.0046***
	(0.0022)	(0.0006)	(0.0010)
Female × Math × Experience	0.0019	-0.0009	-0.0011
	(0.0029)	(0.0009)	(0.0017)
Complementarity - Social × Math			
Social × Math	0.0070	-0.0057	0.0021
	(0.0090)	(0.0090)	(0.0097)
Female × Social × Math	-0.0068	0.0124	-0.0175
	(0.0125)	(0.0122)	(0.0191)
Social × Math × Experience	-0.0012	0.0008	0.0007
	(0.0023)	(0.0006)	(0.0010)
Female × Social × Math × Experience	0.0019	-0.0004	-0.0020
	(0.0030)	(0.0009)	(0.0019)
Adjusted R^2	0.3607119	0.3471127	0.3058669
F	73.10786	138.1925	43.45902
N	25,142	75,045	25,672

Notes: I fit the regression model (4) separately for observations in three groups: (1) before the birth of the first kid, (2) after the birth of first kid, and (3) never have kid in the sample period. Please see notes under Table 3 for model specifications. * for p<0.10, ** for p<0.05, *** for p<0.01

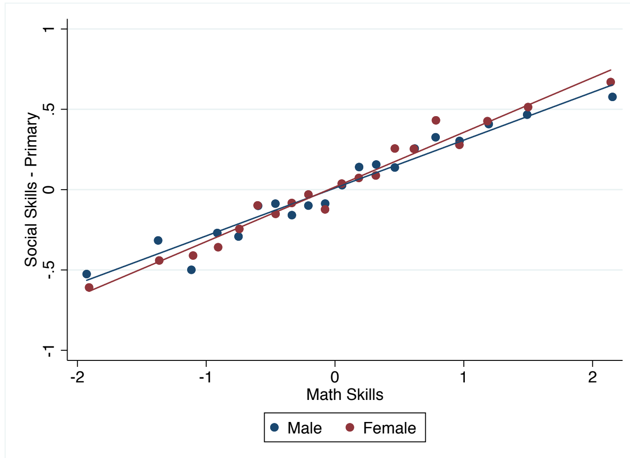
Table 6: Returns to Skills and Growth of Returns with Experience

	Log Real Wage				
	(1) LTHS	(2) HS	(3) Some college	(4) College	(5) Postgrad
Female	-0.1516***	-0.1544***	-0.1640***	-0.0762*	-0.0657
	(0.0537)	(0.0185)	(0.0245)	(0.0396)	(0.0526)
Experience	0.0579***	0.0660***	0.0624***	0.0616***	0.0442***
	(0.0075)	(0.0034)	(0.0042)	(0.0056)	(0.0056)
Female × Experience	0.0115***	0.0037***	-0.0002	-0.0051*	0.0021
	(0.0043)	(0.0010)	(0.0013)	(0.0027)	(0.0039)
Social Skills					
Social	0.0518*	0.0122	0.0300**	0.0343	-0.0121
	(0.0287)	(0.0093)	(0.0136)	(0.0250)	(0.0358)
Female × Social	-0.0739*	0.0026	-0.0171	0.0133	0.0433
	(0.0429)	(0.0130)	(0.0162)	(0.0305)	(0.0405)
Social × Experience	-0.0002	0.0014**	0.0010	-0.0002	-0.0000
	(0.0023)	(0.0006)	(0.0010)	(0.0023)	(0.0039)
Female × Social × Experience	0.0066*	-0.0014	-0.0007	0.0011	0.0011
	(0.0035)	(0.0009)	(0.0012)	(0.0028)	(0.0043)
ASVAB Math Skills					
Math	0.0757***	0.0657***	0.0298*	0.0532***	0.0236
	(0.0255)	(0.0105)	(0.0166)	(0.0202)	(0.0284)
Female × Math	-0.0370	-0.0176	0.0265	0.0318	0.0420
	(0.0419)	(0.0160)	(0.0209)	(0.0283)	(0.0352)
Math × Experience	0.0001	0.0025***	0.0016	0.0037**	0.0071***
	(0.0024)	(0.0006)	(0.0012)	(0.0015)	(0.0026)
Female × Math × Experience	0.0040	0.0010	0.0012	-0.0029	-0.0027
	(0.0034)	(0.0011)	(0.0015)	(0.0022)	(0.0031)
Complementarity					
Social × Math	0.0104	-0.0081	-0.0271*	0.0011	0.0367
	(0.0242)	(0.0095)	(0.0155)	(0.0181)	(0.0250)
Female × Social × Math	-0.0311	-0.0050	0.0225	-0.0171	-0.0328
	(0.0377)	(0.0147)	(0.0191)	(0.0237)	(0.0303)
Social × Math × Experience	0.0001	0.0015**	-0.0013	0.0001	0.0027
	(0.0022)	(0.0007)	(0.0013)	(0.0018)	(0.0026)
Female × Social × Math × Exp	0.0049	-0.0017	0.0019	0.0020	-0.0034
	(0.0035)	(0.0012)	(0.0016)	(0.0024)	(0.0030)
Adjusted R^2	.2756315	.2978214	.3092299	.3576079	.3134928
F	.	76.79112	64.98341	52.69625	40.30848
N	8,872	54,661	31,636	16,383	14,307

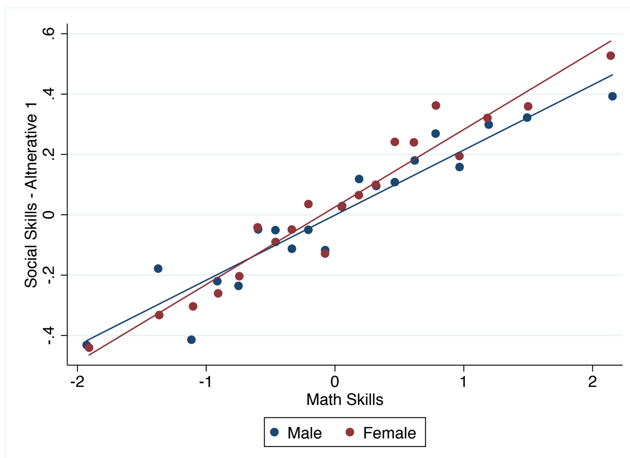
Notes: I estimate model (4) that controls for social skills, math skills and their interactions simulataneously, separately for each education level. The other controls in the regression remain unchanged (see notes under Table 3). * for p<0.10, ** for p<0.05, *** for p<0.01

Appendix Figure 1: Binned Scatter Plots for Social Skills against Math Skills

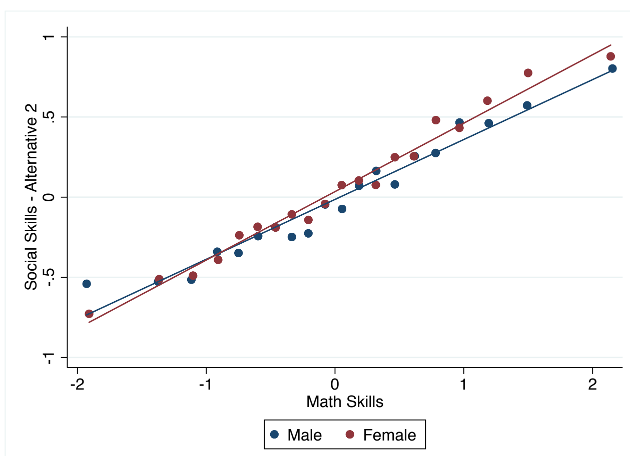
(a) Primary Measure of Social Skills



(b) Alternative 1 - exclude Athletics



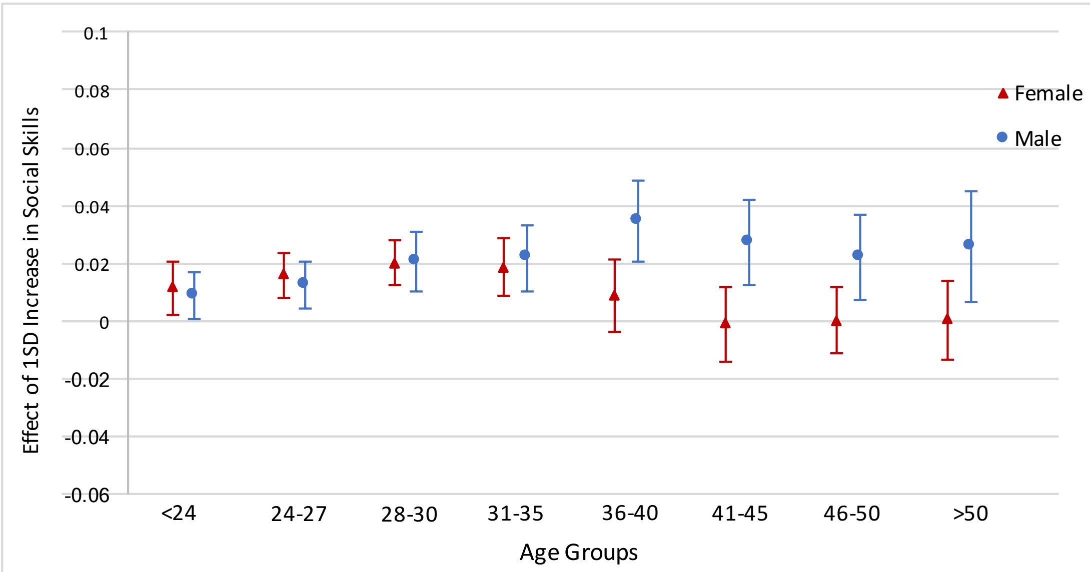
(c) Alternative 2 - HS clubs only



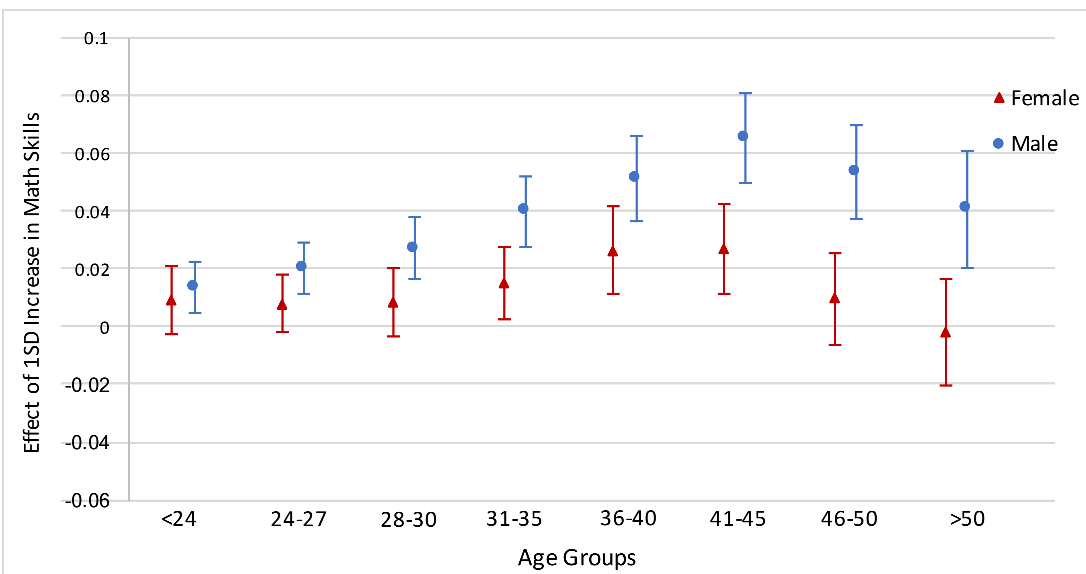
Please see Section 3.2 for the construction of the three different measures of social skills.

Appendix Figure 2: Selection into Managerial Occupations

(a) Sorting by Social Skills



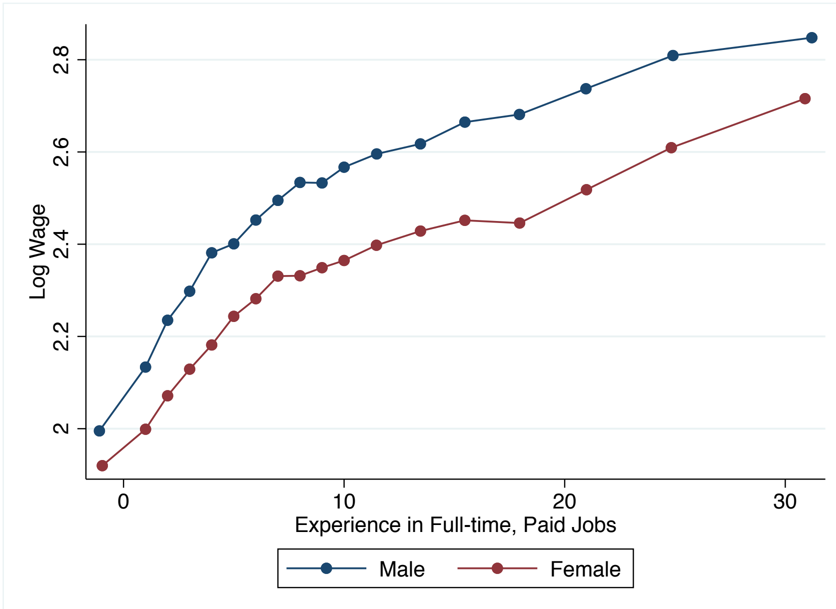
(b) Sorting by Math Skills



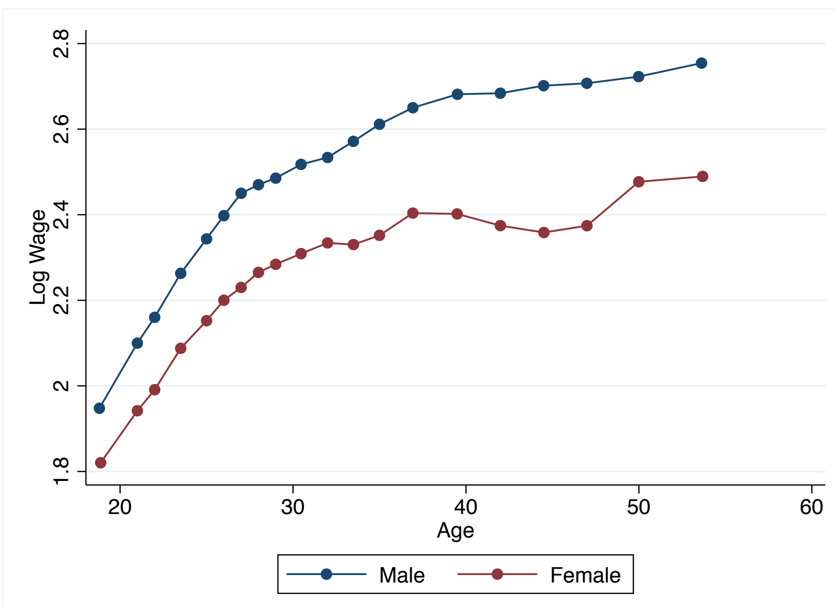
Each subfigure shows the estimated regression coefficients $\hat{\beta}_1$ for males and $\hat{\beta}_1 + \hat{\beta}_3$ for females in model (1), fitted separately for each age group. The dependent variable is 1 if an occupation is managerial, based on 3-digit occupation codes.The data is at person-year level. Each regression also includes a constant,race and education levels, year fixed effects, region fixed effects, and an indicator for urban/rural. Standard errors are robust and clustered at person level.

Appendix Figure 3: Earning Profiles

(a) Experience-Earning Profiles



(b) Age-Earning Profiles



The binned scatter plots show the relationship between log wage and experience and age, respectively. The data is at person-year level. Labor market experience is defined by cumulative sum of tenure (in weeks) in full-time, paid positions divided by 50 and rounded to an integer. When the measure of experience exceeds potential experience (age - 6 - yrs in school) by 3 years or above, I replace it by potential experience instead.

Appendix Table 1: Returns to Skills and Growth of Returns with Experience (Restrictive Sample)

	Log Real Wage			
	(1)	(2)	(3)	(4)
Female	-0.1140***	-0.1040***	-0.1117***	-0.1124***
	(0.0163)	(0.0159)	(0.0160)	(0.0161)
Experience	0.0635***	0.0598***	0.0601***	0.0598***
	(0.0022)	(0.0022)	(0.0022)	(0.0022)
Female × Experience	0.0010	0.0016**	0.0016**	0.0017**
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Social Skills				
Social	0.0092		0.0179***	0.0181***
	(0.0066)		(0.0066)	(0.0066)
Female × Social	0.0177**		0.0079	0.0078
	(0.0089)		(0.0088)	(0.0089)
Social × Experience	0.0032***		0.0016***	0.0015***
	(0.0005)		(0.0005)	(0.0005)
Female × Social × Experience	-0.0025***		-0.0013**	-0.0012*
	(0.0006)		(0.0007)	(0.0006)
ASVAB Math Skills				
Math		0.0314***	0.0281***	0.0282***
		(0.0078)	(0.0080)	(0.0080)
Female × Math		0.0375***	0.0409***	0.0409***
		(0.0115)	(0.0117)	(0.0117)
Math × Experience		0.0053***	0.0049***	0.0049***
		(0.0004)	(0.0005)	(0.0005)
Female × Math × Experience		-0.0024***	-0.0022***	-0.0022***
		(0.0007)	(0.0007)	(0.0007)
Complementarity - Social × Math				
Social × Math				0.0010
				(0.0060)
Female × Social × Math				-0.0008
				(0.0090)
Social × Math × Experience				0.0006
				(0.0005)
Female × Social × Math × Experience				-0.0004
				(0.0008)
Adjusted R^2	0.3226816	0.3309089	0.332988	0.33307
F	179.0782	189.068	179.6823	173.2067
N	108820	111706	108820	108820

Notes: This table replicates Table 3 but restricts to workers who have at least one full-time paid job in their 20's, 30's and 40's respectively. Please see notes under Table 3 for model specifications. * for p<0.10, ** for p<0.05, *** for p<0.01