Online Appendix:

The Gender Wage Gap: Skills, Sorting, and Returns

John Eric Humphries

Juanna Schrøter Joensen

Gregory F. Veramendi *

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*Humphries: Yale University (email: johneric.humphries@yale.edu); Joensen: University of Chicago, Stockholm School of Economics, Aarhus University, and IZA (email: jjoensen@uchicago.edu); Veramendi: Royal Holloway – University of London (email: Gregory.Veramendi@rhul.ac.uk). We gratefully acknowledge financial support from the Swedish Foundation for Humanities and Social Sciences (Riksbankens Jubileumsfond) grant P12-0968, and the Stockholm School of Economics for hosting our research project. This project has been evaluated for ethical compliance by the Swedish Central Ethical Review Board (EPN) approval 2013/428-31 and privacy compliance by Statistics Sweden (SCB) disclaimer 231046/878029-8. We also gratefully acknowledge financial support from the Becker Friedman Institute's (BFI) Initiative for the Study of Gender in the Economy grant "*The Causes and Consequences of Gender Differences in Skill Specialization*". Finally, we thank our discussant Donna Ginther for insightful comments and Lukas Jonsson, Xinyue Liang, and Henry Shi for excellent research assistance. The usual disclaimers apply.

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This Appendix provides more background and detail on the empirical analysis in the accompanying paper. Appendix A describes the data. Appendix B describes the measurement system, including the identification of latent skills and the estimation strategy.

Appendix C presents additional results. First, Appendix C.1 shows sorting on skills graphically to expand on the results shown in **Table 1** along multiple dimensions. Second, Appendix C.2 describes the gender gap through a series of regressions expanding on the results presented in **Figure 1** in the paper. Finally, in Appendix C.3 we provide additional results on the within-major decompositions in **Figure 2** in the paper. All results in the last two sub-sections are presented for the yearly earnings measure in addition to the full-time monthly wage measure that we focus on in the paper.

The last Appendix D presents estimates from the measurement system as well as the wage and income models.

A Data Description

We combine data from several Swedish administrative registers for the cohorts born in 1972-77. We merge the ninth grade, high school, and higher education registers to obtain longitudinal education histories. Finally, we merge the data from the education registries with the Wage Structure data ("*Lönestrukturstatistik*") and the longitudinal integration database for health insurance and labour market studies (*LISA*) to obtain information on earnings, employment, occupation, and additional background variables. The administrative data for the full population is quite detailed from 9th grade through college, and we supplement these data with the Evaluation Through Follow-up surveys (ETF72) and (ETF77) focusing on 3rd through 9th grade for the oldest and youngest cohort in our sample, respectively.

In the following, we describe the data sources and variable definitions in more detail. Appendix A.1 describes the labor market data, Appendix A.2 the education registers and survey data, while the last two sections describe the last two data sources we utilize for skill measurement: Appendix A.3 describes the Swedish scholastic aptitude test data and Appendix A.4 describes the military enlistment archives. We use some of the same data sources as in our other work, and the following data description builds on the data descriptions in Fiala et al. (2022), Humphries, Joensen and Veramendi (2023), and Gallen et al. (2023).

A.1 Labor Market Data

Wages and work intensity: The Wage Structure ("Lönestrukturstatistik") data is a yearly snapshot that is intended to get an overview of the evolution of the wage structure in the economy. The data is collected by SCB and employer organisations through a survey of employers during a sample week once a year. The sampling differs by sector. The public sector has the broadest coverage, since data is collected for everyone employed in the state, regions, and municipalities during the sample week. For the private sector, however, only a subset of employers are surveyed about their workers during the sample week. The two key variables we use to construct our primary outcome measure are full-time-equivalent (FTE) wages (measured by *MLON*) and actual work time as a fraction of full-time (measured by *TJOMF*). Our primary outcome is log monthly wages for full-time workers. We report wages in 1000s SEK and real 2010 prices.

Earnings: Our secondary outcome variable is log yearly earnings observed in the *LISA* database. Earnings is the yearly gross labor income from all employment spells (based on the variable *LoneInk*). We also report earnings in 1000s SEK and real 2010 prices.

Occupation: For the exploratory empirical analysis we also include measures of occupation skill requirements based on the first digit of the Swedish occupation code (*SSYK3*) in LISA. We construct two indicators for whether an individual is jobs which require managerial responsibilities (1st digit of SSYK96 code equal to 1) or "High" theoretical special competence (1st digit of SSYK96 code equal to 2).

The 3-digit occupation code is organized hierarchically, with increasing levels of granularity. The first digit is defined as the "occupation area", which is the broadest category. Each "occupation area" is split into multiple "primary groups" (represented by the second digit); these, in turn, are split into multiple "occupation groups" (represented by the third digit). In total, there are 11 "occupation areas", 27 "primary groups", and 113 "occupation groups". The first 3-digits of the Swedish occupation code (`SSYK96`) have an almost one-to-one mapping to the international `ISCO88` code that we use to merge with the O*Net data to construct measures of workplace flexibility, based on Goldin (2014) applied to the Swedish population distributions across occupations. The measure includes seven primary occupation characteristics in O*Net to characterize flexibility. These seven characteristics are the variables from O*Net called Structured Work, Freedom to Make Decisions, Contact with Others, Time Pressure, Establish Interpersonal Relationships with Others, Frequency of Decision Making, and Face to Face Discussions.

A.2 Education Data

We classify specialized education investments within each level of education following Humphries, Joensen and Veramendi (2023).

9th grade registry: We use data on course choices to define two binary indicator variables for whether an individual took a more advanced track in math and/or English or not. We also use data on Swedish, English, math, physical education (PE) grades, and grade point average (GPA) as proxies for skills in the measurement system described in more detail in Appendix B.

High school registry: Similarly to the 9th grade registry, we focus on specialization choices and performance measured by Swedish, English, math, PE grades, and GPA. We classify high school students into three tracks: vocational and two academic tracks in non-STEM and STEM. A reform implied that the high school graduating cohorts from 1996 and earlier are classified according to the high school lines they attend, while those graduating in 1997 are classified according to the programs they attend. The academic STEM track consists of the science (76) and technical (80,81) lines pre-reform, the science program (49) is also added during the transition years, and the science program (NV) for the post-reform cohorts. The academic non-STEM track comprises the humanities line (74), business (72), and social science lines (78) pre-reform, the arts program (19) and social science program (53) are also added during the transition years, and the arts program (ES) and the social science program (SP) for the post-reform cohorts. Finally, all vocational high school lines and programs are grouped in the vocational high school track.

Higher education registry: From the Higher Education registry, we use data on acquired college degrees. We classify all academic programs into two levels ($\leq$ 3 years; $\geq$ 4 years) according to the SUN2000Niva code and nine fields (1. Education; 2. Humanities and Art; 3. Social Sciences and Services; 4. Math, Natural, Life and Computer Sciences; 5. Engineering and Technical Sciences; 6. Medicine; 7. Health Sciences, Health and Social Care; 8. Business; 9. Law) according to the SUN2000Inr code. The Swedish education nomenclature (SUN2000) codes build on the International Standard Classification of Education (ISCED97), and we group programs into majors according to the first digit of the SUN2000Inr code. We single out Business and Law from the Social Sciences major and Medicine from the Health Sciences major to better compare to previous literature. Some of the 3-year programs have few students, so we group them into STEM (Science, Math, Engineering) and non-STEM (Humanities, Social Science) majors. Students in the 3- and 4-year Education and Health Sciences majors (excluding medicine) look similar on observables and labor market outcomes, so these are grouped together.

We merge these registers to the **Evaluation Through Follow-up** (ETF72 and ETF77) surveys administered to 3rd, 6th, and 10th grade students by the Department of Education and Special Education at Gothenburg University.[1] This survey was administered to a random sample of the oldest and youngest cohorts in our population who were sampled when in 3rd grade in the 1981/82 and 1986/87 school-years, respectively. These individuals are mostly born in 1972 (10% sample) and 1977 (5% sample). This data includes extensive measures of aptitude and achievement tests, absenteeism, special education and tuition, and grades in various courses through compulsory schooling, as well as extensive student and parent surveys related to student achievement, confidence, inputs, grit, and interpersonal skills.

[1] Härnqvist (1998) and Giota (2006) provide additional details on the construction of the survey.

A.3 Swedish Scholastic Aptitude Test

The Swedish Scholastic Aptitude Test (SweSAT) is a norm-referenced test whose primary aim is to assess the test-takers' general aptitude for studies. The test should, as fairly as possible, rank the applicants with respect to expected success in higher education. The test consists of 160 multiple choice questions and is given twice a year, once in spring for admission the following autumn, and once in autumn for admission the following spring. All sections are taken in one day, lasting between 7.5-8 hours including breaks between each section and a lunch break. Apart from the English language reading comprehension test, all sections are taken in Swedish. The result on the test is normalized to a scale between 0.0 and 2.0, with 0.05 increments. Around a third of those enrolled in college in the cohorts we study are admitted based on high performance in the SweSAT. We have data on the overall test scores and sub-scores on every attempt through the Department of Applied Educational Science at *Umeå Universitet*. The sub-scores include: Vocabulary; Swedish and English Reading Comprehension; General Information; Data Sufficiency; Interpretation of Diagrams, Tables, and Maps.

A.4 Military Enlistment Archives

The Military Enlistment archives contain cognitive test scores, psychological assessments, health and physical fitness measures collected during the entrance assessment at the Armed Forces' Enrollment Board. The enlistment was mandatory for all Swedish males at age 18 until 2010, thus for all males in our sample who are Swedish citizens. The entrance assessment spans two days. Each conscript is interviewed by a certified psychologist with the aim to assess the conscript's ability to fulfill the psychological requirements of serving in the Swedish defense, ultimately in armed combat. The set of personal characteristics that give a high score include persistence, social skills, and emotional stability (Lindqvist and Vestman, 2011).

B Measurement System

Since most proxies of skill are measured with error, we use a factor model to recover latent skills.[2] In Section B.1, we briefly describe the identification of latent skills when some measures are taken after schooling investments have been made. In Section B.2, we describe our estimation strategy for models that include latent skills.

[2] The measurement system in this paper is an extension of Humphries, Joensen and Veramendi (2023), where latent skills were only estimated for men. Much of the motivation and estimation strategy here follows.

B.1 Identification of Latent Skills

If skills were directly observable, we could include them in our models along with other observables on demographics and family background. Instead, skills need to be identified from proxies such as test scores or behavior. In this paper, we identify latent skills using evaluations done as part of the compulsory military enlistment, the SweSAT college admission test, and course grades in compulsory and high school. Let the measurement system, $\boldsymbol{M}$, denote a vector of proxies (or measures) of skills. One challenge in identifying latent skills is that students may be evaluated after they have been exposed to different types or levels of education. For example, students are evaluated by the military at age 18 when most are still enrolled in different tracks in high school. Let s denote the schooling state of the student and M_{ks} denote the kth measure evaluated at schooling state s. We define $\widetilde{M}_{ks}$ as latent variables that map into observed measures M_{ks},

$$M_{ks} = \begin{cases} \widetilde{M}_{ks} & \text{if } M_{ks} \text{ is continuous} \\ \mathbf{1}[\widetilde{M}_{ks} \geq 0] & \text{if } M_{ks} \text{ is a binary outcome} \\ j & \text{if } \mu_{j-1} \geq \widetilde{M}_{ks} \geq \mu_j \\ & \quad \text{when } M_{ks} \text{ is an ordered discrete outcome.} \end{cases} \tag{1}$$

The latent variables are assumed to be separable in observables, latent skills, and an idiosyncratic error term:

$$\widetilde{M}_{ks} = \alpha_{ks} + \boldsymbol{\beta}_k^M \boldsymbol{X} + \boldsymbol{\lambda}_k^M \boldsymbol{\theta} + u_k, \tag{2}$$

where α_{ks} represents schooling-state specific intercepts for measure k, $\boldsymbol{X}$ is a vector of observables, $\boldsymbol{\theta}$ is a vector of latent skills, and u_k is the error term. We assume that u_k are mutually independent across each k and are independent of $\boldsymbol{\theta}$, $\boldsymbol{X}$, and the error terms in schooling decisions and labor market outcomes.

The inclusion of the schooling-state specific intercepts and observables in the measurement system has important implications for the interpretation of the latent skills. The term α_{ks} captures the direct effect of schooling at the time of the test. For example, students who take the academic STEM track in high school may perform better on the cognitive evaluations given by the military due to having taken more cognitively challenging math and science classes. The inclusion of α_{ks} in the measurement system implies that our latent skills are measured relative to a reference schooling state ($s = 0$). In Humphries, Joensen and Veramendi (2023), we show that the schooling-state specific intercepts are separately identified from differences in how students sort across schooling states. The key assumption is that we have as many pre-specialization measures as factors. Since pre-specialization measures have not been affected by future investments, the conditional means of the pre-specialization measures are informative of how students sort into different schooling paths. Any additional difference in later measures by, for example, vocational vs. academic schooling, must be due to the different types of skills learned in those programs beyond the skills of the students in ninth grade.[3]

B.2 Estimation Strategy

Our measurement system consists of measures from the compulsory Swedish military enlistment taken at age 18, the SweSAT college admission test, and course grade data from ninth grade and high school registers. We have to make some normalizations to both identify the model and also make the factors more interpretable.[4] The location and scale of the factors are not identified, so we assume that the factors are mean-zero ($E[\theta] = 0$) and have unit variance ($Var[\theta] = 1.0$) in our population.

In order to facilitate interpretation of the factors, we specify a triangular measurement system with orthogonal factors.[5] On one hand, the measures from the military data could be treated as dedicated measures, and we would be able to use a different specification that has correlated factors. On the other hand, it would be difficult to argue that the grade measures are dedicated measures of a third factor and do not directly depend on the cognitive skill that is measured in the military enlistment. For this reason, we prefer the triangular measurement system.

We estimate a model with three factors. The first set of measures labelled as "cognitive" by the military psychologists and the Swedish SAT scores depend exclusively on the first factor.[6] The second set of measures include the variables from the psychological evaluation performed by the military psychologists. They provide two variables that measure "leadership" skill and "emotional stability". The second set of measures depend on both the first and second factors. The last set of measures includes grades from ninth grade and high school: Math, Swedish, English, and PE grades from both ninth and tenth grades, Physics from tenth grade, and residual GPA from both ninth and tenth grades.[7] This last set of measures depends on all three factors. Taking the

[3]In Humphries, Joensen and Veramendi (2023), we build on a long line of seminal work including Cunha et al. (2006), Cunha, Heckman and Schennach (2010), Heckman, Humphries and Veramendi (2016), Heckman, Humphries and Veramendi (2018*a*), and Heckman, Humphries and Veramendi (2018*b*) and the identification result builds on Hansen, Heckman and Mullen (2004), where they show identification for a factor model with dedicated measures. In the Swedish setting, Carlsson et al. (2015) also show that schooling can have an effect on the cognitive military test scores. Particularly the crystallized intelligence scores (synonyms and technical comprehension) but not to the same extent the fluid intelligence scores (spatial and logic). Lindqvist and Vestman (2011) have also shown that both the cognitive and interpersonal measures are important predictors of labor market outcomes, and Edin et al. (2022) show that the interpersonal measures have become increasingly important over time in Sweden.

[4]See Williams (2020) for more details on the identification of factor models.

[5]A triangular measurement system is one in which the measures are partitioned into groups based on how they depend on the factors and by design the factors are orthogonal.

[6]The military psychologists select about half of the enlistees to be rated on a leadership scale based on their performance on the cognitive tests. We include this selection as a separate measure of cognitive skill. See Grönqvist and Lindqvist (2016) for more details on this selection.

[7]We include individual course grade measures as covariates in the GPA models to create

Swedish SAT is endogenous and we include a probit model that depends on all three factors to account for selection into taking the SAT.

The schooling states in the measurement system are (i) taking advanced English in ninth grade, (ii) taking advanced math in ninth grade, and (iii) taking one of three tracks in high school. The identification of the schooling-state specific intercepts requires three measures that are not affected by schooling states. In our model, those are the ninth grade Swedish grade, PE grade, and residual GPA. Table 1 summarizes the measurement system.

Rather than using the measure descriptions to interpret and label the factors, we instead validate our skill measures using an independent survey. As described in the data section, the Department of Education and Special Education, Gothenburg University, administered surveys to a random sample of third, sixth, and tenth grade students. The surveys include extensive measures of school performance and survey questions related to achievement, confidence, input, grit, and interpersonal skills. We estimate an outcome model for each survey item, grade, and test score in the survey dataset, resulting in over 250 items. We then calculate the explained variance from each orthogonal factor and calculate the fraction of total explained variance accounted for by each factor. We make three separate rankings of the proportion of the explained variance accounted for by each factor. Table 2 summarizes the five items from the survey that were most informed by one dimension of skill. In the case of the first factor, ten out of the top twenty items were test scores and grades. Hence, we label the first factor "Cognitive Skill". The second factor is relatively most informative about items relating to sports and social interactions. Hence, we label the second factor "Interpersonal Skill". Lastly, the third factor is relatively most informative about the academic persistence of the students and their feelings about their performance in school. Hence, we label the last factor "Grit". While these labels for the factors assist in the interpretation of our results, others may interpret them in other ways. For example, the third factor might also be associated with "Conscientiousness", "Self-regulation", or "Motivation".

We assume that the parameters in the measurement system (2) are the same for all genders. The only exception is that we allow the average PE grade (intercept) to differ for men and women. According to several reports and academic articles based on survey data, by far the most common activities in physical education are traditional team-based ball games, for example; soccer, basketball, and floorball (Skolverket, 2003; Redelius, Fagrell and Larsson, 2009; Skolverket, 2010; Skolinspektionen, 2018; Lagercrantz Varvne, 2021). Ball games are often characterized by what are traditionally perceived as masculine values, where competition and to some extent aggressiveness are highly rewarded (Larsson, Fagrell and Redelius, 2009; Fagrell, Larsson and Redelius, 2012) and boys also experience to a greater extent that they get the opportunity to show what they can do in the lessons in physical education and health (Skolverket, 2010). Experience playing organized sports outside of school and physical strength gave boys an advantage (Svennberg, Meckbach and Redelius, 2018;

the "residual GPA" measures.

Lagercrantz Varvne, 2021; Alfredsson, 2022) in PE grades that we do not see reflected in other measures of interpersonal skills. To corroborate our finding that PE grades are particularly informative for interpersonal skills, Annerstedt and Larsson (2010) and Klapp (2015) also find that PE teachers largely reward socio-emotional skills such as initiative and leadership skills in their evaluation, while students' self-determination, attitude, ambition, ability to arrive and be ready to start on time also played a role.

In the following sections, we show that these three factors are important for understand sorting into college majors, and are also important for understanding labor market outcomes.

Table 1: Structure of Measurement System

Measures	θ_1	θ_2	θ_3
Military Enlistment Registers (Men only)			
Four Cognitive measures:[b]	x		
Inductive, Verbal, Spatial, and Technical			
Leadership Evaluation[a,b]	x		
Leadership Ability[b]	x	x	
Emotional Stability[b]	x	x	
Swedish SAT Exam Registers			
Six SweSAT Sub-scores:[b]	x		
Vocab; Read Comp; English ; Info; Data; Interpret Diagrams/Maps			
Take SweSAT Test[b]	x	x	x
Ninth Grade Education Registers			
Ninth Grade Math & English Grades[c,g]	x	x	x
Ninth Grade Swedish & PE Grades[f,g]	x	x	x
Ninth Grade residual GPA[d,f]	x	x	x
High School Education Registers			
Tenth Grade Math, Swedish, English, Physics & PE Grades[b,g]	x	x	x
High School residual GPA[e]	x	x	x

Notes: [a] Binary discrete choice models. [b] Ninth grade advanced course indicators and high school track indicators are included. [c] Advanced course indicators included. [d] Math, English, Swedish and PE grades are included in the Ninth grade residual gpa model.[e] Tenth grade Math, Swedish, English, Physics, and PE grades are included. [f] These measures do not include any schooling-state specific intercepts. [g] Ordered Probit models.

Table 2: Validation and Interpretation of Factors

θ_1: **"Cognitive Skill"**
Test Scores: Math, Reading, Spatial, Verbal skills (10 of top 20)
How often do you spend time doing a hobby (-)
Would you like to ask the teacher for help more often than you do?
How often do you read newspapers and comics?
Do you often think you would like to understand more of what you read?
θ_2: **"Interpersonal Skill"**
Do you think that you are bad at sports and physical exercise? (-)
How do you feel about talking about things to the whole class?
How often do you do sports?
Has participated in any form of childcare
Do you often spend time on your own during breaks? (-)
θ_3: **"Grit Skill"**
Do you think that you do well in school?
Do you always do your best even when the tasks are boring?
How often do you do homework or other school work at home?
How do you feel about drawing and painting? (-)
Do you think that you have to learn lots of pointless stuff in school? (-)

Notes: "(-)" indicates that the factor is negatively related to these items.

C Additional Results

In this Appendix, we present additional results. First, Appendix C.1 shows sorting patterns graphically to expand on the results shown in **Table 1** in the paper along multiple dimensions. Second, Appendix C.2 describes the gender gap through a series of regressions expanding on the results presented in **Figure 1** in the paper. Finally, in Appendix C.3 we provide additional results on the within-major decompositions in **Figure 2** in the paper. All results in the last two sub-sections are presented for the yearly earnings measure in addition to the full-time monthly wage measure that we focus on in the paper.

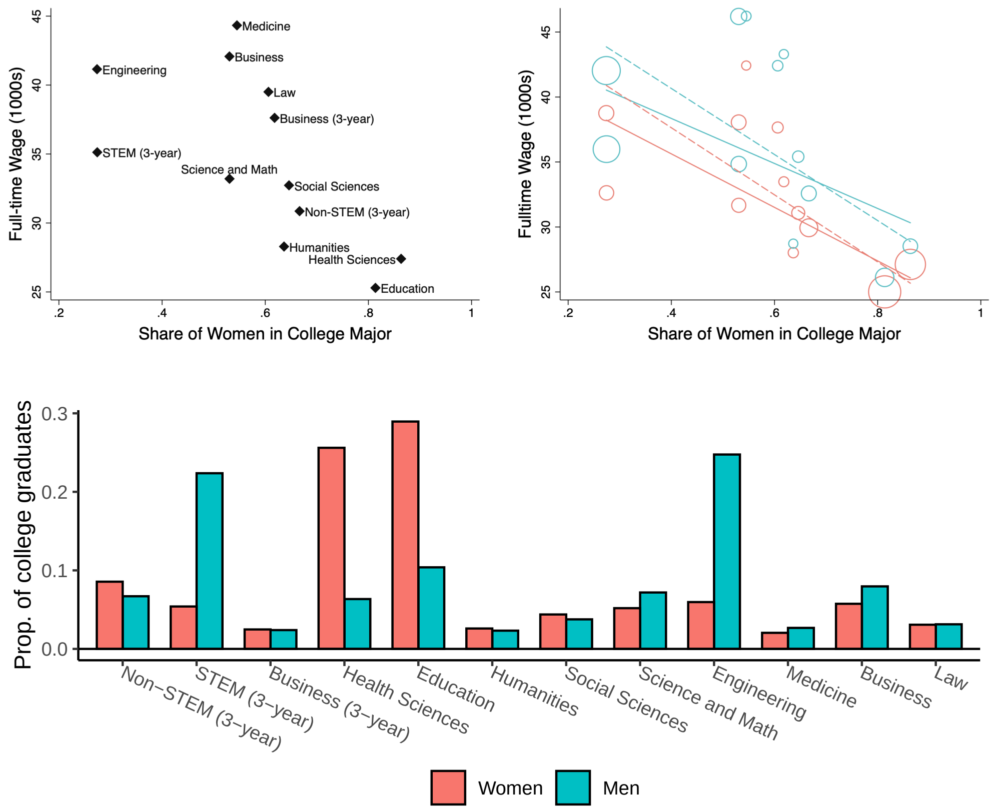
C.1 Additional Results on Sorting and Skills

This Appendix first provides a graphic display of the sorting patterns presented in Table 1 in the paper, and then expands upon these sorting patterns along multiple dimensions.

Figure 1 shows sorting into college majors by gender, and the top panel graphically shows how majors with a higher female share pay less for both men and women as shown in the second and third columns of Table 1. Figure 2 graphs sorting into college majors on the three dimensions of skill as shown in the last six columns of Table 1 in the paper. Figure 3 graphs the last two rows of Table 1, while Figure 4 presents average skills by gender in each college major.

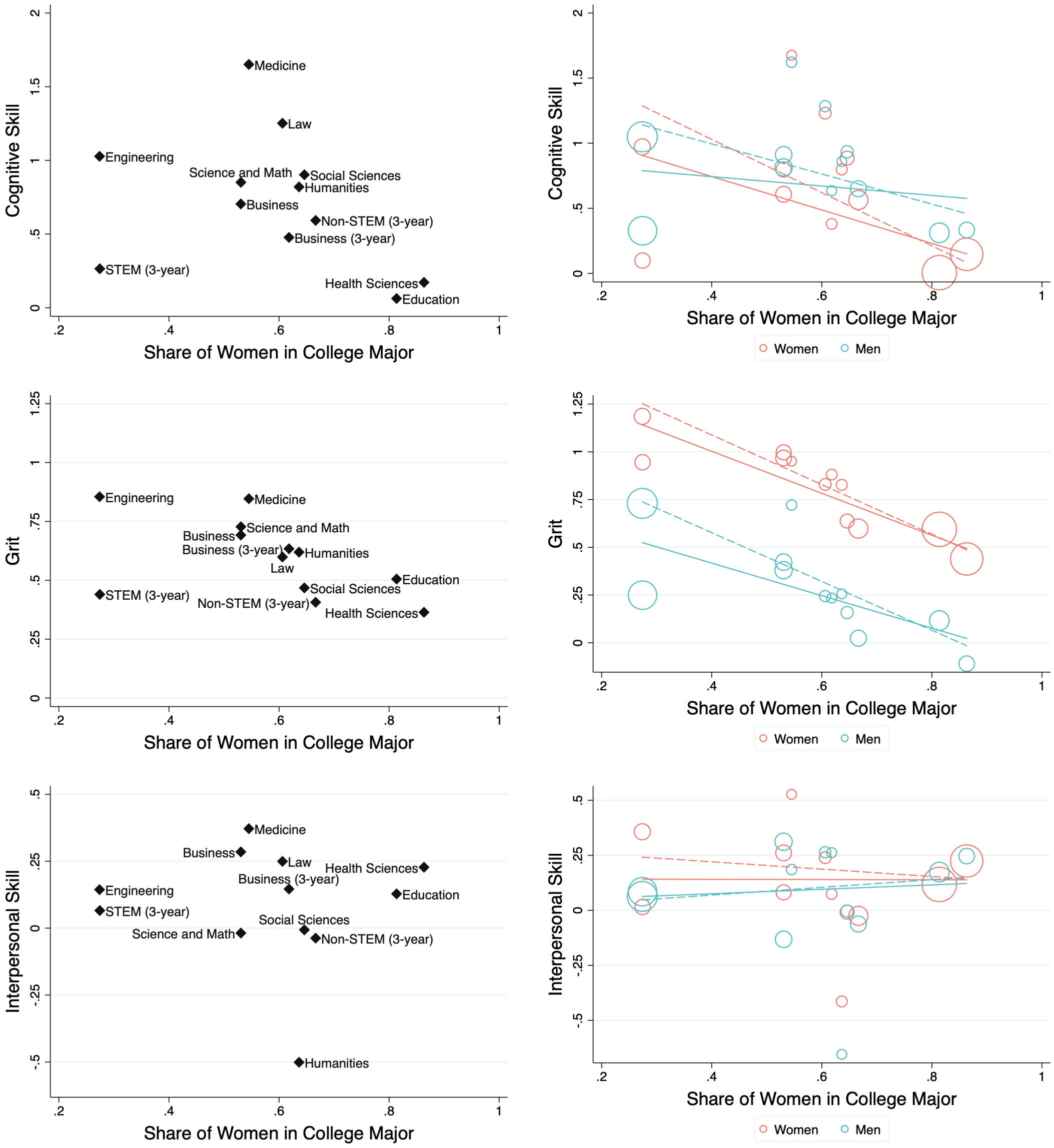
The following five-part Figure 5 shows sorting into 3-digit fields of study within each of the twelve college majors. Exemplified by the Social Sciences (Figure 6) and the Science and Math (Figure 7) majors, we show similar sorting patterns within college major (cf. Figure 1) as fields with a higher share of women pay less. This is related to the math intensity of the field (cf. Figure 5, Part IV) and we expand on these observations in the last two figures. Figure 8 shows that women are less likely to choose college majors that require more math-preparation, while Figure 9 shows that wages and earnings are higher for both men and women in college majors that attract individuals with more math-preparation in high school. These sorting patterns are consistent with the large body of evidence that women shy away from more math-intensive college majors and field of study; see e.g. Ceci et al. (2014) and the literature reviewed in Altonji, Blom and Meghir (2012), Altonji, Arcidiacono and Maurel (2016), Kahn and Ginther (2018), and Patnaik, Wiswall and Zafar (2021).

Figure 1: Sorting into College Major by Gender



Notes: The sample is Swedish college graduates born between 1972 and 1977. The top left panel shows the share of women in each major (x-axis) plotted against the average full-time wage for those with that college major between the ages of 33 and 37. The top right panel provides similar estimates but by gender. The size of the circle represents the size of the major. The solid lines are the linear fit from a regression of full-time wages on share female weighted by the size of the majors. The red line is for women and the blue line is for men. The dashed lines show the same regression, but restricted to 4-year majors. The bottom panel shows the proportion of women (red bars) and men (blue bars) in each major among college graduates.

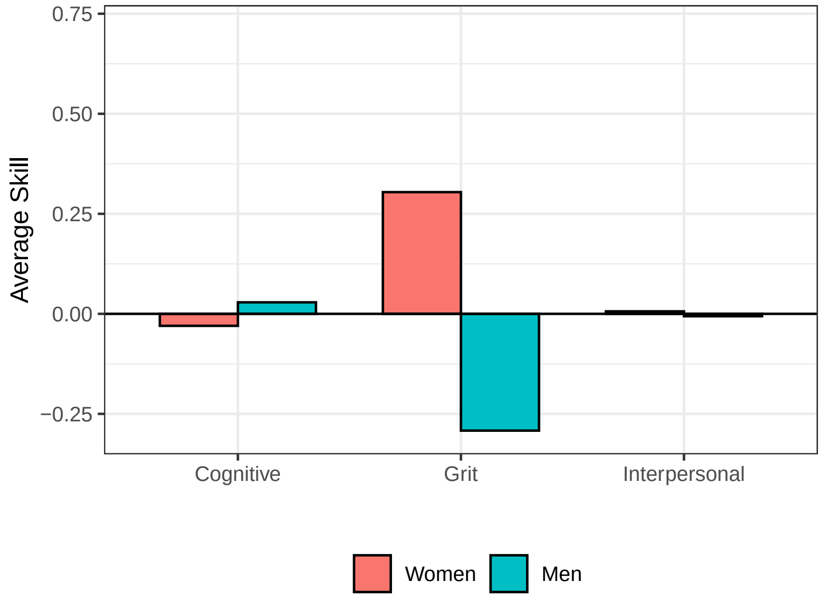
Figure 2: Sorting into College Major by Skills



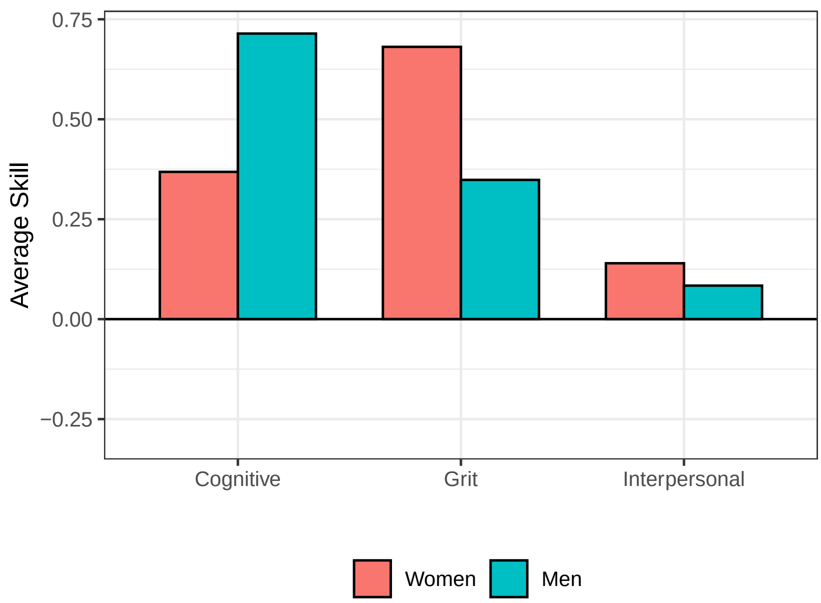
Notes: The sample is Swedish college graduates born between 1972 and 1977. Left panels plot the share of women in the college major (x-axis) against the average skill level of individuals in the major (y-axis) for each of the three skills (cognitive, grit, and interpersonal). The right panel repeats this exercise by gender. The size of the circles represent the number of individuals. The solid lines show the linear fit from a regression of average skill on share female weighted by the size of the majors. The red line is for women and the blue line is for men. The dashed lines show the same regression, but restricted to 4-year majors.

Figure 3: Average Skills by Gender

High School Graduates

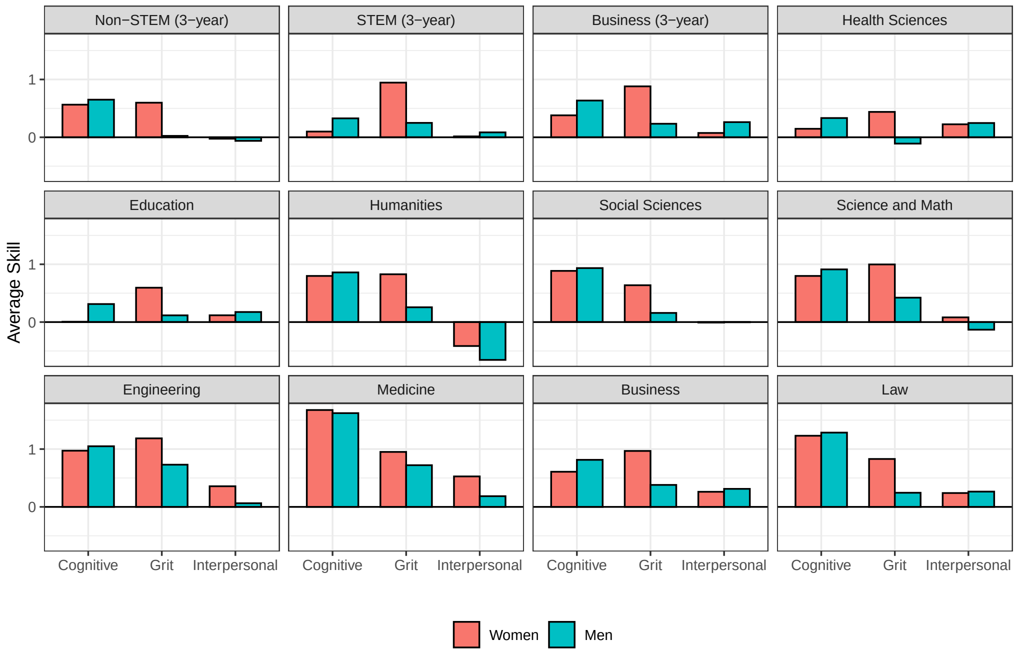


College Graduates



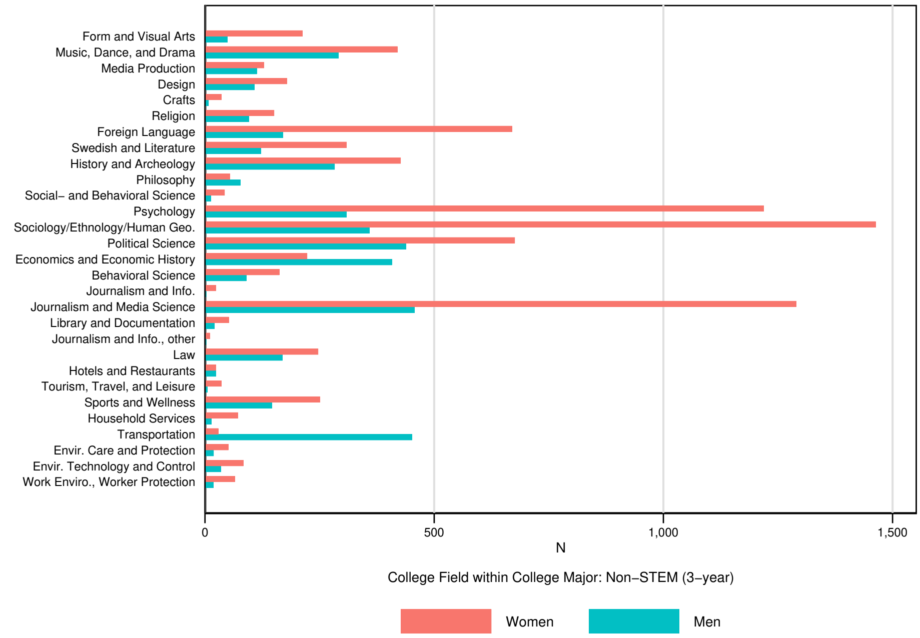
Notes: The top panel reports the estimated average levels of cognitive, grit, and interpersonal skills among high school graduates by gender. The skills have been normalized to be mean 0 sd 1 in the population of high school graduates. The bottom panel reports the average skill levels among those who graduate from college. Note that 41% of women who graduate from high school earn college degrees in this sample, but only 25% of men.

Figure 4: Average Skills by Gender and College Major

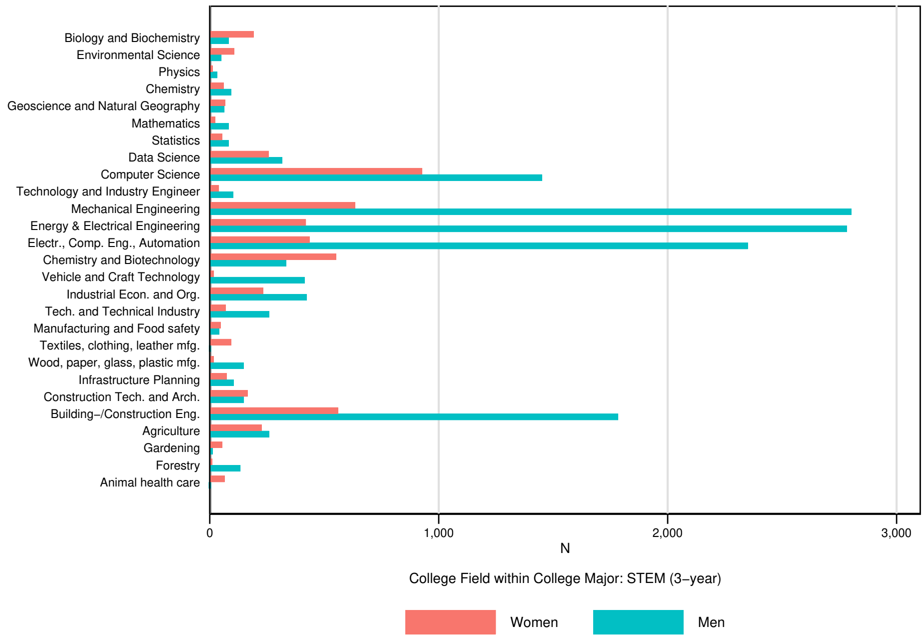


Notes: This figure reports the estimated average skills of men and women who graduate in each broad major. Panels show majors. The first (red) bar is the average for women and the second (blue) bar is the average for men. Each panel shows the avearge for cognitive, grit, and interpersonal skills. The skills have been normalized to be mean 0 sd 1 in the population of high school graduates.

Figure 5: Sorting into College Field by Gender (Part I)



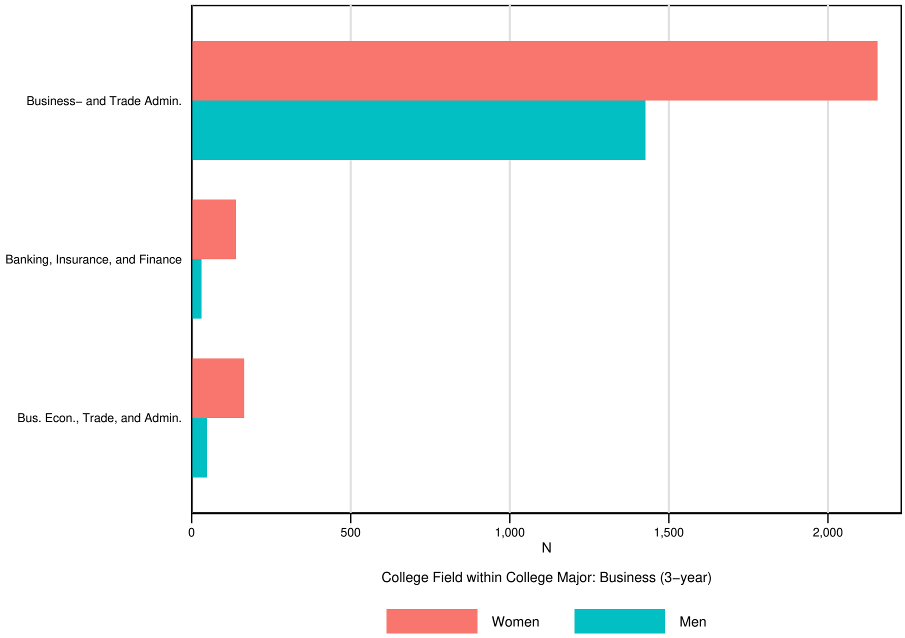
(a) Non-STEM (3-year)



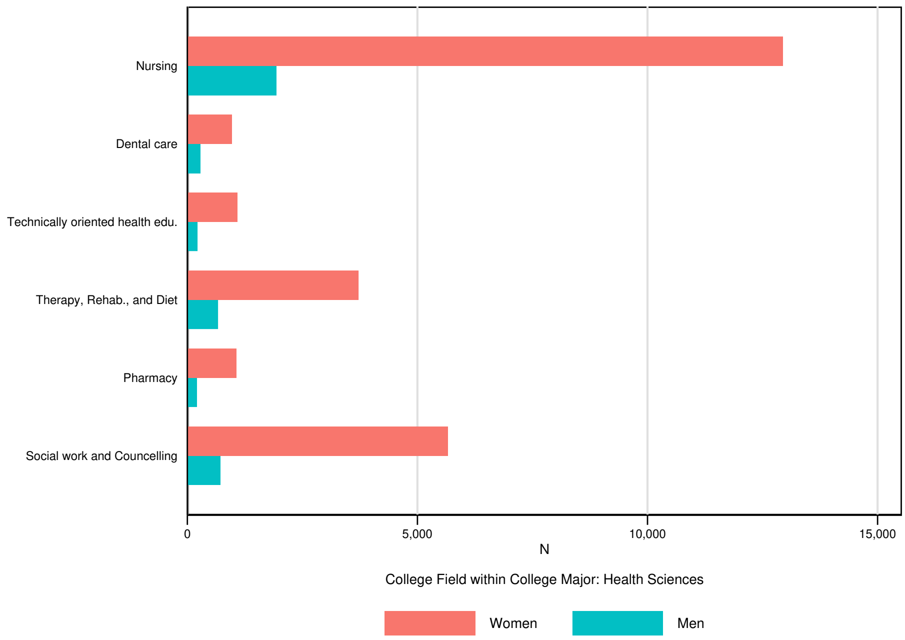
(b) STEM (3-year)

Notes: This figure shows the number of men and women in the (3-digit SUN2000Inr) fields we group under the college major "Non-STEM (3-year)" in panels (a) and those we group under the college major "STEM (3-year)" in panel (b). Sample: Swedish college graduates born between 1972 and 1977.

Figure 5: Sorting into College Field by Gender (Part II)



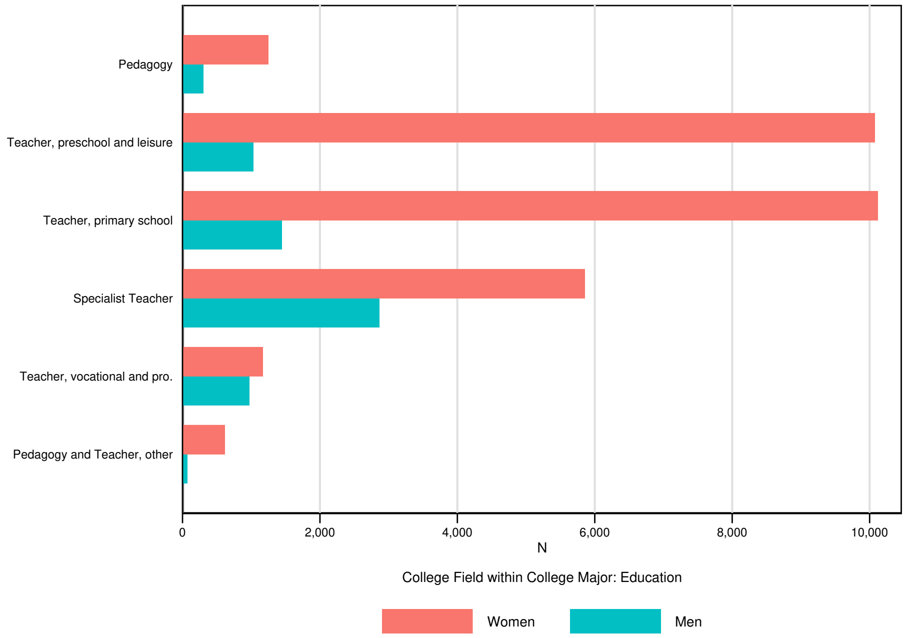
(c) Business (3-year)



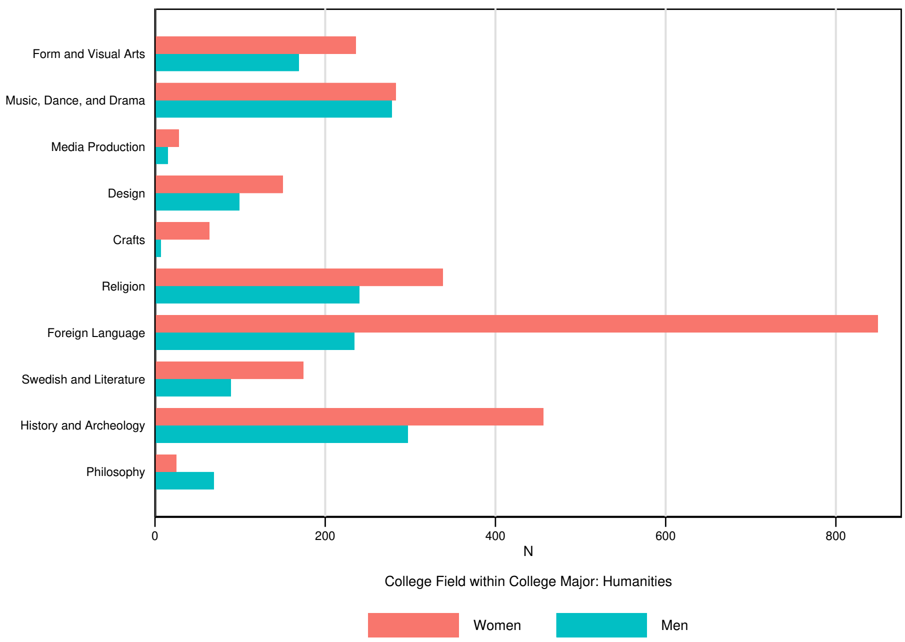
(d) Health Sciences

Notes: This figure shows the number of men and women in the (3-digit SUN2000Inr) fields we group under the college major "Business (3-year)" in panels (a) and those we group under the college major "Health Sciences" in panel (b). Sample: Swedish college graduates born between 1972 and 1977.

Figure 5: Sorting into College Field by Gender (Part III)



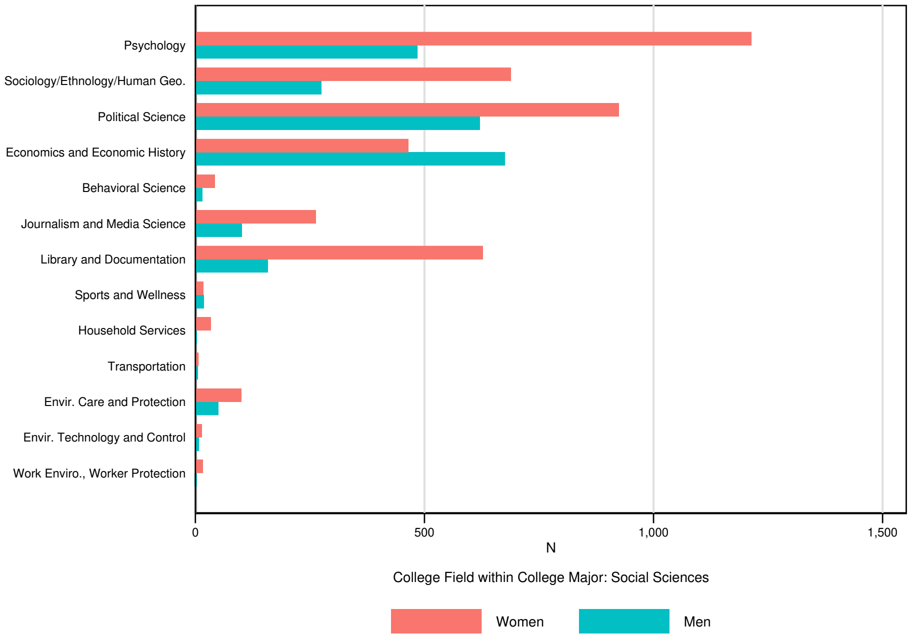
(e) Education



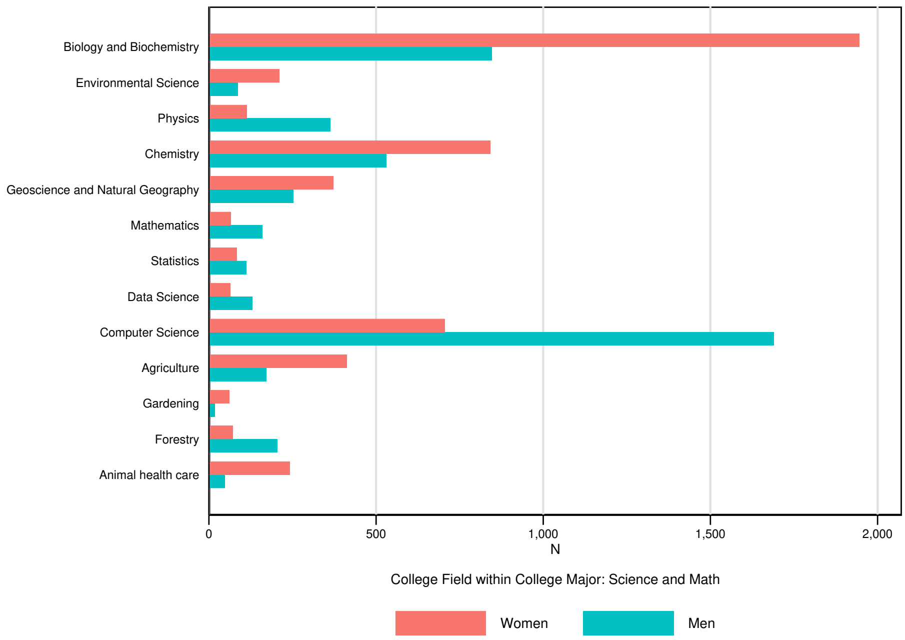
(f) Humanities

Notes: This figure shows the number of men and women in the (3-digit SUN2000Inr) fields we group under the college major "Education" in panels (a) and those we group under the college major "Humanities" in panel (b). Sample: Swedish college graduates born between 1972 and 1977.

Figure 5: Sorting into College Field by Gender (Part IV)



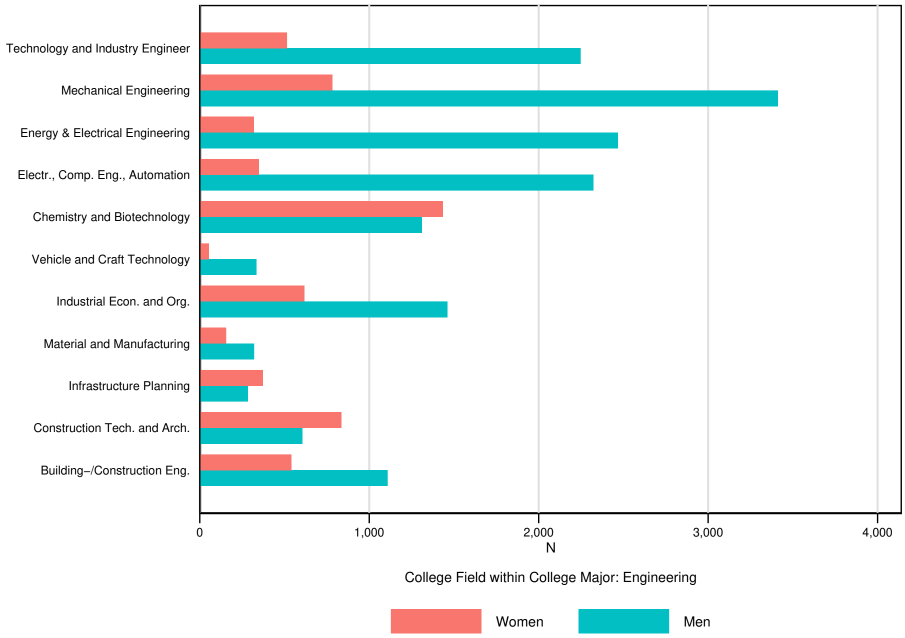
(g) Social Sciences



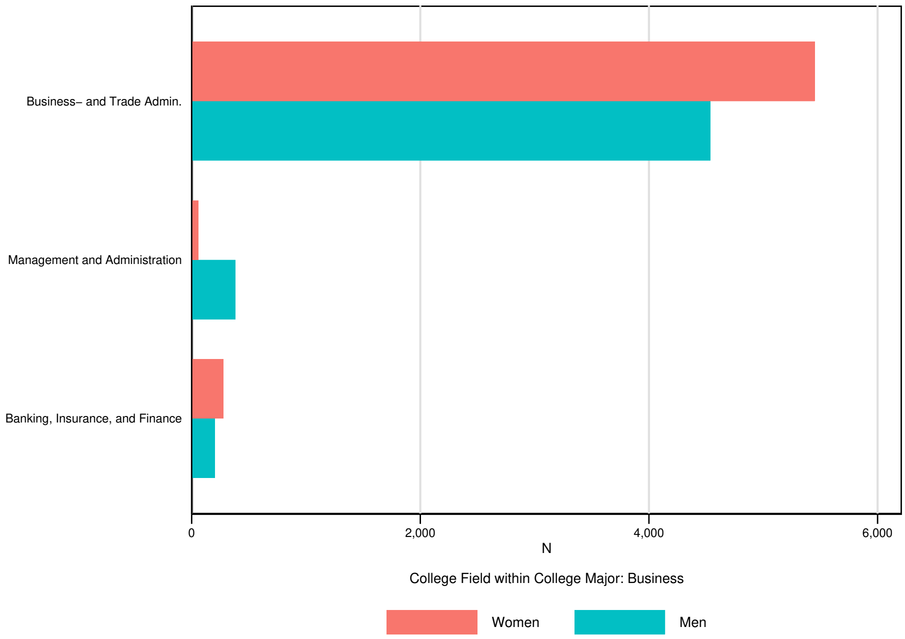
(h) Science and Math

Notes: This figure shows the number of men and women in the (3-digit SUN2000Inr) fields we group under the college major "Social Sciences" in panels (a) and those we group under the college major "Science and Math" in panel (b). Sample: Swedish college graduates born between 1972 and 1977.

Figure 5: Sorting into College Field by Gender (Part V)



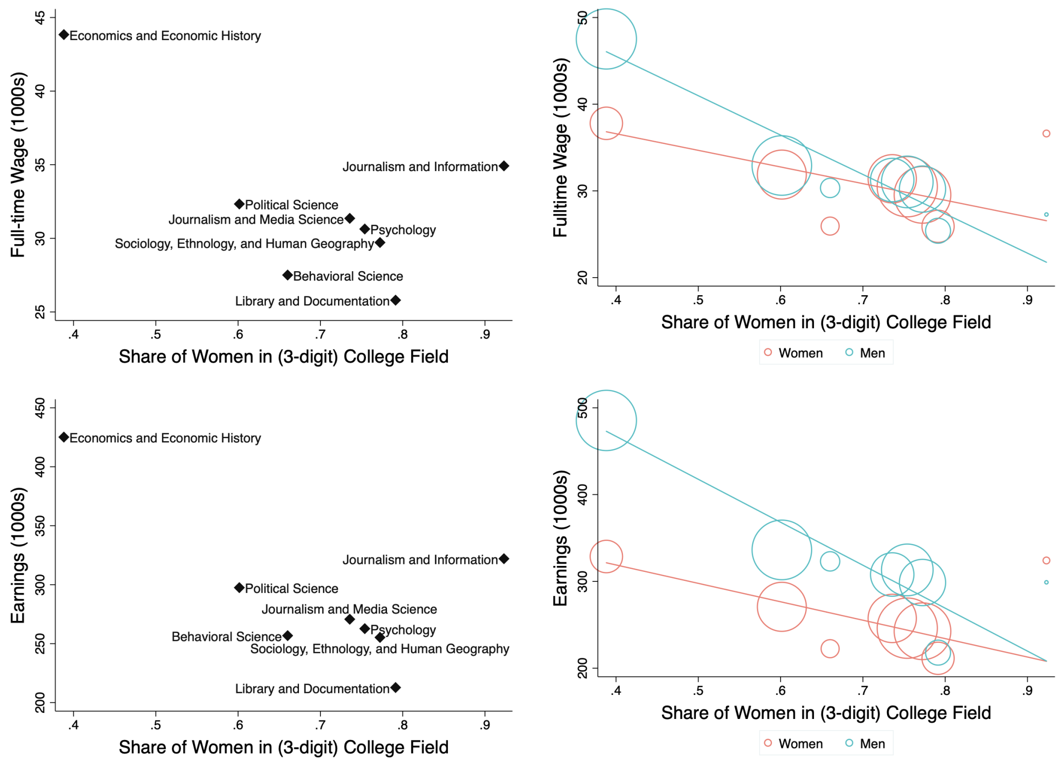
(i) Engineering



(j) Business

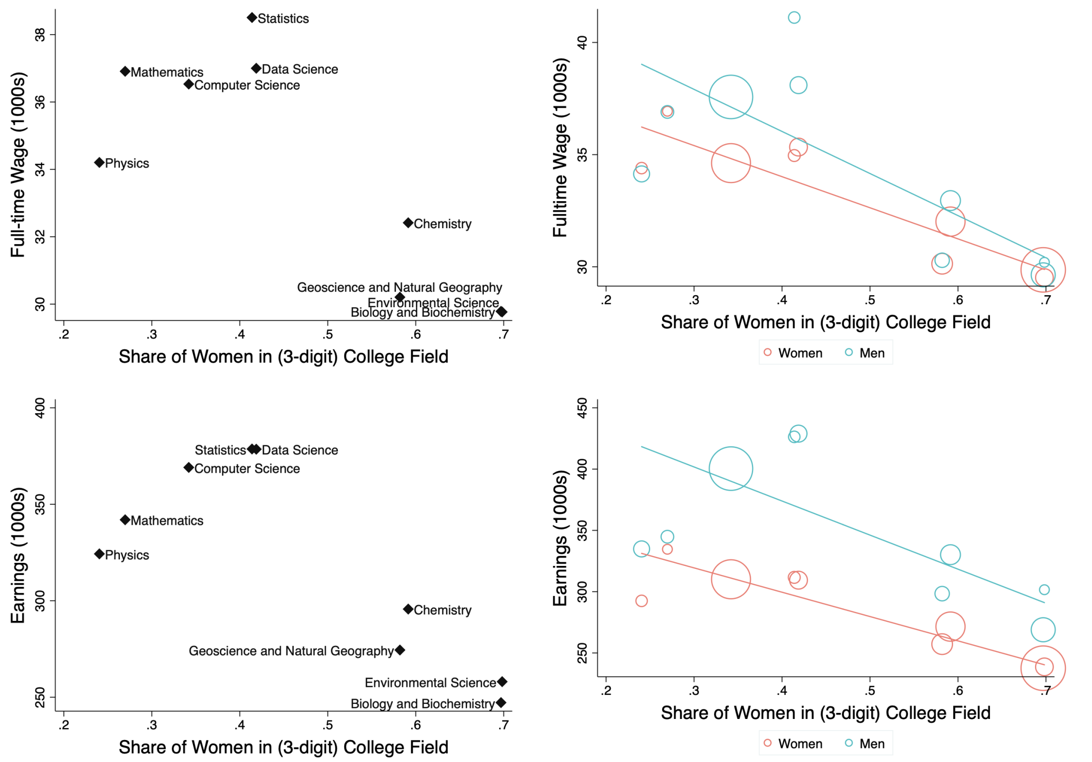
Notes: This figure shows the number of men and women in the (3-digit SUN2000Inr) fields we group under the college major "Engineering" in panels (a) and those we group under the college major "Business" in panel (b). Sample: Swedish college graduates born between 1972 and 1977.

Figure 6: Wages and Earnings by Field and Share of Women (Social Sciences)



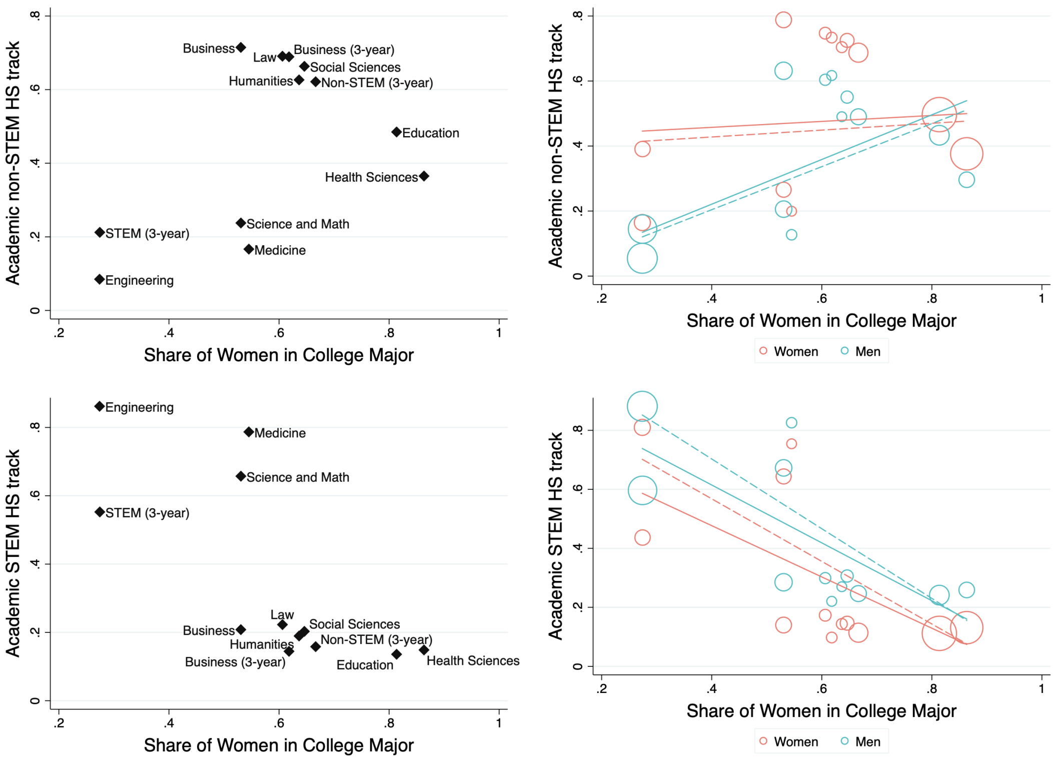
Notes: Left panels plot the share of women in the college major (x-axis) against the average income (y-axis) for each income measure: full-time wage (top) and yearly earnings measure (bottom) in 1000s real 2010 SEK. The right panel repeats this exercise by gender. The size of the circles represent the number of individuals. The solid lines show the linear fit from a regression of average income on share women weighted by the size of the 3-digit field. The red line is for women and the blue line is for men. Sample: Swedish college graduates with a Social Sciences major that are born between 1972 and 1977.

Figure 7: Wages and Earnings by Field and Share of Women (Science and Math)



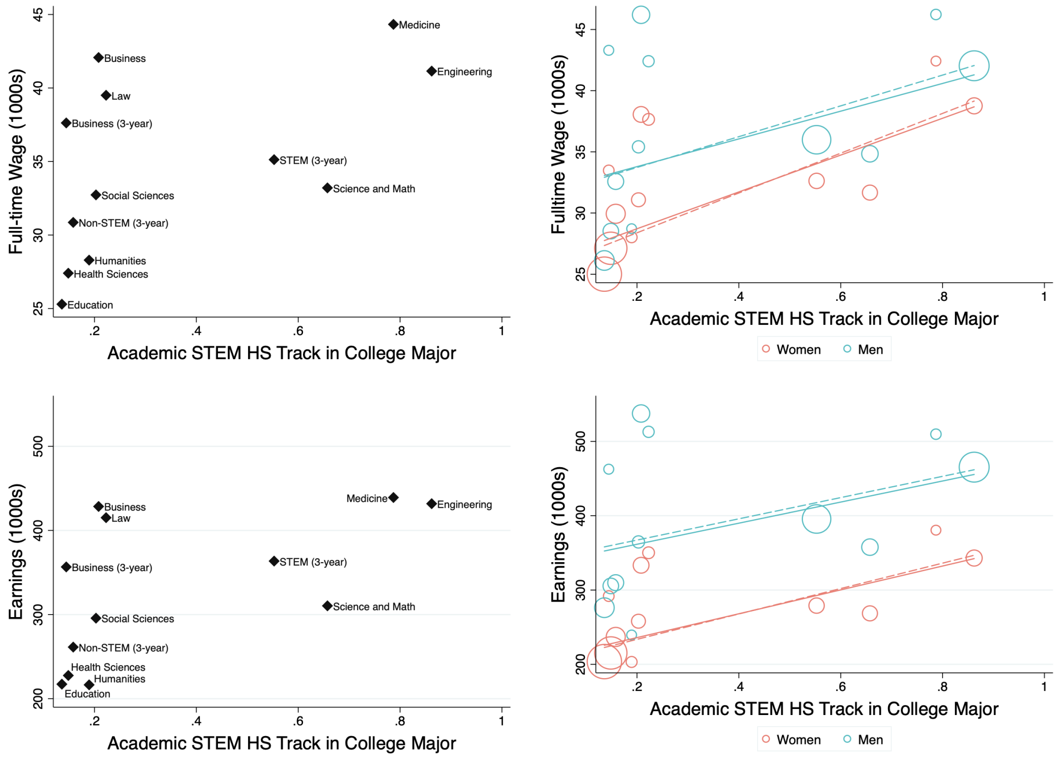
Notes: Left panels plot the share of women in the college major (x-axis) against the average income (y-axis) for each income measure: full-time wage (top) and yearly earnings measure (bottom) in 1000s real 2010 SEK. The right panel repeats this exercise by gender. The size of the circles represent the number of individuals. The solid lines show the linear fit from a regression of average income on share women weighted by the size of the 3-digit field. The red line is for women and the blue line is for men. Sample: Swedish college graduates with a Science and Math major that are born between 1972 and 1977.

Figure 8: High School Math-Preparation by Major and Share of Women



Notes: Left panels plot the share of women in the college major (x-axis) against high school track (y-axis) for each academic track: non-STEM (top) and STEM (bottom). The right panel repeats this exercise by gender. The size of the circles represent the number of individuals. The solid lines are the linear fit from a regression of high school track share on share women weighted by the size of the major. The red line is for women and the blue line is for men. Dashed fitted lines only include 4+ year majors. Sample: Swedish college graduates that are born between 1972 and 1977.

Figure 9: Wages and Earnings by Major and Math-Preparation



Notes: Left panels plot the share of graduates from the STEM high school track in the college major (x-axis) against the average income (y-axis) for each income measure: full-time wage (top) and yearly earnings measure (bottom) in 1000s real 2010 SEK. The right panel repeats this exercise by gender. The size of the circles represent the number of individuals. The solid lines show the linear fit from a regression of the income measure on STEM high school track share weighted by the size of the major. The red line is for women and the blue line is for men. Dashed fitted lines only include 4+ year majors. Sample: Swedish college graduates that are born between 1972 and 1977.

C.2 Additional Description of the Gender Gap in Wages and Income

In this sub-section, we expand on the regression results presented in Figure 1 in the paper. Motivated by a large and growing literature documenting that preferences for workplace amenities like work hours (Bertrand, Goldin and Katz, 2010; Gicheva, 2013; Wiswall and Zafar, 2018; Wasserman, 2023; Altonji, Humphries and Zhong, 2023), occupation and flexibility (Goldin, 2014; Cortés and Pan, 2018), as well as career interruptions (Bertrand, Goldin and Katz, 2010) – largely related to having children – have been found to be important for gender gaps in the labor market among highly educated.[8] Bronson (2014) and Wiswall and Zafar (2021) analyze the relationship between college major and future family and fertility expectations, Sloane, Hurst and Black (2021) focus on the relationship between college major and occupation, while Altonji, Kahn and Speer (2014) focus on the relationship between college major and job tasks.[9]

We explore the potential importance of these (likely endogenous) post-college choices in the following. Figure 10 is an expanded version of Figure 1 in the paper. It displays the coefficient estimates ($\widehat{\beta}_1$) on the indicator for being a woman (W_i) in the linear regression:

$$Y_i = \beta_0 + \beta_1 W_i + Z_i\gamma + \theta_i\alpha + \varepsilon_i,$$

where Z_i is a vector of additional controls and θ_i is a vector of multidimensional skills (cognitive, grit, and interpersonal). The outcome variable (Y_i) is log full-time monthly wage in the top panel (a) and log yearly earnings in the bottom panel (b). The red circles denote that the vector of multidimensional skills (θ_i) is not included, while the gray triangles denote that cognitive, grit, and interpersonal skills are included in the regression. The first four specifications are the same as in Figure 1. The first pair of estimates (top left) correspond to the regressions were the only controls (Z_i) are *birth cohort* indicators. Each additional pair of coefficient estimates (from darker to lighter colors) moving down along the y-axis sequentially include additional controls in Z_i. The second pair (*HS track*) adds indicators for having the academic non-STEM and the academic STEM high school tracks. The third pair adds indicators for the twelve broad *college major* categories, while the fourth (*college program*) adds more detailed controls for field of study and institution. In the last three specifications, we sequentially add controls for post-college job, workplace, and

[8] While we focus on college graduates in this paper, Binder et al. (2023) and Binder et al. (2024) show that the gender wage gap is even larger among individuals with less education and the nature of the gap may differ too; for example, labor supply plays a more important role in explaining the gap. This is consistent with Gallen et al. (2023) who stress the importance of work hours and labor market sorting in explaining the narrowing gender wage gap in Denmark from 1980-2010.

[9] Cortés et al. (2023) also stress the importance of gender differences in the job search process and risk aversion, whereby women who graduate with a Business major enter the labor market with lower initial wages partly because they accept job offers earlier.

occupation measures. First, we add *work intensity* (an indicator for working full-time and work hours). Then we add *flexibility* (an indicator for having a job requiring the highest specialist competencies, an indicator for having managerial responsibility, and Goldin's flexibility index), and lastly indicators for 3-digit *occupation*. We find that these additional controls explain some, but not all, of the remaining gap. Figure 11 shows the same specifications for the *within* college major gap in log wages for all twelve majors, while Figure 12 shows these specifications for the *within* college major gap in log earnings.

Finally, we describe how the gender wage gap changes with age and how it relates to parenthood.[10] Figure 13 displays the coefficient estimates $(\widehat{\beta}_1, \widehat{\beta}_2, \widehat{\beta}_3)$ on the indicators for being a woman (W_i), a parent (P_i), and being a mother ($W_i * P_i$) in the linear regression:

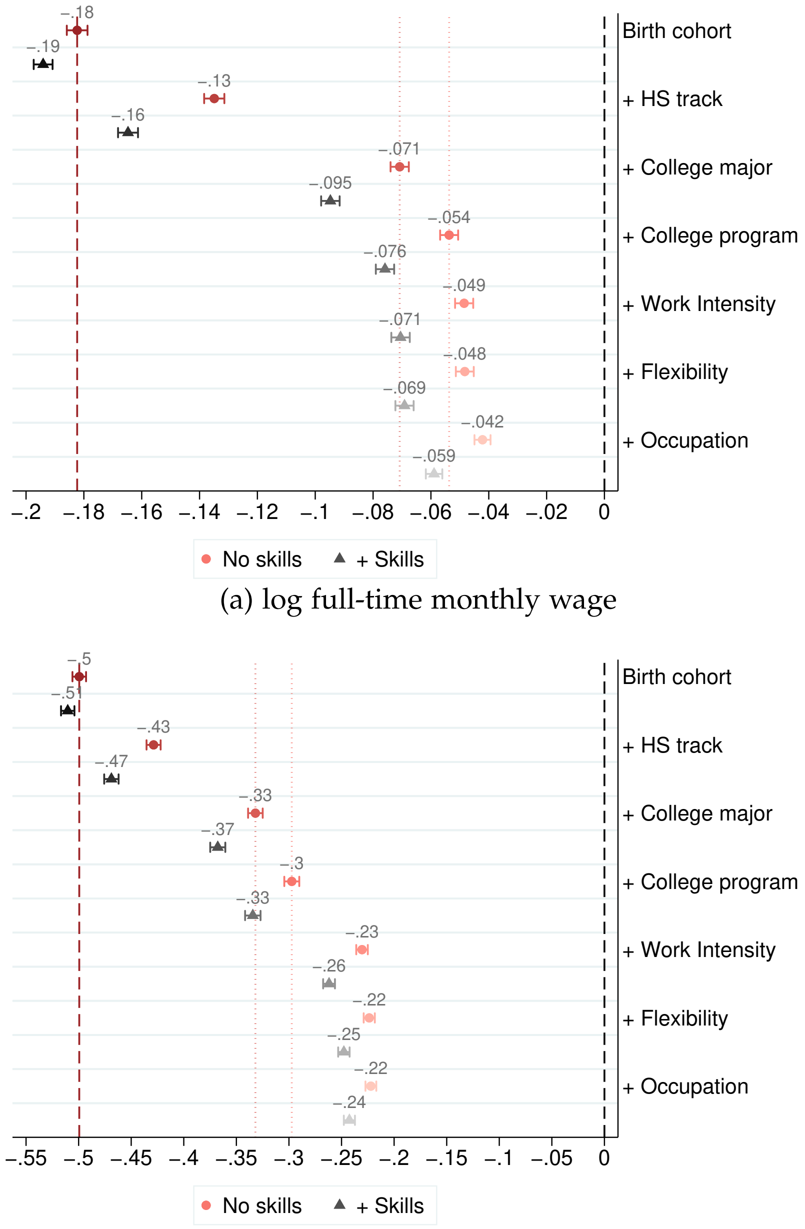
$$Y_i = \beta_0 + \beta_1 W_i + \beta_2 P_i + \beta_3 W_i * P_i + Z_i \gamma + \theta_i \alpha + \varepsilon_i,$$

where Z_i is a vector of additional controls and θ_i is a vector of multidimensional skills (cognitive, grit, and interpersonal). The outcome variable (Y_i) is log monthly wages at age 35 in the top panel (Figure 13a) and log yearly earnings at age 35 in the bottom panel (Figure 13b). The last two figures show these estimates at at age 27, 30, 33, and 37 for log monthly wages (Figure 14) and log yearly earnings (Figure 15).[11] These figures show that the gender wage gap for non-parents grows with age, while the gender earnings gap for non-parents shrinks with age. College major is by far the most important predictor of both the gender wage and earnings gap ($\widehat{\beta}_1$) among non-parents. These figures also show that both the wage and earnings gaps between mothers and fathers increase with age, and this also seems related to choices of work intensity, flexibility, and occupation – especially the earnings gaps between mothers and fathers. This is consistent with the literature finding that motherhood is associated with a higher labor market cost than fatherhood; see e.g. Angelov, Johansson and Lindahl (2016); Kleven, Landais and Søgaard (2019); Kleven et al. (2019); Andresen and Nix (2022). Future research will hopefully reveal how this parenthood gap is related to skills and specialization choices – both in the household, in education, and in the labor market.

[10] Contemporaneous work (Andrews et al., 2022; Choi et al., 2023) highlights how college major specific earnings profiles may differ over the life-cycle.

[11] Age 27 is the 25th percentile, age 30 is the median, while age 33 is the 75th percentile in age at first birth distribution. Age 33 and age 37 also represent the lowest and oldest ages at which we measure our main outcome variables in this paper.

Figure 10: The Gender Gap in Wages and Earnings

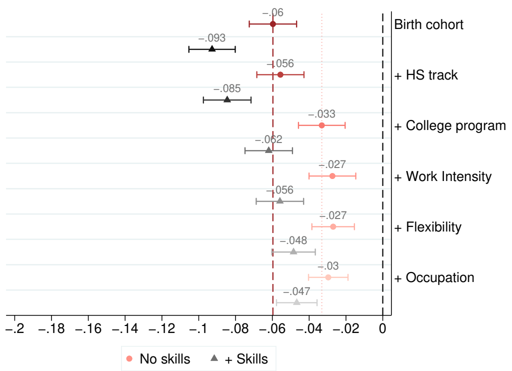


(a) log full-time monthly wage

(b) log yearly earnings

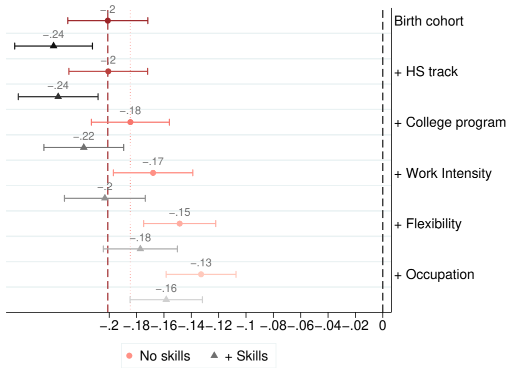
Notes: This figure displays the coefficient estimates ($\widehat{\beta}_1$) on the indicator for being a woman (W_i) in the linear regression: $Y_i = \beta_0 + \beta_1 W_i + Z_i\gamma + \theta_i\alpha + \varepsilon_i$, where Z_i is a vector of additional controls and θ_i is a vector of multidimensional skills (cognitive, grit, and interpersonal). The outcome variable (Y_i) is log full-time monthly wage in the top panel (a) and log yearly earnings in the bottom panel (b). The red circles denote that (θ_i) is not included, while the gray triangles denote that cognitive, grit, and interpersonal skills are included in the regression. The first pair of estimates (top left) correspond to the regressions were the only controls (Z_i) are birth cohort indicators. Each additional pair of coefficient estimates (from darker to lighter colors) moving down along the y-axis sequentially adds additional controls. See intro to Appendix C.2 for details on the controls we include. The three vertical red dashed lines are from left: the gap when only including birth cohort indicators, the gap when further adding high school track and college major indicators, and the gap when further adding indicators for the 3-digit field and institution of the college degree. Capped lines represent 95% confidence intervals. Sample: Swedish college graduates born between 1972 and 1977.

Figure 11: The within College Major Gender Gap in Wages (Part I)



(a) Non-STEM (3-year)

(b) STEM (3-year)



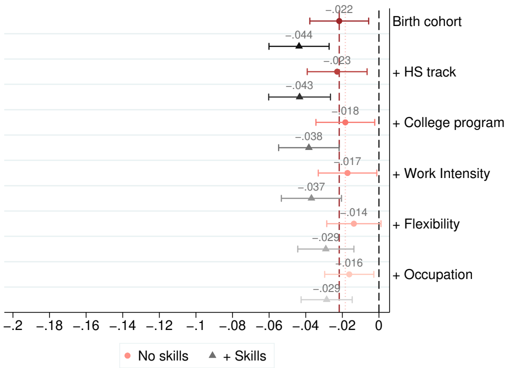
(c) Business (3-year)

(d) Health Sciences

Notes: This figure displays the coefficient estimates ($\widehat{\beta}_1$) on the indicator for being a woman (W_i) in the linear regression: $Y_i = \beta_0 + \beta_1 W_i + Z_i\gamma + \theta_i\alpha + \varepsilon_i$, where Z_i is a vector of additional controls and θ_i is a vector of multidimensional skills (cognitive, grit, and interpersonal). The outcome variable (Y_i) is log full-time monthly wage. The red circles denote that (θ_i) is not included, while the gray triangles denote that cognitive, grit, and interpersonal skills are included in the regression. The first pair of estimates (top left) correspond to the regressions were the only controls (Z_i) are birth cohort indicators. Each additional pair of coefficient estimates (from darker to lighter colors) moving down along the y-axis sequentially adds additional controls. See intro to Appendix C.2 for details on the controls we include. The three vertical red dashed lines are from left: the gap when only including birth cohort indicators, the gap when further adding high school track and college major indicators, and the gap when further adding indicators for the 3-digit field and institution of the college degree. Capped lines represent 95% confidence intervals. Sample: Swedish college graduates born between 1972 and 1977.

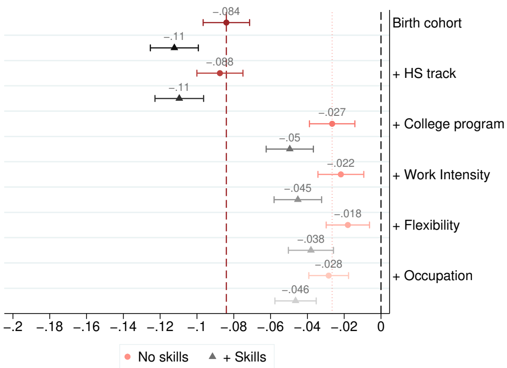
Figure 11: The within College Major Gender Gap in Wages (Part II)

(e) Education



(f) Humanities

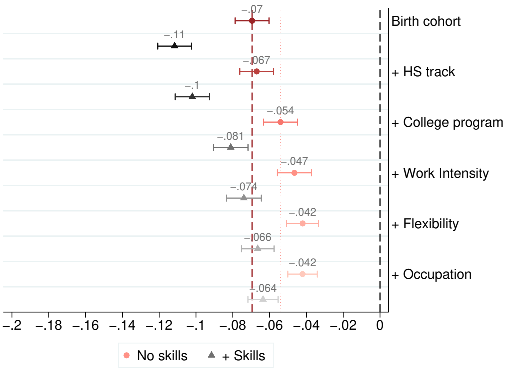
(g) Social Sciences



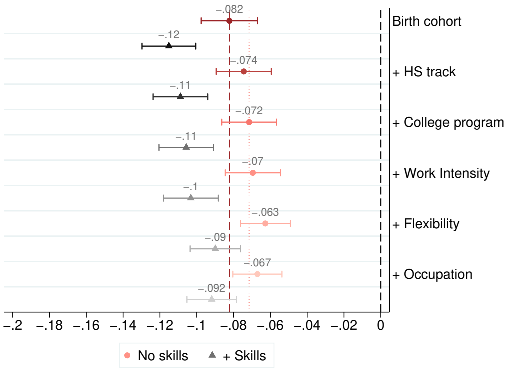
(h) Science and Math

Notes: This figure displays the coefficient estimates ($\widehat{\beta}_1$) on the indicator for being a woman (W_i) in the linear regression: $Y_i = \beta_0 + \beta_1 W_i + Z_i\gamma + \theta_i\alpha + \varepsilon_i$, where Z_i is a vector of additional controls and θ_i is a vector of multidimensional skills (cognitive, grit, and interpersonal). The outcome variable (Y_i) is log full-time monthly wage. The red circles denote that (θ_i) is not included, while the gray triangles denote that cognitive, grit, and interpersonal skills are included in the regression. The first pair of estimates (top left) correspond to the regressions were the only controls (Z_i) are birth cohort indicators. Each additional pair of coefficient estimates (from darker to lighter colors) moving down along the y-axis sequentially adds additional controls. See intro to Appendix C.2 for details on the controls we include. The three vertical red dashed lines are from left: the gap when only including birth cohort indicators, the gap when further adding high school track and college major indicators, and the gap when further adding indicators for the 3-digit field and institution of the college degree. Capped lines represent 95% confidence intervals. Sample: Swedish college graduates born between 1972 and 1977.

Figure 11: The within College Major Gender Gap in Wages (Part III)

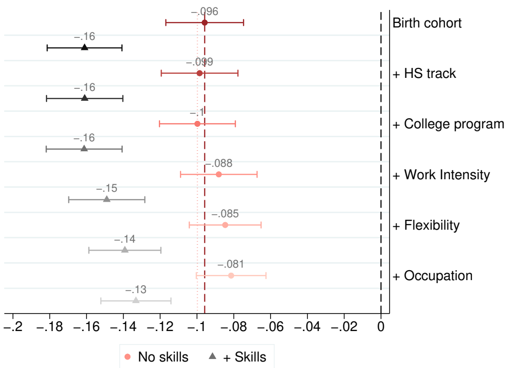


(i) Engineering



(j) Medicine

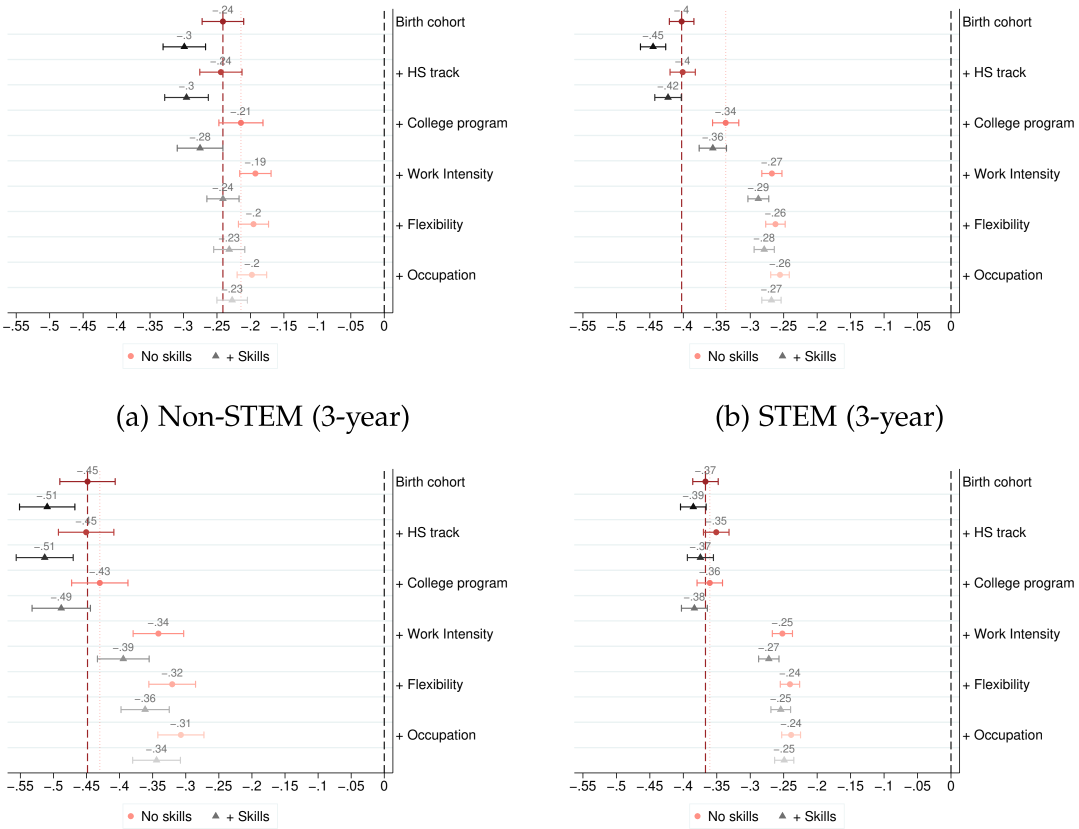
(k) Business



(l) Law

Notes: This figure displays the coefficient estimates ($\widehat{\beta}_1$) on the indicator for being a woman (W_i) in the linear regression: $Y_i = \beta_0 + \beta_1 W_i + Z_i\gamma + \theta_i\alpha + \varepsilon_i$, where Z_i is a vector of additional controls and θ_i is a vector of multidimensional skills (cognitive, grit, and interpersonal). The outcome variable (Y_i) is log full-time monthly wage. The red circles denote that (θ_i) is not included, while the gray triangles denote that cognitive, grit, and interpersonal skills are included in the regression. The first pair of estimates (top left) correspond to the regressions were the only controls (Z_i) are birth cohort indicators. Each additional pair of coefficient estimates (from darker to lighter colors) moving down along the y-axis sequentially adds additional controls. See intro to Appendix C.2 for details on the controls we include. The three vertical red dashed lines are from left: the gap when only including birth cohort indicators, the gap when further adding high school track and college major indicators, and the gap when further adding indicators for the 3-digit field and institution of the college degree. Capped lines represent 95% confidence intervals. Sample: Swedish college graduates born between 1972 and 1977.

Figure 12: The within College Major Gender Gap in Earnings (Part I)



(a) Non-STEM (3-year)

(b) STEM (3-year)

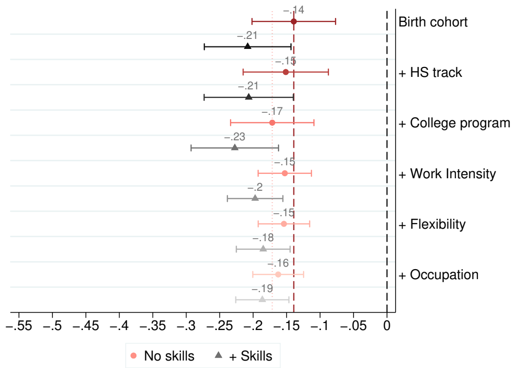
(c) Business (3-year)

(d) Health Sciences

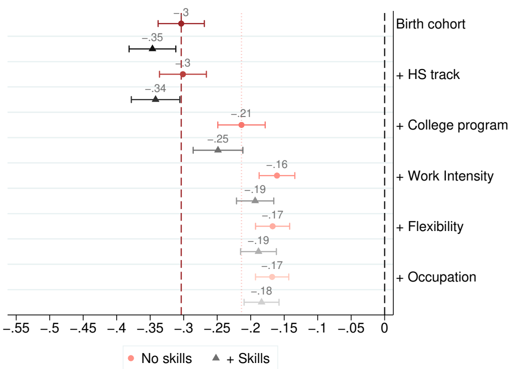
Notes: This figure displays the coefficient estimates ($\widehat{\beta}_1$) on the indicator for being a woman (W_i) in the linear regression: $Y_i = \beta_0 + \beta_1 W_i + Z_i\gamma + \theta_i\alpha + \varepsilon_i$, where Z_i is a vector of additional controls and θ_i is a vector of multidimensional skills (cognitive, grit, and interpersonal). The outcome variable (Y_i) is log yearly earnings. The red circles denote that (θ_i) is not included, while the gray triangles denote that cognitive, grit, and interpersonal skills are included in the regression. The first pair of estimates (top left) correspond to the regressions were the only controls (Z_i) are birth cohort indicators. Each additional pair of coefficient estimates (from darker to lighter colors) moving down along the y-axis sequentially adds additional controls. See intro to Appendix C.2 for details on the controls we include. The three vertical red dashed lines are from left: the gap when only including birth cohort indicators, the gap when further adding high school track and college major indicators, and the gap when further adding indicators for the 3-digit field and institution of the college degree. Capped lines represent 95% confidence intervals. Sample: Swedish college graduates born between 1972 and 1977.

Figure 12: The within College Major Gender Gap in Earnings (Part II)

(e) Education



(f) Humanities

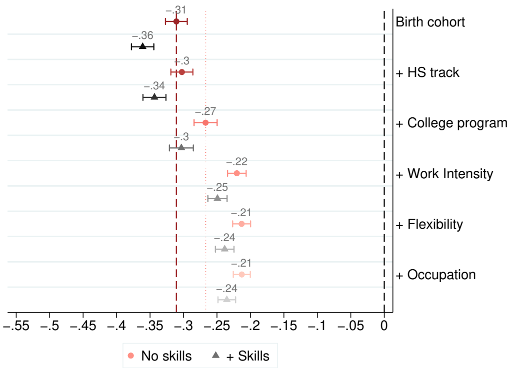


(g) Social Sciences

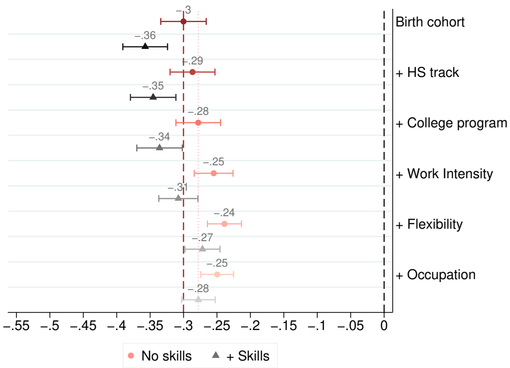
(h) Science and Math

Notes: This figure displays the coefficient estimates ($\widehat{\beta}_1$) on the indicator for being a woman (W_i) in the linear regression: $Y_i = \beta_0 + \beta_1 W_i + Z_i\gamma + \theta_i\alpha + \varepsilon_i$, where Z_i is a vector of additional controls and θ_i is a vector of multidimensional skills (cognitive, grit, and interpersonal). The outcome variable (Y_i) is log yearly earnings. The red circles denote that (θ_i) is not included, while the gray triangles denote that cognitive, grit, and interpersonal skills are included in the regression. The first pair of estimates (top left) correspond to the regressions were the only controls (Z_i) are birth cohort indicators. Each additional pair of coefficient estimates (from darker to lighter colors) moving down along the y-axis sequentially adds additional controls. See intro to Appendix C.2 for details on the controls we include. The three vertical red dashed lines are from left: the gap when only including birth cohort indicators, the gap when further adding high school track and college major indicators, and the gap when further adding indicators for the 3-digit field and institution of the college degree. Capped lines represent 95% confidence intervals. Sample: Swedish college graduates born between 1972 and 1977.

Figure 12: The within College Major Gender Gap in Earnings (Part III)

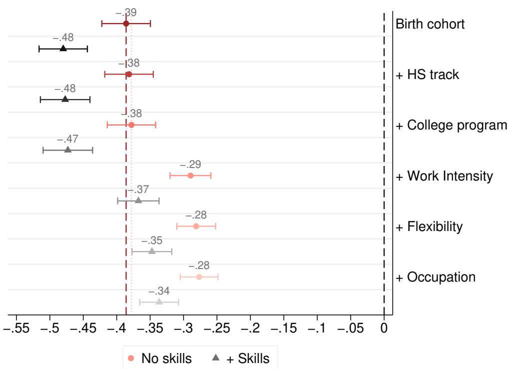


(i) Engineering



(j) Medicine

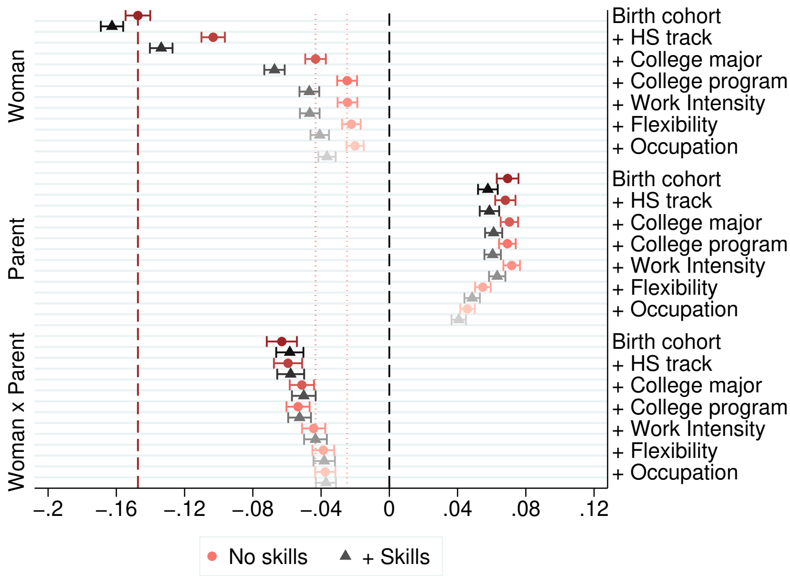
(k) Business



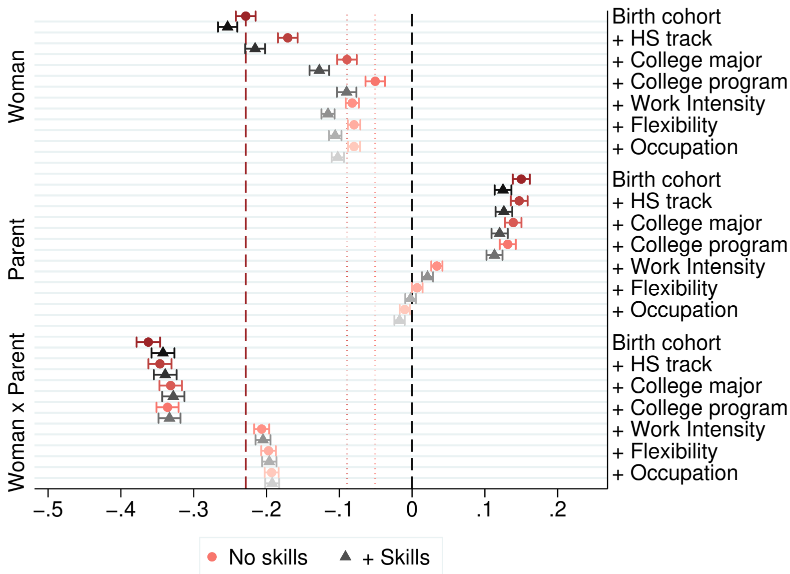
(l) Law

Notes: This figure displays the coefficient estimates ($\widehat{\beta}_1$) on the indicator for being a woman (W_i) in the linear regression: $Y_i = \beta_0 + \beta_1 W_i + Z_i\gamma + \theta_i\alpha + \varepsilon_i$, where Z_i is a vector of additional controls and θ_i is a vector of multidimensional skills (cognitive, grit, and interpersonal). The outcome variable (Y_i) is log yearly earnings. The red circles denote that (θ_i) is not included, while the gray triangles denote that cognitive, grit, and interpersonal skills are included in the regression. The first pair of estimates (top left) correspond to the regressions were the only controls (Z_i) are birth cohort indicators. Each additional pair of coefficient estimates (from darker to lighter colors) moving down along the y-axis sequentially adds additional controls. See intro to Appendix C.2 for details on the controls we include. The three vertical red dashed lines are from left: the gap when only including birth cohort indicators, the gap when further adding high school track and college major indicators, and the gap when further adding indicators for the 3-digit field and institution of the college degree. Capped lines represent 95% confidence intervals. Sample: Swedish college graduates born between 1972 and 1977.

Figure 13: The Gender Gap in Wages and Earnings, Parenthood (Age 35)



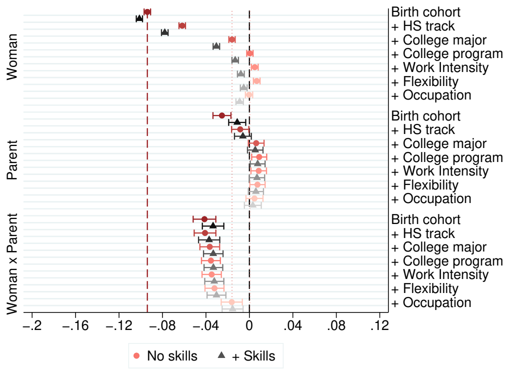
(a) log full-time monthly wage



(b) log yearly earnings

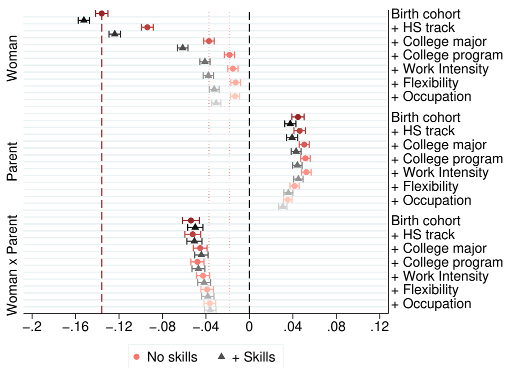
Notes: This figure displays the coefficient estimates $(\widehat{\beta}_1, \widehat{\beta}_2, \widehat{\beta}_3)$ on the indicators for being a woman (W_i), a parent by age 35 (P_i), and being a mother by age 35 ($W_i * P_i$) in the linear regression: $Y_i = \beta_0 + \beta_1 W_i + \beta_2 P_i + \beta_3 W_i * P_i + Z_i\gamma + \theta_i\alpha + \varepsilon_i$, where Z_i is a vector of additional controls and θ_i is a vector of multidimensional skills (cognitive, grit, and interpersonal). The outcome variable (Y_i) is log full-time monthly wage in the top panel (a) and log yearly earnings in the bottom panel (b). The red circles denote that (θ_i) is not included, while the gray triangles denote that cognitive, grit, and interpersonal skills are included in the regression. The first pair of estimates (top left) correspond to the regressions were the only controls (Z_i) are birth cohort indicators. Each additional pair of coefficient estimates (from darker to lighter colors) moving down along the y-axis sequentially adds additional controls. See intro to Appendix C.2 for details on the controls we include. The three vertical red dashed lines are from left: the gap when only including birth cohort indicators, the gap when further adding high school track and college major indicators, and the gap when further adding indicators for the 3-digit field and institution of the college degree. Capped lines represent 95% confidence intervals. Sample: Swedish college graduates born between 1972 and 1977.

Figure 14: The Gender Gap in Wages, Parenthood by Age

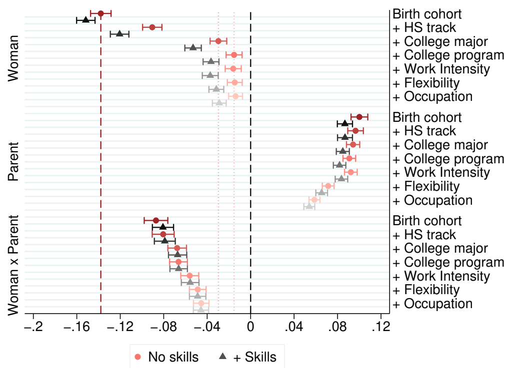


(a) Age 27

(b) Age 30



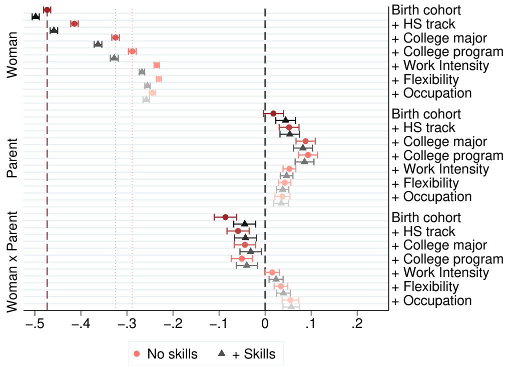
(c) Age 33



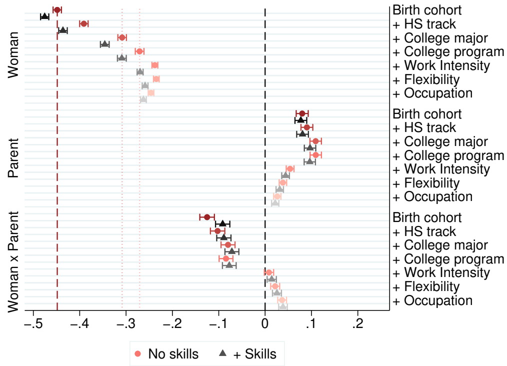
(d) Age 37

Notes: This figure displays the coefficient estimates $(\widehat{\beta}_1, \widehat{\beta}_2, \widehat{\beta}_3)$ on the indicators for being a woman (W_i), a parent (P_i), and being a mother ($W_i * P_i$) in the linear regression: $Y_i = \beta_0 + \beta_1 W_i + \beta_2 P_i + \beta_3 W_i * P_i + Z_i \gamma + \theta_i \alpha + \varepsilon_i$, where Z_i is a vector of additional controls and θ_i is a vector of multidimensional skills (cognitive, grit, and interpersonal). The outcome variable (Y_i) is log full-time monthly wage. Panels (a)-(d) separately display estimates for 27, 30, 33, and 37 year olds. The red circles denote that (θ_i) is not included, while the gray triangles denote that cognitive, grit, and interpersonal skills are included in the regression. The first pair of estimates (top left) correspond to the regressions were the only controls (Z_i) are birth cohort indicators. Each additional pair of coefficient estimates (from darker to lighter colors) moving down along the y-axis sequentially adds additional controls. See intro to Appendix C.2 for details on the controls we include. The three vertical red dashed lines are from left: the gap when only including birth cohort indicators, the gap when further adding high school track and college major indicators, and the gap when further adding indicators for the 3-digit field and institution of the college degree. Capped lines represent 95% confidence intervals. Sample: Swedish college graduates born between 1972 and 1977.

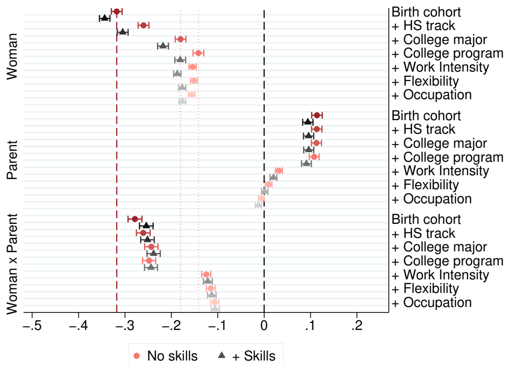
Figure 15: The Gender Gap in Earnings, Parenthood by Age



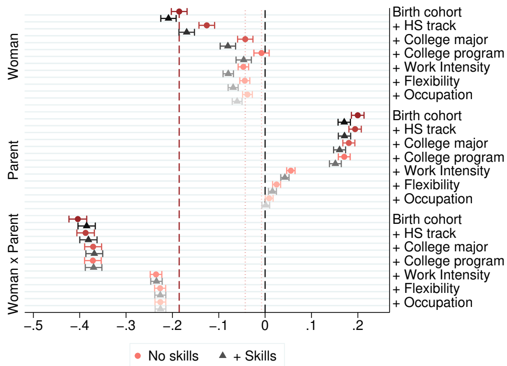
(a) Age 27



(b) Age 30



(c) Age 33



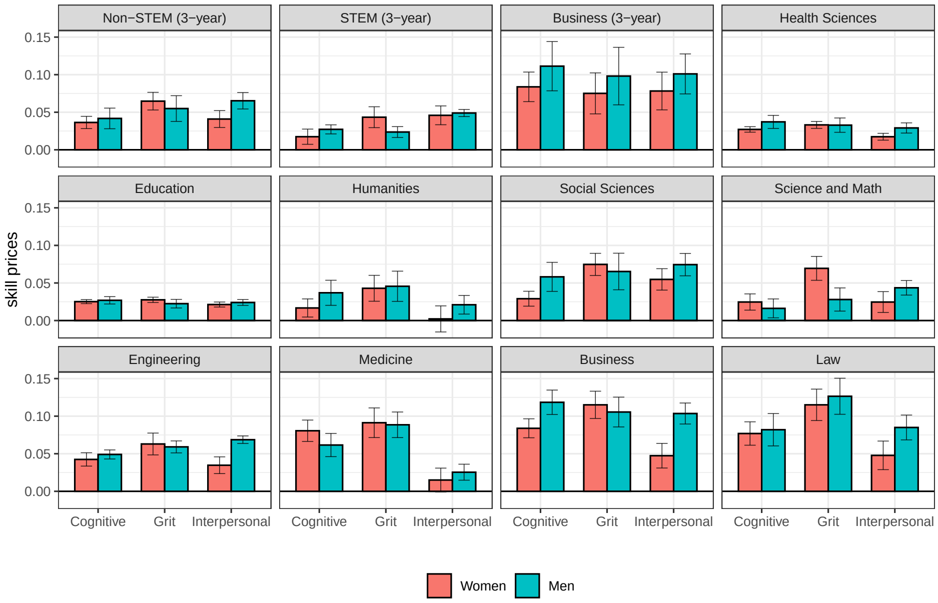
(d) Age 37

Notes: This figure displays the coefficient estimates $(\widehat{\beta}_1, \widehat{\beta}_2, \widehat{\beta}_3)$ on the indicators for being a woman (W_i), a parent (P_i), and being a mother ($W_i * P_i$) in the linear regression: $Y_i = \beta_0 + \beta_1 W_i + \beta_2 P_i + \beta_3 W_i * P_i + Z_i\gamma + \theta_i\alpha + \varepsilon_i$, where Z_i is a vector of additional controls and θ_i is a vector of multidimensional skills (cognitive, grit, and interpersonal). The outcome variable (Y_i) is log yearly earnings. Panels (a)-(d) separately display estimates for 27, 30, 33, and 37 year olds. The red circles denote that (θ_i) is not included, while the gray triangles denote that cognitive, grit, and interpersonal skills are included in the regression. The first pair of estimates (top left) correspond to the regressions were the only controls (Z_i) are birth cohort indicators. Each additional pair of coefficient estimates (from darker to lighter colors) moving down along the y-axis sequentially adds additional controls. See intro to Appendix C.2 for details on the controls we include. The three vertical red dashed lines are from left: the gap when only including birth cohort indicators, the gap when further adding high school track and college major indicators, and the gap when further adding indicators for the 3-digit field and institution of the college degree. Capped lines represent 95% confidence intervals. Sample: Swedish college graduates born between 1972 and 1977.

C.3 Additional Results on the Wage and Income Decomposition

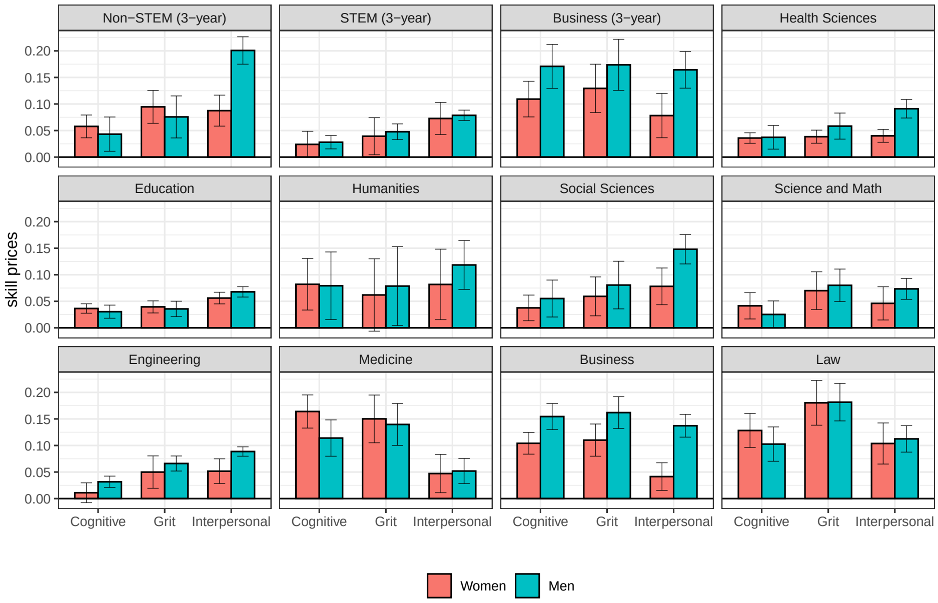
In this Appendix, we provide additional results on the within-major decompositions in Figure 2 in the paper. Figure 16 presents skill prices by gender within each of the twelve college majors for the full-time monthly wage measure that we focus on in the paper. That is, the $\widehat{\alpha}_{jg}$ for $g = w, m$ that form the basis for the decompositions in Figure 2 in the paper. Figure 17 shows these skill prices for the yearly earnings measure, while Figure 18 is the equivalent of Figure 2 in the paper showing the earnings (instead of wage) decompositions. The red bars report the gender gap in expected full-time income among those in each major. The green bars show the gap when using men's skill prices for calculating the expected log incomes of women: $(\bar{X}_i^{jw}\beta_{jw} - \bar{X}_i^{jm}\beta_{jm}) + (\bar{\theta}_i^{jw} - \bar{\theta}_i^{jm})\alpha_{jm}$. The blue bar shows the gap when using men's covariate coefficients (including the intercepts) $(\bar{X}_i^{jw} - \bar{X}_i^{m})\beta_{jm} + (\bar{\theta}_i^{jw}\alpha_{jw} - \bar{\theta}_i^{jm}\alpha_{jm})$. The purple bar shows the gap when using the men's model for both women and men: $(\bar{X}_i^{jw} - \bar{X}_i^{m})\beta_{jm} + (\bar{\theta}_i^{jw} - \bar{\theta}_i^{jm})\alpha_{jm}$. Similar to what we find for wages, most of the difference is driven by differences in the intercept.

Figure 16: Returns to skill by college major for men and women (log-Wage)



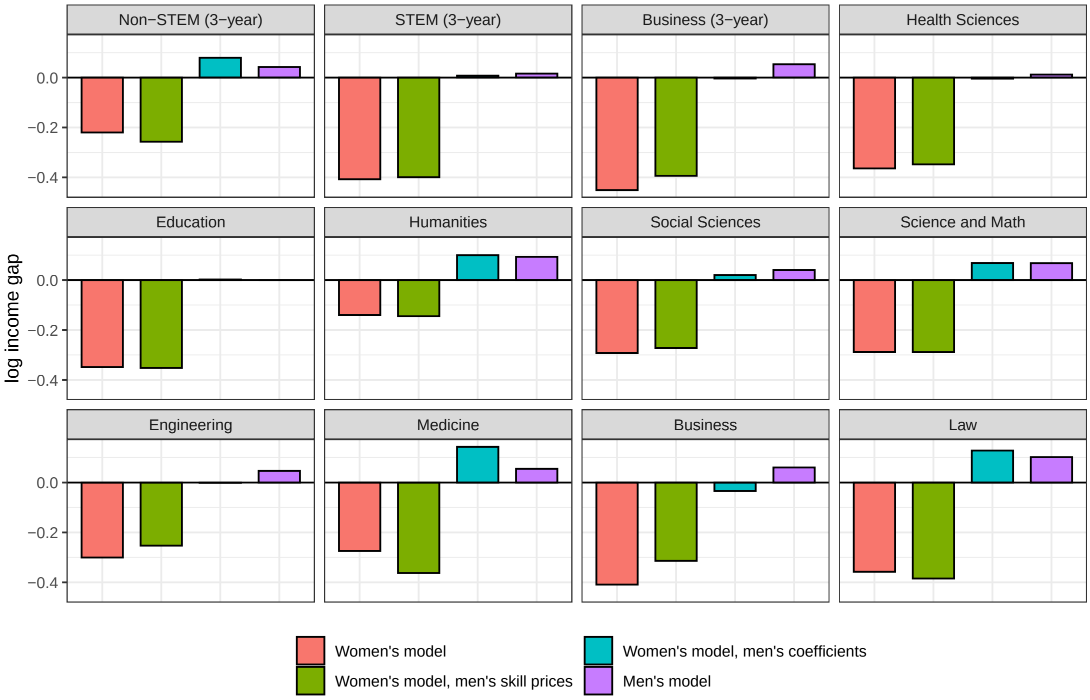
Notes: This figure reports the estimated loadings on skill prices for men and women from the estimated major-specific models of log full time monthly wages. The model additionally controls for high school track indicators, an indicator for taking advanced math in 9th grade, and an indicator for taking advanced english in 9th grade.

Figure 17: Returns to skill by college major for men and women (log-Earnings)



Notes: This figure reports the estimated loadings on skill prices for men and women from the estimated major-specific models of log-Earnings. The model additionally controls for high school track indicators, an indicator for taking advanced math in 9th grade, and an indicator for taking advanced english in 9th grade.

Figure 18: Decomposing the Within-Major Gender Gap (log-Earnings)



Notes: This figure decomposes the gender gap in log-Earnings for men and women within major. The red bars report the gender gap in expected full-time wages among those in the major. The green bars show the gap when using men's skill prices for calculating the expected log wages of women. The blue bar shows the gap when using men's covariate coefficients (including the intercepts). The purple bar shows the gap when using the men's model for both women and men. The calculations for the last three bars are: (1) $(\bar{X}_i^{jw}\beta_{jw} - \bar{X}_i^{jm}\beta_{jm}) + (\bar{\theta}_i^{jw} - \bar{\theta}_i^{jm})\alpha_{jm}$; (2) $(\bar{X}_i^{jw} - \bar{X}_i^{m})\beta_{jm} + (\bar{\theta}_i^{jw}\alpha_{jw} - \bar{\theta}_i^{jm}\alpha_{jm})$; and (3) $(\bar{X}_i^{jw} - \bar{X}_i^{m})\beta_{jm} + (\bar{\theta}_i^{jw} - \bar{\theta}_i^{jm})\alpha_{jm}$ respectively.

D Model Estimates

In this Appendix we present all the model estimates. The measurement system are displayed in the first part of this Appendix D.1 and the income model estimates in the second part of this Appendix D.2.

D.1 Measurement System

Tables 3-8 show the estimates of the measurement system models.

Table 3: Estimates for 9th Grade Models

Variable	English Grade		Math Grade		PE Grade		Swedish Grade		GPA	
	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.
Adv English	-1.037	0.006								
Adv Math			-1.345	0.006						
Male					0.678	0.004				
constant									0.117	0.001
Math Grade									0.058	0.001
English Grade									0.035	0.001
PE Grade									0.048	0.001
Swedish Grade									0.210	0.001
Cognitive	0.999	0.003	0.892	0.003	-0.012	0.003	0.952	0.003	0.338	0.002
Interpersonal	0.008	0.003	0.108	0.003	0.690	0.003	0.145	0.004	0.109	0.002
Grit	0.816	0.004	0.958	0.004	0.726	0.004	1.048	0.004	0.524	0.002
Threshold 1	-4.271	0.010	-4.169	0.010	-2.816	0.008	-3.516	0.008		
Threshold 2	1.973	0.007	1.992	0.007	1.393	0.006	1.802	0.006		
Threshold 3	1.931	0.004	1.756	0.004	2.014	0.005	2.199	0.005		
Threshold 4	1.858	0.005	1.733	0.005	1.567	0.004	2.189	0.006		
1/Precision									0.348	0.001
N	502828		502828		502828		502828		502828	

Notes: Table reports estimates for the ordered probit models of the 9th grade course grades. Thresholds for the orderd probit models are reported as relative to the previous threshold. For example, threshold 2 is at the sum of estimates of threshold 1 and 2. Hence, estimates for thresholds above 1 must be greater than zero. The 9th grade GPA is estimated using a linear model. Boys have higher PE grades than girls on average, but we do not see evidence that boys have higher interpersonal skills from survey data. Hence, we allow boys to have a different intercept. We find that the correlation between survey measures of interpersonal skills and PE grades are similar for boys and girls.

Table 4: Estimates for High School Models

Variable	HS PE Grade		HS English Grade		HS Swedish Grade		HS Math Grade		HS Physics Grade		HS GPA (Vocational)		HS GPA (Academic)	
	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.
Male	0.627	0.004												
Adv English	-0.058	0.005	0.722	0.005	0.441	0.005	-0.178	0.006	-0.293	0.020	-0.025	0.002	-0.075	0.003
Adv Math	-0.044	0.005	-0.075	0.005	0.022	0.005	0.951	0.005	0.243	0.031	0.050	0.002	-0.012	0.002
HS Academic Track	-0.107	0.005	-1.044	0.005	-0.945	0.005	-1.456	0.006						
HS Academic STEM Track	-0.295	0.007	-1.101	0.007	-1.197	0.007	-1.456	0.008						
constant											0.091	0.002	0.004	0.004
Swedish Grade											0.478	0.001	0.457	0.001
PE Grade											0.204	0.001	0.095	0.001
English Grade											0.174	0.001	0.140	0.001
English Grade miss											0.037	0.003	-0.013	0.011
Math Grade											0.231	0.001	0.283	0.001
Math Grade miss											-0.030	0.002	-0.266	0.011
Physics Grade													0.172	0.001
Physics Grade miss													0.029	0.002
Cognitive	0.065	0.003	0.985	0.003	0.911	0.003	0.830	0.003	0.947	0.006	0.133	0.001	0.104	0.002
Interpersonal	0.725	0.003	-0.012	0.003	0.156	0.003	0.109	0.003	0.066	0.005	0.026	0.001	0.041	0.001
Grit	0.687	0.004	0.505	0.004	0.856	0.004	0.770	0.004	0.798	0.007	0.153	0.001	0.184	0.002
Threshold 1	-2.547	0.008	-2.819	0.008	-3.805	0.010	-2.788	0.008	-2.126	0.034				
Threshold 2	1.087	0.005	1.609	0.005	1.823	0.008	1.543	0.005	1.592	0.015				
Threshold 3	1.827	0.004	1.684	0.003	2.041	0.004	1.524	0.004	1.550	0.008				
Threshold 4	1.479	0.004	1.494	0.004	1.773	0.004	1.335	0.004	1.257	0.007				
1/Precision											0.355	0.001	0.324	0.001
N	502828		476721		502828		405696		94053		253192		241492	

Notes: Table reports estimates for the ordered probit models of the high school course grades. Thresholds for the ordered probit models are reported as relative to the previous threshold. For example, threshold 2 is at the sum of estimates of threshold 1 and 2. Hence, estimates for thresholds above 1 must be greater than zero. The high school GPA is estimated using linear models. Boys have higher PE grades than girls on average, but we do not see evidence that boys have higher interpersonal skills from survey data. Hence, we allow boys to have a different intercept. We find that the correlation between survey measures of interpersonal skills and PE grades are similar for boys and girls.

Table 5: Estimates for Military Cognitive Test Models

Variable	General (born≥ 1976)		Inductive		Verbal		Spatial		Technical	
	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.
constant	4.441	0.010	4.379	0.006	4.282	0.006	4.654	0.008	4.710	0.007
Adv English	0.430	0.012	0.585	0.008	0.803	0.008	0.020	0.010	0.108	0.009
Adv Math	0.739	0.012	0.783	0.008	0.264	0.008	0.733	0.010	0.567	0.009
HS Academic Track	0.054	0.013	0.071	0.009	0.373	0.009	-0.361	0.011	-0.486	0.011
HS Academic STEM Track	0.999	0.014	0.697	0.009	0.532	0.009	0.719	0.011	0.880	0.011
Cognitive	1.054	0.005	0.960	0.003	0.930	0.003	0.842	0.004	0.843	0.004
Interpersonal	0.000		0.000		0.000		0.000		0.000	
Grit	0.000		0.000		0.000		0.000		0.000	
1/Precision	0.960	0.004	1.059	0.002	1.028	0.002	1.454	0.003	1.314	0.002
N	62093		175885		176806		176806		168169	

Notes: Table reports estimates for the linear models of the cognitive exam sub-scores of enlisted men. The cognitive test was changed in 1976 and the military does not report cognitive subscores for most men born in 1976 and 1977.

Table 6: Estimates for Military Psychological Models

Variable	No Leadership Evaluation		Emotional Stability		Leadership	
	β	StdEr.	β	StdEr.	β	StdEr.
constant	0.261	0.007	5.013	0.008	4.609	0.009
Adv English	-0.392	0.008	0.062	0.008	0.128	0.008
Adv Math	-0.630	0.008	0.143	0.008	0.191	0.009
HS Academic Track	0.053	0.010	0.062	0.009	0.122	0.009
HS Academic STEM Track	-0.314	0.011	0.399	0.009	0.459	0.009
Cognitive	-0.905	0.005	0.429	0.004	0.546	0.004
Interpersonal	0.000		1.357	0.002	1.285	0.002
Grit	0.000		0.000		0.000	
1/Precision			0.628	0.002	0.592	0.002
N	256613		227958		157650	

Notes: Table reports estimates for the linear models of the psychological evaluation of enlisted men. Some men are not evaluated for leadership if their cognitive skill is deemed too low. We estimate a probit model for this decision (No Leadership Evaluation).

Table 7: Estimates for Taking SweSAT Models

Variable	Take SweSAT	
	β	StdEr.
constant	-0.808	0.005
Adv English	0.348	0.005
Adv Math	0.164	0.005
HS Academic Track	0.880	0.005
HS Academic STEM Track	1.068	0.007
Cognitive	0.231	0.003
Interpersonal	0.056	0.003
Grit	0.127	0.003
N	502828	

Notes: Table reports estimates for the probit model of ever taking the Swedish SAT.

Table 8: Estimates for SweSAT Score Models

Variable	Vocabulary		Reading Comprehension		English		General Information		Data Sufficiency		Interpret Diagrams, Tables, and Maps	
	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.
constant	-0.352	0.006	-0.808	0.005	-0.957	0.005	-0.850	0.009	-0.754	0.005	-0.886	0.005
Adv English	0.431	0.006	0.321	0.006	0.497	0.006	0.221	0.009	0.014	0.006	0.112	0.005
Adv Math	-0.063	0.005	0.195	0.005	0.114	0.005	0.132	0.007	0.504	0.005	0.518	0.005
HS Academic Track	-0.224	0.005	0.162	0.005	0.316	0.004	0.202	0.007	0.020	0.004	0.120	0.004
HS Academic STEM Track	-0.299	0.006	0.348	0.005	0.492	0.005	0.414	0.007	0.663	0.005	0.615	0.005
Cognitive	0.544	0.002	0.644	0.002	0.661	0.002	0.567	0.002	0.460	0.002	0.503	0.002
Interpersonal	0.000		0.000		0.000		0.000		0.000		0.000	
Grit	0.000		0.000		0.000		0.000		0.000		0.000	
1/Precision	0.819	0.001	0.675	0.001	0.616	0.001	0.779	0.001	0.721	0.001	0.694	0.001
N	254308		254315		217360		178557		254263		254241	

Notes: Table reports estimates for the linear models of the Swedish SAT sub-scores.

D.2 Wage and Earnings Models

The two-part Tables 9-10 show the estimates for the wage models for men and women, respectively, while the two-part Tables 11-12 show the corresponding estimates for the earnings models.

Table 9: Estimates for log-Wage Models for Male College Graduates (Part I)

Variable	Non-STEM (3-yr)		STEM (3-yr)		Business (3-yr)		Health Sciences		Education		Humanities	
	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.
constant	10.256	0.021	10.356	0.008	10.376	0.048	10.226	0.009	10.127	0.006	10.210	0.028
Adv English	-0.016	0.021	0.016	0.007	0.003	0.047	-0.012	0.009	0.005	0.006	-0.001	0.028
Adv Math	0.021	0.018	0.030	0.009	0.036	0.044	0.010	0.009	0.001	0.005	-0.013	0.021
HS Academic Track	0.054	0.017	0.040	0.008	0.091	0.043	-0.019	0.009	0.018	0.005	0.022	0.020
HS Academic STEM Track	0.094	0.021	0.080	0.007	0.041	0.051	0.052	0.011	0.031	0.006	0.012	0.023
Cognitive	0.042	0.007	0.027	0.003	0.111	0.017	0.037	0.004	0.027	0.003	0.037	0.009
Interpersonal	0.065	0.006	0.049	0.002	0.101	0.014	0.029	0.003	0.024	0.002	0.021	0.006
Grit	0.055	0.009	0.024	0.004	0.098	0.020	0.033	0.005	0.022	0.003	0.046	0.010
1/Precision	0.272	0.004	0.203	0.002	0.360	0.009	0.173	0.002	0.134	0.001	0.184	0.005
N	2203		8479		826		2797		4991		735	

Notes: Table reports estimates for the linear log-Wage models.

Table 9: Estimates for log-Wage Models for Male College Graduates (Part II)

Variable	Social Sciences		Science and Math		Engineering		Medicine		Business		Law	
	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.
constant	10.278	0.032	10.283	0.025	10.451	0.016	10.485	0.067	10.425	0.034	10.409	0.048
Adv English	0.002	0.032	0.014	0.022	0.015	0.012	0.079	0.066	0.021	0.032	-0.022	0.049
Adv Math	0.045	0.027	0.056	0.024	0.007	0.017	-0.026	0.050	0.024	0.029	0.005	0.035
HS Academic Track	0.047	0.027	0.087	0.019	-0.018	0.014	-0.006	0.032	0.045	0.027	0.075	0.035
HS Academic STEM Track	0.035	0.032	0.050	0.019	0.058	0.012	0.024	0.030	0.072	0.030	0.023	0.039
Cognitive	0.058	0.010	0.016	0.006	0.049	0.003	0.062	0.008	0.118	0.008	0.082	0.011
Interpersonal	0.074	0.008	0.044	0.005	0.069	0.003	0.025	0.005	0.104	0.007	0.085	0.008
Grit	0.065	0.012	0.028	0.008	0.059	0.004	0.088	0.009	0.106	0.010	0.126	0.012
1/Precision	0.300	0.006	0.251	0.003	0.229	0.002	0.204	0.004	0.345	0.005	0.307	0.006
N	1457		2679		9479		1446		2781		1283	

Notes: Table reports estimates for the linear log-Wage models.

Table 10: Estimates for log-Wage Models for Female College Graduates (Part I)

Variable	Non-STEM (3-yr)		STEM (3-yr)		Business (3-yr)		Health Sciences		Education		Humanities	
	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.
constant	10.183	0.015	10.210	0.016	10.204	0.035	10.169	0.004	10.073	0.003	10.174	0.029
Adv English	0.001	0.016	-0.003	0.015	0.009	0.035	-0.002	0.004	0.003	0.003	-0.005	0.031
Adv Math	0.008	0.009	0.043	0.014	-0.016	0.027	0.010	0.003	0.008	0.003	0.024	0.014
HS Academic Track	0.042	0.010	0.078	0.012	0.100	0.025	-0.014	0.003	0.029	0.003	-0.004	0.016
HS Academic STEM Track	0.059	0.014	0.116	0.013	0.091	0.035	0.071	0.005	0.037	0.004	-0.003	0.020
Cognitive	0.036	0.004	0.017	0.005	0.084	0.010	0.027	0.002	0.025	0.001	0.017	0.006
Interpersonal	0.041	0.006	0.046	0.006	0.078	0.013	0.017	0.002	0.021	0.002	0.002	0.009
Grit	0.065	0.006	0.043	0.007	0.075	0.014	0.033	0.002	0.028	0.002	0.043	0.009
1/Precision	0.208	0.002	0.197	0.003	0.241	0.006	0.141	0.001	0.116	0.001	0.158	0.003
N	4140		2927		1132		11088		14305		1145	

Notes: Table reports estimates for the linear log-Wage models.

Table 10: Estimates for log-Wage Models for Female College Graduates (Part II)

Variable	Social Sciences		Science and Math		Engineering		Medicine		Business		Law	
	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.
constant	10.229	0.023	10.215	0.027	10.282	0.037	10.485	0.061	10.229	0.030	10.225	0.045
Adv English	-0.013	0.023	0.027	0.025	0.006	0.029	-0.084	0.058	0.037	0.030	0.037	0.047
Adv Math	0.017	0.013	-0.025	0.022	0.044	0.031	-0.005	0.040	0.040	0.021	0.051	0.024
HS Academic Track	0.024	0.014	0.034	0.017	0.046	0.024	-0.021	0.026	0.046	0.021	0.002	0.024
HS Academic STEM Track	0.031	0.018	0.046	0.017	0.108	0.024	0.037	0.026	0.080	0.025	0.008	0.028
Cognitive	0.029	0.005	0.025	0.006	0.042	0.005	0.081	0.007	0.084	0.006	0.077	0.008
Interpersonal	0.055	0.007	0.025	0.007	0.035	0.006	0.015	0.008	0.047	0.008	0.048	0.010
Grit	0.075	0.008	0.069	0.008	0.063	0.007	0.091	0.010	0.115	0.009	0.115	0.011
1/Precision	0.194	0.003	0.212	0.003	0.199	0.002	0.179	0.004	0.252	0.003	0.245	0.004
N	2371		2860		3527		1442		2860		2015	

Notes: Table reports estimates for the linear log-Wage models.

Table 11: Estimates for log-Earnings Models for Male College Graduates (Part I)

Variable	Non-STEM (3-yr)		STEM (3-yr)		Business (3-yr)		Health Sciences		Education		Humanities	
	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.
constant	5.510	0.049	5.804	0.017	5.727	0.065	5.630	0.023	5.509	0.015	4.950	0.104
Adv English	-0.056	0.049	-0.004	0.015	-0.008	0.064	-0.025	0.025	0.009	0.016	0.169	0.106
Adv Math	0.039	0.042	0.014	0.018	0.065	0.058	-0.006	0.024	-0.007	0.014	0.006	0.079
HS Academic Track	0.034	0.039	0.049	0.016	0.089	0.056	-0.034	0.024	0.051	0.013	0.152	0.073
HS Academic STEM Track	0.056	0.048	0.107	0.014	-0.042	0.066	0.054	0.029	0.059	0.016	0.122	0.087
Cognitive	0.043	0.016	0.028	0.006	0.171	0.021	0.037	0.011	0.030	0.006	0.079	0.032
Interpersonal	0.201	0.013	0.079	0.005	0.164	0.018	0.091	0.009	0.068	0.005	0.118	0.023
Grit	0.076	0.020	0.048	0.008	0.174	0.025	0.058	0.013	0.036	0.007	0.079	0.038
1/Precision	0.863	0.010	0.535	0.003	0.614	0.012	0.541	0.006	0.391	0.003	0.965	0.018
N	3974		13705		1425		3918		6584		1394	

Notes: Table reports estimates for the linear log-Earnings models.

Table 11: Estimates for log-Earnings Models for Male College Graduates (Part II)

Variable	Social Sciences		Science and Math		Engineering		Medicine		Business		Law	
	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.
constant	5.543	0.061	5.661	0.050	5.882	0.030	5.722	0.154	5.911	0.055	5.786	0.075
Adv English	0.006	0.062	0.030	0.043	0.020	0.022	-0.042	0.144	-0.025	0.050	0.001	0.075
Adv Math	0.101	0.051	0.071	0.047	0.016	0.030	0.073	0.112	0.029	0.046	0.064	0.054
HS Academic Track	0.053	0.051	0.075	0.039	-0.023	0.026	0.113	0.069	-0.001	0.042	0.076	0.053
HS Academic STEM Track	0.022	0.060	-0.063	0.039	0.073	0.021	0.123	0.067	-0.032	0.046	0.060	0.058
Cognitive	0.055	0.018	0.025	0.013	0.032	0.005	0.114	0.017	0.154	0.013	0.103	0.017
Interpersonal	0.148	0.014	0.073	0.010	0.089	0.005	0.052	0.012	0.137	0.011	0.112	0.013
Grit	0.081	0.023	0.080	0.016	0.066	0.007	0.140	0.020	0.162	0.015	0.182	0.018
1/Precision	0.692	0.010	0.642	0.007	0.511	0.003	0.501	0.009	0.684	0.007	0.563	0.009
N	2253		4267		14758		1666		4655		1922	

Notes: Table reports estimates for the linear log-Earnings models.

Table 12: Estimates for log-Earnings Models for Female College Graduates (Part I)

Variable	Non-STEM (3-yr)		STEM (3-yr)		Business (3-yr)		Health Sciences		Education		Humanities	
	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.
constant	5.068	0.038	5.296	0.038	5.280	0.058	5.229	0.010	5.106	0.009	4.806	0.103
Adv English	0.051	0.040	-0.062	0.036	0.077	0.057	-0.006	0.011	0.021	0.011	0.002	0.109
Adv Math	0.064	0.025	0.015	0.033	-0.026	0.043	0.036	0.009	0.043	0.008	0.138	0.056
HS Academic Track	0.065	0.026	0.210	0.029	0.076	0.040	-0.048	0.009	0.055	0.008	0.090	0.058
HS Academic STEM Track	0.046	0.036	0.296	0.031	0.061	0.058	0.053	0.013	0.083	0.012	0.117	0.076
Cognitive	0.058	0.011	0.024	0.013	0.109	0.017	0.036	0.005	0.036	0.005	0.082	0.025
Interpersonal	0.087	0.015	0.073	0.015	0.078	0.021	0.040	0.006	0.056	0.006	0.082	0.034
Grit	0.095	0.016	0.039	0.018	0.129	0.023	0.038	0.006	0.039	0.006	0.062	0.035
1/Precision	0.764	0.006	0.632	0.006	0.596	0.009	0.565	0.003	0.530	0.002	0.910	0.013
N	8055		5222		2359		25055		28668		2427	

Notes: Table reports estimates for the linear log-Earnings models.

Table 12: Estimates for log-Earnings Models for Female College Graduates (Part II)

Variable	Social Sciences		Science and Math		Engineering		Medicine		Business		Law	
	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.	β	StdEr.
constant	5.109	0.054	5.273	0.062	5.372	0.074	5.290	0.132	5.379	0.049	5.305	0.094
Adv English	0.085	0.056	-0.045	0.057	0.034	0.062	-0.058	0.130	-0.035	0.047	0.038	0.097
Adv Math	0.085	0.033	0.118	0.048	0.094	0.060	0.183	0.088	0.087	0.035	0.144	0.049
HS Academic Track	0.116	0.034	0.068	0.037	0.067	0.050	-0.046	0.060	0.113	0.034	-0.053	0.051
HS Academic STEM Track	0.113	0.044	0.033	0.038	0.206	0.050	0.062	0.060	0.134	0.040	-0.046	0.059
Cognitive	0.038	0.012	0.041	0.013	0.011	0.010	0.164	0.016	0.104	0.010	0.128	0.016
Interpersonal	0.078	0.018	0.046	0.016	0.052	0.012	0.047	0.018	0.041	0.013	0.104	0.020
Grit	0.059	0.019	0.070	0.018	0.050	0.016	0.150	0.023	0.110	0.015	0.180	0.022
1/Precision	0.635	0.007	0.637	0.007	0.534	0.005	0.493	0.008	0.565	0.005	0.614	0.008
N	4136		4864		5601		2003		5373		2883	

Notes: Table reports estimates for the linear log-Earnings models.

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