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Gendered Pathways: How do STEM Majors Fare in the Labor Market?

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Abstract

Although research in the STEM field has extensively examined its gendered characteristics, the vast majority of the literature has concentrated on educational transitions and young adults. More limited attention has been devoted to the longer-term work-family trajectories of STEM majors, and how these are linked to gender earnings gaps. In response, we exploit Finnish register data to identify the most common work-family trajectories followed by college educated men and women with STEM majors in ages 30–40 (N=150,796). Given marked differences in gender proportions across STEM fields, we distinguish computer science and engineering majors from natural science majors. In a second step, we assess gender differences in the returns to distinct work-family trajectories and within-gender differences. We report three main findings. First, women are able to combine a career in computer science and engineering and having children. Second, across occupations, mothers earn considerably less than fathers. This suggests that even though women can combine work and family, they do not benefit in terms of earnings. Third, beyond uncovering gender gaps, we show that a major mechanism underlying parental gender gaps is that men receive notable fatherhood premiums across work trajectories. For women, findings reveal more heterogeneous patterns. Among computer science and engineering majors, women have similar earnings across trajectories. Conversely, women with natural science majors gain from working in computer science and engineering.

Keywords: Inequality/Social Stratification; Gender; Life Course

Introduction

In the United States and Europe, there has been growing demand for science, technology, engineering, and mathematics (STEM) skills in the labor market and a stark increase in STEM jobs (European Institute for Gender Equality 2017; Deming and Noray 2020; Atalay et al. 2020). Despite government and public initiatives to promote women in STEM, substantial gender disparities in the pursuit of STEM education and occupations persist (Prieto-Rodriguez, Sincock, and Blackmore 2020; Tekniikan akateemiset TEK 2024). However, it remains unclear what mechanisms underlie the persistent underrepresentation of women in STEM occupations and how they structure earnings disparities between men and women.

We address these questions by empirically investigating the longer-term work trajectories of men and women with STEM majors, and by linking these trajectories to observed gender earnings gaps. With the aim of gaining a more holistic understanding of individuals' trajectories, we further assess competing life course events, and in particular family formation. STEM figures centrally in policy debates and typically pertains to three education fields of study: information and communication technology (hereinafter referred to as computer science); engineering, manufacturing, and construction (hereinafter engineering); and natural science, mathematics, and statistics (hereinafter natural science) (following the ISCED 2013 classification at the two-digit level). However, gender imbalances are consistently larger in computer science and engineering than in natural science (Cimpian, Kim, and McDermott 2020; Sassler, Michelmore, and Smith 2017; White and Smith 2022). For example, in Finland the share of women in computer science and engineering has fluctuated between 15% and 30% between the years 1987 and 2022 (Figure 1). Conversely, women comprise more than half of natural science majors since 2010.¹ Assessing gender gaps

¹ The US literature shows that the proportion of women in physics is considerably lower than in other natural science fields, such as biology and chemistry. In Finnish register data, which are used here, the education field of study follows the ISCED 2013 classification (two-digit level). We are therefore unable to differentiate between

in computer science and engineering *versus* natural science, as we do here, is consequently of particular interest. We provide novel insights by addressing two research questions: (1) *How do gender proportions differ across the joint work-family trajectories of college educated computer science and engineering majors in ages 30–40, and how do these compare to natural science and non-STEM majors?* (2) *How do the trajectories relate to gender earnings gaps, measured by annual earnings in ages 41–43?*

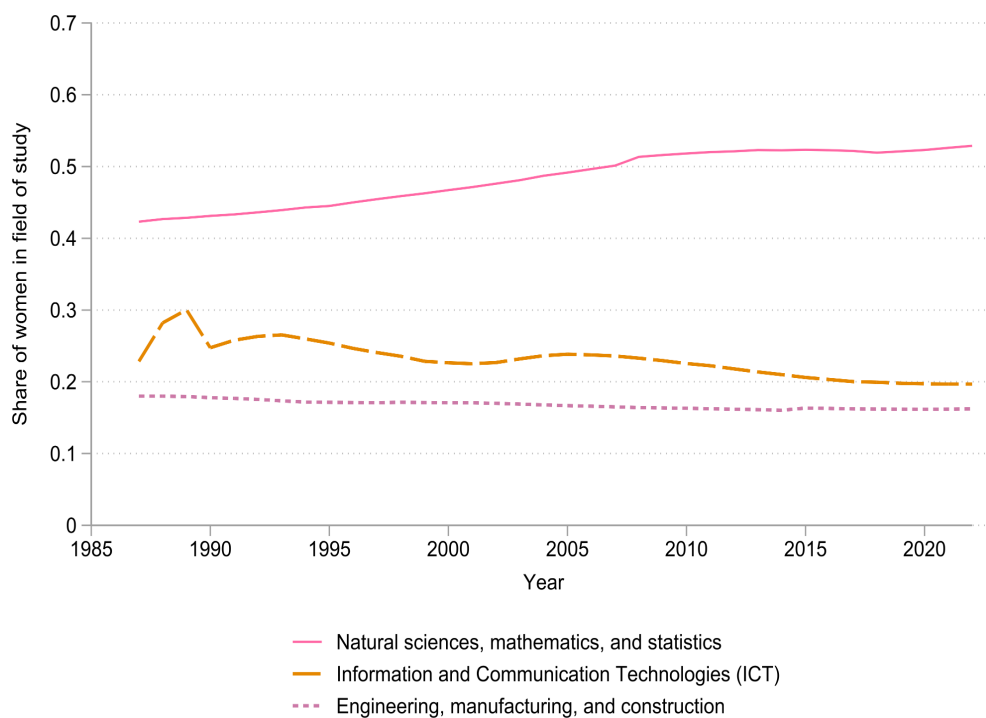


Fig.1 Share of women across STEM fields in Finland 1987–2022.

Notes: Data from authors’ calculations based on Finnish register data 1987–2022.

This study focuses on computer science and engineering majors with a college degree (or tertiary education) to illuminate gender disparities in persistently male dominated fields.

Natural science and non-STEM² majors are included as points of comparison, allowing us to

biology, biochemistry, environmental sciences, natural environments and wildlife, chemistry, earth sciences, physics, mathematics, and statistics (four-digit level).

² Non-STEM includes all fields outside of computer science and engineering, and natural science.

contrast gendered patterns in the most male dominated fields (computer science and engineering) with those observed in more gender mixed fields (natural science and non-STEM).³ This is important, because men do not necessarily serve as an appropriate benchmark for understanding women’s commitment to computer science and engineering careers. According to the *leaky pipeline* hypothesis, women are expected to disproportionately exit male dominated fields and occupations (Calhoun, Jayaram, and Madorsky 2022). However, women exhibit lower persistence than otherwise comparable men in other professional domains as well, at least in part due to family constraints (Glass et al. 2013). Including natural science and non-STEM majors thus allows us to compare women’s retention in computer science and engineering careers with that of similarly skilled women in other careers.

Beyond gender imbalances in employment, differential returns to work trajectories figure centrally in understanding gender disparities. The commonly observed fatherhood premium has been interpreted as the result of selection into parenthood (Mari 2019) and increased household specialization following parenthood (Becker 1985; 1991; Glauber 2018; Ludwig and Brüderl 2018). However, when it comes to the most male dominated fields, we continue to know less about the relationship between trajectories in later stages of adulthood and the gender earnings gap. How do the returns to distinct work-family trajectories compare between men and women? And, how do these returns differ for computer science and engineering, natural science, and non-STEM majors?

Exploiting longitudinal Finnish register data, this study assesses the longer-term trajectories of men and women with computer science and engineering majors, and the returns to these trajectories in terms of annual earnings. We contribute to the literature in three ways.

³ Figure A1 provides the share of women across STEM fields in the analytical population, showing that natural science was gender mixed in all cohorts analyzed. Figure A1 is to be compared to Figure 1, which provides shares for the total Finnish population. All tables and figures designated with an “A” appear in the online appendix.

First, our study adopts a life course perspective to illuminate gender dynamics in the STEM fields in later stages of adulthood. Prior studies have focused on gendered educational choices in STEM fields (Cimpian, Kim, and McDermott 2020; Delaney and Devereux 2019; Griffith 2010; Koch et al. 2022; Speer 2023) and gender differences in labor market entry (Sassler, Michelmore, and Smith 2017; Schwerter and Ilg 2023; White and Smith 2022). By contrast, less attention has been paid to gender disparities in the STEM fields through to the forties. Second, we examine how men and women majoring in STEM fields fare in the labor market, in terms of annual earnings. This is central in improving our understanding of the equality of earnings in the most male dominated fields. Third, we go beyond describing gaps and assess within-gender differences to gain insight into the mechanisms underlying observed gender disparities. We distinguish between gendered rewards to family and career paths and assess to what extent they differ across majors.

We situate our research in Finland, as it presents a particularly interesting case for understanding gender disparities in STEM. During the late 1980s, the Nokia company was a large employer in Finland. Since then, a sizable share of the Finnish population has continued to work in the technology industry and, on an international scale, the proportion of students majoring in computer science and engineering is higher than in most other European countries (Rouvinen and Ylä-Anttila 2003). Yet, gender disparities in these education fields and occupations remain high (Tekniikan akateemiset TEK 2024). Studying Finland further provides opportunities to work with longitudinal individual-level register data that cover the full population, and to assess gender disparities in a setting where differences likely provide lower bound estimates, because Finland follows a dual-earner or earner-carer family policy model (Korpi, Ferrarini, and Englund 2013; Tekniikan akateemiset TEK 2024).

In the following, we discuss the prior literature on gender disparities in STEM and computer science and engineering as well as the theoretical background, leading us to make

four distinct hypotheses. Then, we discuss the context, data, and methods used. Finally, we present the results and conclude.

Literature review and theoretical framework

The STEM fields play a crucial role in offering high-earning job opportunities and have been argued to drive economic growth and boost productivity (European Institute for Gender Equality 2017). Thus, the fields have undergone intense scrutiny, consistently revealing a significant underrepresentation of women within them. Women are less likely to enroll in STEM education and more prone to drop out than men (Delaney and Devereux 2019; Griffith 2010; Koch et al. 2022; Speer 2023). However, even among the select few who major in STEM, women face lower chances of being hired in the STEM sector than men with equal qualifications (Sassler, Michelmore, and Smith 2017) and they experience disproportionate attrition from STEM employment (Cech and Blair-Loy 2019). This gender imbalance is often attributed to a leaky pipeline, reflecting that despite women's interest and ability to succeed in STEM industries, their representation tends to decrease over the course of their career (Calhoun, Jayaram, and Madorsky 2022).

Although research in STEM has extensively examined its gendered characteristics, the vast majority of the literature has concentrated on educational transitions and thus primarily focused on young individuals. More limited attention has been paid to pathways beyond schooling. The growing body of literature on the labor market destinations of STEM majors is based on data from the United States and focuses on the first jobs after graduation (for some notable exceptions with evidence for the UK and Germany, see White and Smith 2022; Schwerter and Ilg 2023). Existing studies on the gendered trajectories after graduation have thus predominantly concentrated on labor market entry, leaving a notable gap in our understanding of gender dynamics in later stages of adulthood.

Gender differences in computer science and engineering

Gender disparities are particularly pronounced in computer science and engineering education fields of study and employment (Cimpian, Kim, and McDermott 2020; Sassler, Michelmore, and Smith 2017; White and Smith 2022). In the United States, gender imbalances are consistently larger in physics, engineering, and computer science than in other STEM fields, with about four men to every woman (Cimpian, Kim, and McDermott 2020). Student attributes, such as parental socioeconomic status, explain most of the gender difference among high achievers but only one third among low achievers. Other explanations include gendered educational experiences, societal gender pressures, a lack of female role models, biological differences, an inherent masculine worldview, and a chilly climate for girls and women in STEM (Blickenstaff 2005).

When it comes to employment in the computer science and engineering sector, Sassler, Michelmore, and Smith (2017) find that women who major in these fields are about ten percentage points less likely to work in STEM than their male counterparts. Women with a computer science major are particularly less prone than their male peers to work in computer science occupations (Sassler, Smith, and Michelmore 2023). Computer science and engineering majors are also the main driver of gender differences in early-career outcomes in Germany, where the transition rate into STEM occupations is lower for women than for men (Schwerter and Ilg 2023).

Examining different career stages, White and Smith (2022) find that women with STEM majors in the UK are less likely than their male peers to gain graduate-level employment, to work in highly-skilled STEM jobs, and in managerial positions in the year after graduation. These differences are largely attributable to the fact that male dominated subject areas have higher graduate employment rates. Still, within-subject differences in graduate level-work are also evident, and largest in computer science and engineering.

Among older graduates, women are underrepresented in managerial positions, and when found in managerial positions, they are less likely to work in science and industry.

Family formation has been highlighted as a potential explanation for the underrepresentation of women in STEM employment (Buffington et al. 2016; Correll, Benard, and Paik 2007; Williams, Phillips, and Hall 2016). Different domains of individuals' social lives are inherently intertwined and the accumulation of resources in one domain, such as work, tends to facilitate or hinder other life domains, such as family (Bolano and Berchtold 2021). However, the ways in which life domains interact are clearly gendered (Sirniö, Kauppinen, and Martikainen 2017). For example, family formation may hinder women's careers in STEM, while promoting men's. Yet, prior evidence remains inconclusive. Whereas Sassler, Michelmore, and Smith (2017) show that demographic characteristics and family formation account for half of the gender gap, Schwerter and Ilg (2023) find no such contribution in Germany. Assessing the propensity of computer science and engineering majors to work in the field, Sassler, Smith, and Michelmore (2023) find that family factors contribute to gender difference in employment in the field, but that half of the difference remains unexplained. This suggests that family formation may contribute at least partly to gender differences in employment in the field. This evidence leads us to our first hypothesis:

Hypothesis 1 (H1: Leaky pipeline hypothesis): Women, and particularly mothers, are underrepresented in computer science and engineering occupations relative to men.

Gender earnings gaps in STEM

The STEM sector not only lacks gender balance, but it also features earnings disparities that place women at a disadvantage (Michelmore and Sassler 2016; Cech 2013). Women have lower entry-level wages than men (Sterling et al. 2020) and their wage growth falls behind that of men (Xu 2015; Bairoh 2019). In computer science jobs, the hourly wages earned by

women are on average 13 percentage points lower than those for their male peers and compositional differences in age and family formation only explain part of these gender earnings gaps (Sassler and Meyerhofer 2023). However, in comparison to other occupations, technology and science occupations feature smaller gender earnings gaps. This has been in part attributed to higher work flexibility in the technology industry (Goldin 2014).

Across occupations, men tend to earn more than women, yet gender earnings gaps are accentuated by parenthood (Blau and Kahn 2017; Boye, Halldén, and Magnusson 2017; Kleven et al. 2024). An established literature has addressed the effects of parenthood on earnings, highlighting the role of selection into fatherhood (Mari 2019). Unobserved characteristics, such as ambition, health, and motivation, can be important for becoming a father and are simultaneously remunerated in the labor market. Likewise, fatherhood may provide a signal to employers that the person is trustworthy and dependable. In general, we do not expect that selection into fatherhood markedly differs across occupations. The impact of parenthood is thus expected to differ systematically by gender but not by occupation.

Hypothesis 2 (H2: Consistent parental gender gap hypothesis): Parents will exhibit larger gender earnings gaps compared to non-parents, and these gaps will be consistent in magnitude across occupations.

Conversely, specialization theory argues that commonly observed fatherhood premiums and motherhood penalties, or smaller motherhood premiums, are the result of increased household specialization following parenthood (Becker 1985; 1991; Bygren, Gähler, and Magnusson 2021; Glauber 2018; Jalovaara and Fasang 2020; Ludwig and Brüderl 2018). Whereas men spend more time and energy on paid work after becoming parents, women tend to shoulder greater responsibility for childcare (Glauber 2008; Killewald and García-Manglano 2016).

Fatherhood is often associated with a modest increase in housework, no change in paid work hours, and an increase in earnings (Glauber 2008; Killewald and García-Manglano 2016; Ludwig and Brüderl 2018). By contrast, motherhood tends to be associated with an increase in housework, a decrease in paid work hours, and a decrease in earnings (Glauber 2008).

Given greater work flexibility in the technology industry, specialization theory leads us to expect smaller gender earnings gaps for parents in computer science and engineering occupations relative to parents in other occupations. Substantiating this idea, studies actually indicate a positive association between motherhood and earnings in the STEM sector (Buchmann and McDaniel 2016; Michelmore and Sassler 2016), and a motherhood premium in earnings for married women (Beutel and Schleifer 2022). This leads us to expect that gender earnings gaps differ across occupations.

Hypothesis 3 (H3: CSE gender gap hypothesis): Parents in computer science and engineering occupations will experience smaller gender earnings gaps relative to parents in natural science and non-STEM occupations.

Beyond describing gaps, we illuminate potential mechanisms underlying observed disparities by assessing within-gender variation. As aforementioned, gaps may be more pronounced for parents than non-parents because fathers receive fatherhood premiums (Ludwig and Brüderl 2018; Mari 2019). Conversely, this difference may be driven by women facing motherhood penalties or smaller motherhood premiums (Bygren, Gähler, and Magnusson 2021). Prior studies indicate stronger variation by family trajectory for men's than women's earnings in Finland (Jalovaara and Fasang 2020). This leads us to expect that fatherhood premiums play a central role. With regards to differences in gender earnings gaps across work trajectories, prior evidence shows that technology and science occupations feature smaller gaps (Goldin

2014). This leads us to expect that women especially gain from pursuing computer science and engineering careers.

Hypothesis 4 (H4: Within-gender hypothesis): Fatherhood premiums and rewards accrued by women in computer science and engineering careers will help explain trajectory-specific differences in the gender earnings gap.

There is a dearth of studies addressing gender disparities in earnings among STEM majors from a life course perspective. To gain deeper insight into how women with majors in the most male dominated STEM fields fare, it is therefore crucial to take a life course perspective and examine both family and work life concurrently.

Context

Finland experienced a significant technology boom in the late 1980s, marked by the rapid expansion of Nokia and the broader technology industry. This period is commonly referred to as the Nokia boom (Rouvinen and Ylä-Anttila 2003). Although the economy faced a severe downturn in the early 1990s, recovery was facilitated by the established technology sector. Since then, the proportion of students pursuing STEM majors has remained high in Finland, and markedly higher than in Sweden, Denmark, and notably Norway, where, only 15% of students majored in STEM fields compared to Finland's 26% (Rouvinen and Ylä-Anttila 2003).

Finland further has a high degree of gender equality that is particularly apparent in the domains of education and work (European Institute for Gender Equality 2023). Education is free at all levels and a well-established system of study grants and loans provides education opportunities to everyone. Similarly, affordable high-quality day care and policies promoting

a more equitable distribution of parental leave have contributed to high labor force participation among women. Part-time employment is somewhat more common among women, although on an international comparison, it is relatively low and gender differences are small (Öun 2012; Kuitto and Kuivalainen 2021).

Yet, gender segregation both within the educational system and labor market persists. Most students in the fields of health, teaching, and humanities are women, whereas men dominate in computer science and engineering (Statistics Finland 2021). This gender disparity is significant even on an international scale, revealing differences that are similar in magnitude to the OECD average (OECD 2022). The same pattern is reflected in the labor market (Teräsaho and Närvi 2019). Across occupations, there is a 16% gender earnings gap that disadvantages women (Statistics Finland 2022). The gender earnings gap in STEM fields is at least as pronounced as in other sectors, and it tends to widen with age (Ojala 2020).

Data

Our analysis is based on Finnish individual-level register data that cover the total population between 1987 and 2022. Each person can be observed longitudinally on a rich set of demographic and socioeconomic indicators. The data provide us with information on individuals' education level and field of study. The data further provide yearly information on individuals' employment status, occupation, family situation, and earnings. All data access, data preparation, and analyses were performed within Statistics Finland's remote access system FIONA. The contract number is TK-52-694-18.

Population restrictions

We make several successive population restrictions (see Table 1). Our analysis follows six entire birth cohorts (individuals born in 1974–1979) from ages 30 to 43 (between the calendar years 2004 and 2022). We restrict our analysis to individuals who are living in Finland at the

end of every calendar year between ages 30 and 43, to avoid problems resulting from missing information (excluding 13%). We start observing individuals at age 30, as most have completed their education by this age. The average age of obtaining a master’s degree is 29 in Finland (OECD, 2024). By ages 40–43, most men and women have stable work and family situations which allows us to assess their labor market position (employment status, occupation, and earnings) and family situation (cohabitation, marriage, and parenthood).

Table 1 Population restrictions

Finnish register data	Person-years	Individuals	Percentage excluded	
Full population file	195,319,818	7,670,456		
1. Restrict to six birth cohorts	5,700,154	434,832	94%	
2. Restrict to individuals observed yearly ages 30–43	5,278,994	377,071	13%	
3. Restrict to individuals with college educ or higher	2,199,848	157,132	58%	
4. Restrict to the Finnish born population	2,112,558	150,897	4%	
5. Restrict to individuals with info on graduation year	2,111,144	150,796	0.1%	
Final population		150,796		
Education field of study		All	Male	Female
Computer science and engineering majors (CSE)		38,860	30,927	7,933
Natural science majors		5,364	1,997	3,367
Non-STEM majors		106,572	27,290	79,282

Notes: Data are from authors' calculations based on Finnish register data 1987–2022.

Subsequently, we restrict our analytical population to individuals with college degrees (excluding 58%). Disentangling the field at levels below the college degree is difficult because all students in academic tracks in high school pursue generic programs. We further restrict our analysis to the Finnish-born population and to individuals with information on all variables (excluding 4% and 0.1%, respectively). Our analytical population comprises 150,796 individuals: 38,860 computer science and engineering majors, 5,364 natural science majors, and 106,572 non-STEM majors. Our analysis of non-STEM majors is restricted to a random

sample of 40,000 individuals, as we were unable to compute the multi-channel sequence analysis on 106,572 individuals in Statistics Finland's remote access system.

Education field of study

Throughout the analysis, we differentiate between individuals who majored in: computer science and engineering, hereinafter abbreviated to CSE; natural science; and non-STEM. As aforementioned, CSE includes information and communication technology, engineering, manufacturing, and construction (based on the ISCED 2013 classification at the two-digit level). Natural science includes natural science, mathematics, and statistics. Non-STEM includes teaching, arts and humanities, social science, business, administration, and law, agriculture, health, and services. Non-STEM is included as a point of comparison to assess whether gendered patterns are specific to STEM, though it should not be over-interpreted.

Employment status and occupation

Finnish register data provide yearly information on each individual's employment status and occupation. This allows us to identify whether the person is employed or self-employed, unemployed, or outside of the labor force (e.g., a homemaker, on disability pension, studying, or in the army) at the end of each calendar year. Individuals on parental leave are recorded as employed. For individuals who work, we assess the recorded occupation.

Occupations are categorized as CSE, natural science, and non-STEM occupations. Occupational classifications available in Finnish register data have changed over time, in line with ISCO classifications. In years 2004–2009, Statistics Finland's classification of occupations 2001 is available (similar to ISCO-88 at the three-digit level). Since 2010, Statistics Finland's classification of occupations 2010 is available (following ISCO-08 at the three-digit level). In order to identify STEM occupations, we follow, to the greatest extent possible, a classification provided by the European Institute for Gender Equality (2017, 82).

Given that we have access to more detailed occupation codes (at the three- rather than two-digit level), we are further able to refine the existing categorization. We provide the full list of occupations classified as CSE and natural science occupations in Tables A1 and A2.

Given that occupation structures differ across contexts and change over time, there is no one established way of classifying STEM and CSE occupations. Whereas some studies include actuaries among CSE and technology occupations (Goldin 2014), we categorize them as natural science occupations because we cannot differentiate between mathematicians, actuaries, and statisticians (ISCO-08). Others include health scientists among STEM occupations (Goldin 2014). We are, however, unable to differentiate between health professionals and health scientists, and therefore categorize health professionals as non-STEM. With this in mind, we recognize that differences across classifications can be viewed as a source of bias in estimating gender differences. We have explored different descriptive statistics to assess our categorization in Tables A1 and A2 and Figures A2 and A3, and elaborate on these in the Appendix.

Family situation

With regard to individuals' family situation, the data provide yearly information on cohabitation and marriage, as well as whether children are in the household. This allows us to distinguish between individuals who are in couples with children (including married and cohabiting couples), in couples without children or childless couples, single parents, and singles at the end of every calendar year.

Earnings

The information on earnings is derived from tax registers and refers to total annual taxable income from employment and self-employment, alongside taxable social benefits, adjusted to 2022's prices using the consumer price index. To circumvent problems in which information

from the same ages would be used in the multi-channel sequence analysis identifying work-family trajectories and in the earnings analysis, we analyze average earnings between ages 41 and 43. This ensures that the trajectories are distinct from patterns observed in the earnings analysis.

Given that women's earnings tend to be more volatile during prime working ages than men's (Brenner 2010) and women's earnings often peak later in life than men's (Mincer and Polachek 1974), we would ideally capture earnings over a longer time frame. However, by the forties the ratio of male to female earnings has been found to stabilize and current earnings provide a reasonable proxy of lifetime earnings (Goldin 2014; Haider and Solon 2006). We therefore rely on average earnings in the early 40s to proxy differences in life time earnings (Finnish Centre for Pensions 2020).

Descriptive statistics

A larger number of women graduate from college (tertiary education) than men in Finland, with about 91,000 women in the study population graduating from college versus 60,000 men (last row of Table 2). Among those with a college degree, two thirds of men and women graduate from lower tertiary education or obtain a Bachelor degree. However, the education fields of study and occupations held by men and women point to stark gender differences. More than 50% of men major in CSE, and 40% work in such occupations at age 30. The corresponding numbers for women are 9% and 7%, respectively. The share of individuals in natural science (both in the educational system and the labor force) is considerably lower and points to smaller gender differences, with about 4% of men and women pursuing natural science in college and 2% working in commensurate occupations. We also find that a higher share of women than men is non-employed, or outside of the labor force, at age 30 (13% of women versus 5% of men). Nearly half of women who have a college degree are in couples with children at age 30, while one in three men is single at age 30.

Table 2 Education, work and family outcomes of women and men at age 30

	Men	Women		Total
Education level				
Lower tertiary	0.66	0.68	***	0.67
Upper tertiary	0.34	0.32	***	0.33
Field of study¹				
Computer science and engineering (CSE)	0.51	0.09	***	0.26
Natural science	0.03	0.04	***	0.04
Non-STEM	0.45	0.88	***	0.71
Average age finish education	27	27		27
Occupation and employment status				
Computer science and engineering (CSE)	0.39	0.07	***	0.20
Natural science	0.02	0.01	***	0.02
Non-STEM	0.50	0.75	***	0.65
Unemployed	0.04	0.04	***	0.04
Non-employed	0.05	0.13	***	0.10
Family status				
Couple with children	0.36	0.46	***	0.42
Couple without children	0.35	0.29	***	0.31
Single parent	0.01	0.03	***	0.02
Single	0.29	0.22	***	0.25
N	60,214	90,582		150,796

Notes: The population is restricted to individuals with college education. Data are from authors' calculations based on Finnish register data 1987–2022.

¹This share does not correspond to the one reported in Tables 3–5, as proportions within gender are provided here. That is, Table 2 indicates that, among college educated women, 9% major in computer science and engineering. By contrast, Tables 3–5 refer to proportions within education field of study. That is, the share of women among college educated computer science and engineering majors.

Methods

Multi-channel sequence analysis

We use multi-channel sequence analysis to study individuals' trajectories, which is a widely used approach (Jalovaara and Fasang 2020; Sirniö, Kauppinen, and Martikainen 2017; Fasang and Aisenbrey 2022; Aisenbrey and Fasang 2017). Using this method, we capture individuals' entire work and family trajectories defined by multiple discrete states between ages 30 and 40 (Abbott and Forrest 1986). For individual work trajectories, the annually measured states are defined as (1) non-employed, (2) unemployed, (3) employed in non-STEM, (4) employed in

natural science, and (5) employed in CSE. Family trajectories relate to information recorded on the couple (including non-marital cohabitation) and children. The annually measured states are (1) single, (2) single parent, (3) childless couple, and (4) couple with children.

The multi-channel sequence analysis proceeds in three steps. First, we construct a work trajectory (sequence) and a family trajectory for each individual during the observation window of eleven years (ages 30–40, years 2004–2019). In each year, an individual takes one of the five work and four family statuses. Secondly, we use optimal matching to identify similarity between sequences (MacIndoe and Abbott 2004). Similarity between any two sequences is systematically determined by the total “costs” of transforming one sequence into another, also called substitution costs (Pollock 2007; Gauthier et al. 2010). In contrast to other methods for dealing with multi-dimensional sequences, substitution costs in multi-channel sequence analysis are first specified separately for each dimension (i.e., work and family). Then, the two dimensions are aligned jointly, and the total substitution costs at each time point are summed up from the two separate cost matrices. This approach generates one large combined substitution cost matrix. Therefore, interactions between the two dimensions are taken into account by combining the separate cost matrices into one large cost matrix that spans work and family trajectories. This joint substitution cost matrix sums all possible combinations of states from the two dimensions, allowing us to use the transition probability between any two different work and family states. We have assessed other cost specifications and obtained similar results.

Thirdly, the joint substitution cost matrix is used in cluster analyses that group similar sequences. We determine the best number of clusters using Ward weighted clustering (Studer 2013). Guided by several cluster cut-off criteria (see Figure A4), we retain six clusters as the most suitable groupings. This number also proved substantively most meaningful, satisfying

the criterion of construct validity (Studer 2013). All analyses are conducted separately for CSE, natural science, and non-STEM majors.

We visualize the work-family trajectories of the six clusters using sequence distribution plots (Tables 3–5). These plots visualize the distribution of the different states by rendering a series of stacked bar charts at each position of the sequence (i.e., over age). The plots do not visualize individual trajectories, instead they display aggregated distributional information in repeated cross-sections. Gender proportions in each cluster inform about gender differences in trajectories without separating men and women a priori. Clusters are ordered with the aim of enhancing intuitive understanding and to highlight points of interest.

Earnings regressions

Having identified six clusters (i.e., the most common work-family trajectories), we assess how different clusters relate to men’s and women’s average earnings between ages 41 and 43. We analyze men and women jointly and include an interaction term between gender and cluster. This approach informs both on the earnings gaps between men and women who belong to the same cluster (i.e., follow similar work-family trajectories) and within-gender differences. We specify the model:

$$Y_i = \alpha + \beta female_i + \delta cluster_i + \mu(female_i \times cluster_i) + \gamma X_i + \epsilon_i, \quad (1)$$

where Y_i refers to average log earnings in ages 41–43 for individual i . The outcome variable is thus continuous and we estimate linear regressions with ordinary least squares. Due to the skewed distribution of earnings, we use the log transformation of the variable. The intercept is referred to as α . The term $female_i$ is a dummy indicator equal to one when individual i is female, and zero when individual i is male. β represents the corresponding coefficient vector, which gives the average difference in earnings between women and the reference category

(men). The term $cluster_i$ is a set of dummy variables that indicates the cluster individual i pertains to between ages 30 and 40, ranging from two to six. The (omitted) reference category is the first cluster. The corresponding coefficient vector, δ , provides the difference in earnings, in each cluster, compared to the reference group (the first cluster). We also include interaction terms between female and cluster. This allows the gender earnings gap to vary across clusters. μ refers to the coefficient vector for all possible combinations between the two sets of dummies (in total five coefficients, i.e., five for women). X_i is a set of time-constant control variables and γ is the corresponding coefficient vector. The control variables include educational attainment, age when finished education, being a Swedish speaker, region of residence at age 41, and occupation fixed effects (at age 41). The error term is represented by ϵ_i . We present adjusted predictions, which provide the estimated mean earnings in the six clusters for men and women (Figure 3).⁴

Results

Work-family clusters

We begin by assessing whether women are underrepresented in CSE occupations relative to men, and the extent to which this relates to having children. Table 3 presents the work and family trajectories of CSE majors obtained from multi-channel sequence analysis. Columns 2 and 3 provide sequence distribution plots for the six clusters. Thereafter, gender proportions in each cluster inform about gender differences in trajectories. We also provide the percentage of individuals (with a CSE majors) in each cluster and the total number of individuals in each cluster. The last row shows that a mere 20% of all CSE majors are women.

⁴ Adjusted predictions are estimated using the Stata command: margins, at(cluster=(1(1)6) female=(0 1)) post (Williams, 2012).

The first two clusters (from the top) comprise *parents in CSE* and *parents in non-STEM*. Based on their family trajectories, we find that individuals in both clusters tend to be in couples with children throughout their 30s. However, the clusters are distinct with regards to their work trajectories. Whereas individuals in the first cluster predominantly work in CSE occupations, individuals in the second cluster generally work in non-STEM occupations. The share of women also differs markedly across the two clusters. Whereas only 22% of parents in CSE are women, about one in three parents in non-STEM is a woman (32%). Women are thus proportionately (under)represented among parents in CSE, relative to the overall share of women among CSE majors (20%). By contrast, they are overrepresented among parents in non-STEM. Parents in CSE comprise 37% of CSE majors or the largest cluster, whereas parents in non-STEM are a smaller group (15%). In short, a considerable share of CSE majors work in CSE occupations and become parents.

The two clusters of *later parents in CSE* and *singles in CSE* comprise particularly few women. Only 14% and 12% are women in these clusters, respectively. Later parents have children in their mid-30s, whereas singles remain unpartnered and childless between ages 30 and 40. Singles in CSE are a small group (12% of all CSE majors), whereas later parents in CSE comprise 20% of CSE majors or the second largest cluster.

The remaining two clusters comprise *childless partners in CSE (mixed)* and *singles with mixed work trajectories*. About 20% of each cluster are women, which is close to the average. Among childless couples in CSE (mixed), individuals are married or live in cohabitation but do not have children throughout their 30s. A majority or more than half of childless couples in CSE (mixed) work in CSE occupations, whereas the remainder is in non-STEM occupations, unemployed, or non-employed. The terminology *mixed* aims to reflect this heterogeneity, while showing that there is one dominant occupation. Conversely, singles in mixed work trajectories are relatively evenly split across employment in CSE, employment

in non-STEM, unemployment, and non-employment. Both of these clusters are small in size, comprising 9% and 7% of CSE majors, respectively.

Table 3 Work-family trajectories of computer science and engineering majors for ages 30-40

Clusters	Work trajectories	Family trajectories	Percent women	Percent of total	N
Parents in CSE			22%	37%	14,262
Parents in Non-STEM			32%	15%	5,874
Later parents in CSE			14%	20%	7,806
Childless couples in CSE (mixed)			23%	9%	3,566
Singles in CSE			12%	12%	4,717
Singles with mixed work trajectories			22%	7%	2,635
Total			20%	100%	38,860

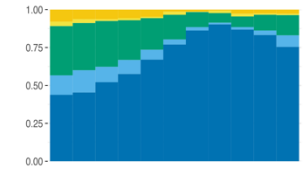
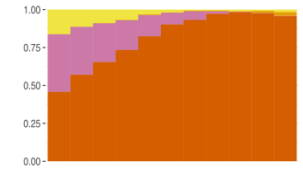

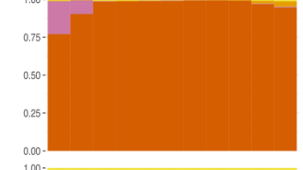
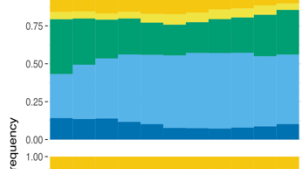


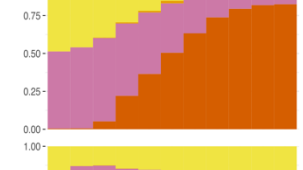


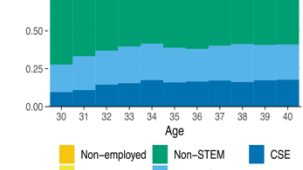
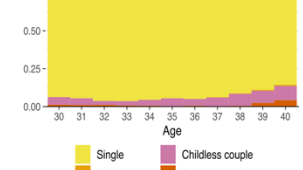


Notes: Results from sequence distribution plots presented. CSE stands for computer science and engineering. Non-STEM stands for all occupations outside of computer science and engineering and natural science. *Percent women* stands for the percentage of women in each cluster. *Percent of total* stands for the percentage of individuals (with a CSE major) in each cluster. *N* provides the total number of individuals in each cluster. Data are from authors' calculations based on Finnish register data 1987-2022.

Among natural science majors (Table 4), women are underrepresented among *parents in CSE*. That is, 63% of natural science majors are women, whereas 45% of parents in CSE are women. This cluster is relatively small, comprising 8% of natural science majors. Women are instead overrepresented in the three clusters that make up a bulk of natural science majors (67%): *parents in non-STEM*, *parents in natural science (mixed)*, and *later parents in non-STEM*.

Among non-STEM majors (Table 5), women are underrepresented in four of the six clusters: *later parents in non-STEM*, *parents in mixed work trajectories*, *childless couples in non-STEM*, and *singles in non-STEM*. That is, 75% of non-STEM majors are women, whereas women make up less than 70% of each of these clusters. Conversely, women are overrepresented among *parents in non-STEM* and *single parents in non-STEM*. We also find that nearly 50% of non-STEM majors are represented by the cluster *parents in non-STEM*.


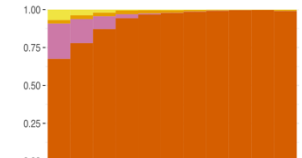

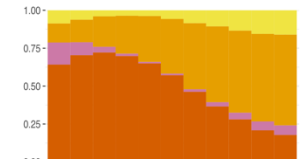

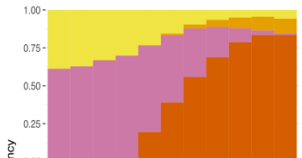

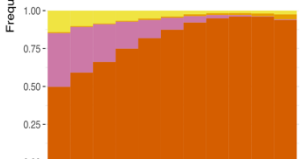






These findings provide mixed support for H1, which posits that women, and particularly mothers, are underrepresented in CSE occupations. On the one hand, women are underrepresented in CSE careers, but more strongly when these careers are coupled with later parenthood and staying single than with parenthood. This indicates that family constraints are not the main deterring factor, which keeps women from pursuing a career in CSE. On the other hand, among CSE majors women are the most strongly overrepresented among parents in non-STEM. This suggests that factors, such as a chilly climate for women in STEM and a lack of female role models, likely contribute to women leaving CSE. We likewise find that about 4% of men and 5% of women, who worked in CSE occupations at age 30, have left these occupations by age 40. In natural science and non-STEM, few majors pursue CSE occupations, and yet the small group of natural science majors who go on to work in CSE are the cluster in which women are the most strongly underrepresented.

Table 4 Work-family trajectories of natural science majors for ages 30-40

Clusters	Work trajectories	Family trajectories	Percent women	Percent of total	N
Parents in CSE			45%	8%	443
Parents in Non-STEM			69%	22%	1,180
Parents in Natural Science (mixed)			69%	29%	1,566
Later parents in Non-STEM			67%	16%	866
Childless couples in mixed work trajectories			60%	12%	620
Singles in mixed work trajectories			49%	13%	689
Total			63%	100%	5,364

Notes: Results from sequence distribution plots presented. CSE stands for computer science and engineering. Non-STEM stands for all occupations outside of computer science and engineering and natural science. *Percent women* stands for the percentage of women in each cluster. *Percent of total* stands for the percentage of individuals (with a natural science major) in each cluster. *N* provides the total number of individuals in each cluster. Data are from authors' calculations based on Finnish register data 1987-2022.

Table 5 Work-family trajectories of non-STEM majors for ages 30-40

Clusters	Work trajectories	Family trajectories	Percent women	Percent of total	N
Parents in Non-STEM			78%	48%	19,024
Single parents in Non-STEM			83%	10%	4,066
Later parents in Non-STEM			71%	12%	4,674
Parents in mixed work trajectories			70%	10%	3,910
Childless couples in Non-STEM			71%	7%	2,861
Singles in Non-STEM			65%	14%	5,465
Total			75%	100%	40,000

Notes: Results from sequence distribution plots presented. CSE stands for computer science and engineering. Non-STEM stands for all occupations outside of computer science and engineering and natural science. *Percent women* stands for the percentage of women in each cluster. *Percent of total* stands for the percentage of individuals (with a non-STEM major) in each cluster. *N* provides the total number of individuals in each cluster. Data are from authors' calculations based on Finnish register data 1987-2022.

Gender earnings gap

Next, we assess gender differences in the returns to distinct work-family trajectories using log earnings in ages 41–43. We begin by plotting the distribution of men’s and women’s earnings across education fields of study (Figure 2). Women tend to earn less than men in all fields. Yet, gender differences are more pronounced for CSE and non-STEM majors than for natural science majors. Log earnings are close to normally distributed, motivating our methodological choice to estimate linear regressions with ordinary least squares in the subsequent analysis.

Figure 3 presents estimates based on Equation 1. Models are estimated separately for CSE, natural science, and non-STEM majors and reported as adjusted predictions. We provide the coefficients and standard errors of the control variables in Table A3. This table shows that few individuals, or less than 150, were excluded due to zero income.

Figure 3 shows that women earn less than men, but gender earnings gaps differ substantively across clusters. Among CSE majors (top panel), gender earnings gaps are most pronounced among parents in CSE, parents in non-STEM, and later parents in CSE. By contrast, gender differences are smaller for childless couples in CSE (mixed) and singles in CSE, when we compare individuals with similar individual level characteristics and who work in the same occupations. Differences in the gender earnings gaps are largely attributable to across-cluster-variation in men’s earnings. That is, women have similar earnings across clusters, while men appear to receive a strong fatherhood premium. The sizeable gender earnings gaps observed in the clusters parents in CSE, parents in non-STEM, and later parents in CSE are therefore attributable to men receiving higher earnings. We observe an outlier group of singles in mixed work trajectories, in which men and women have much lower earnings and experience no gender differences.

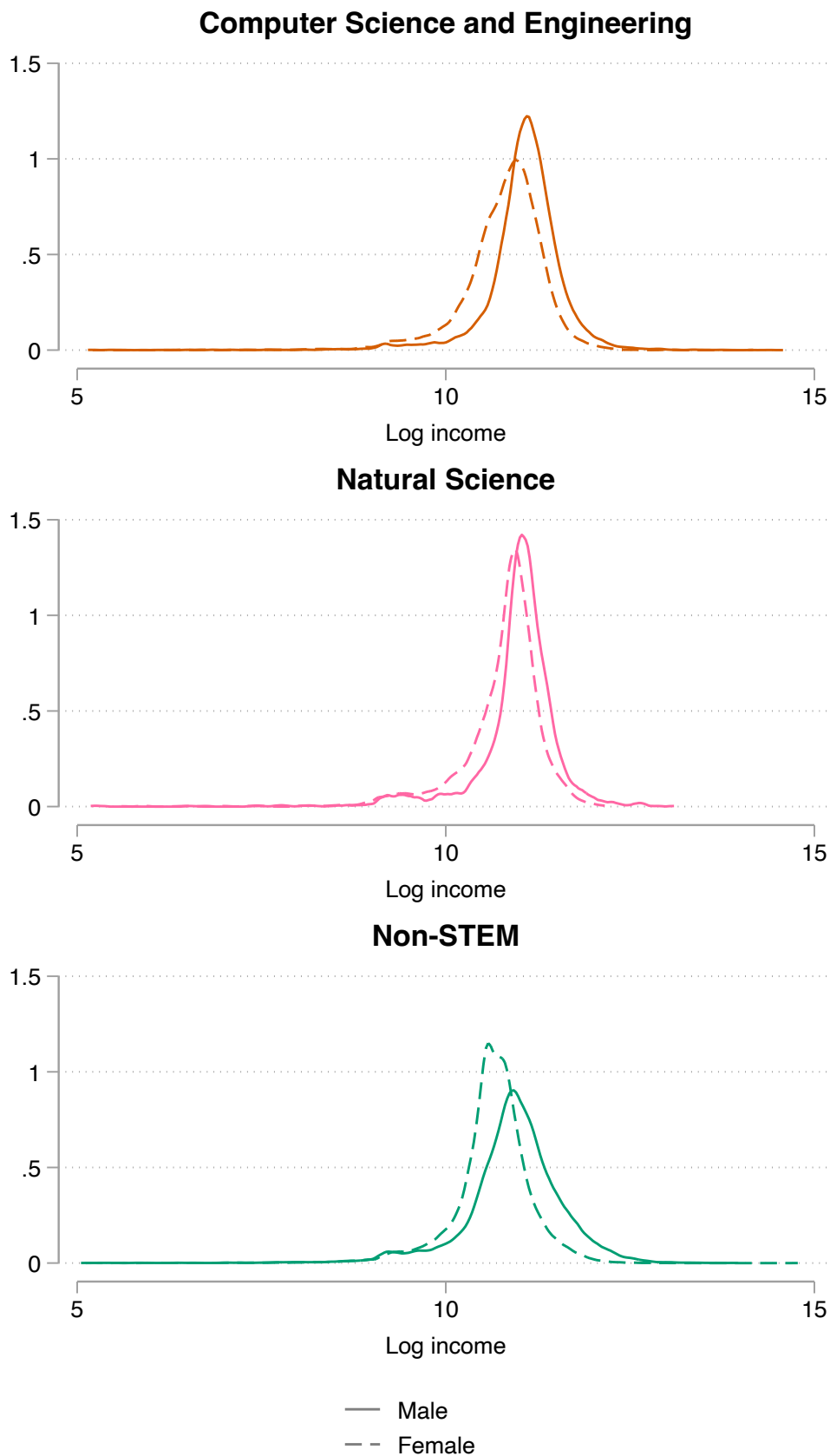


Fig. 2 Earnings distribution across education fields of study and gender.

Note: Figures provide results from kernel density estimations of the average log earnings in ages 41–43. Note that outliers are excluded. Data from authors’ calculations based on Finnish register data 1987–2022.

Gender disparities are less pronounced among natural science majors (middle panel). Still, we also find significant gender earnings gaps, and particularly so among parents in natural science (mixed) and later parents in non-STEM. We observe the same outlier group of singles in mixed work trajectories, who are characterized by lower earnings and no gender earnings gap. In contrast to the patterns observed for CSE majors, we find that men's *and* women's earnings differ across clusters.

Among non-STEM majors (bottom panel), the gender earnings gap is largest for parents in mixed work trajectories. It is also sizeable for parents in non-STEM, single parents in non-STEM, and later parents in non-STEM. Similar to patterns observed among natural science majors, earnings vary across clusters for men and women. We also note an outlier group of singles in non-STEM, for whom we observe no gender earnings gap.

These findings corroborate H2, which posits the existence of consistent parental gender gaps across occupations, rather than H3, which posits reduced gaps in CSE. They are also consistent with H4, which predicts fatherhood premiums to play a considerable role. Still, patterns are more heterogeneous when it comes to the rewards accrued by women in CSE careers. Among CSE majors, the larger gender earnings gaps observed for parents appear fully attributable to men's fatherhood premium, as women's earnings do not vary across clusters. Even though some women are therefore able to combine CSE employment and parenthood, they do not seem to benefit in terms of earnings. We similarly observe a fatherhood premium among natural science and non-STEM majors, but women who major in these fields also benefit from different career choices.

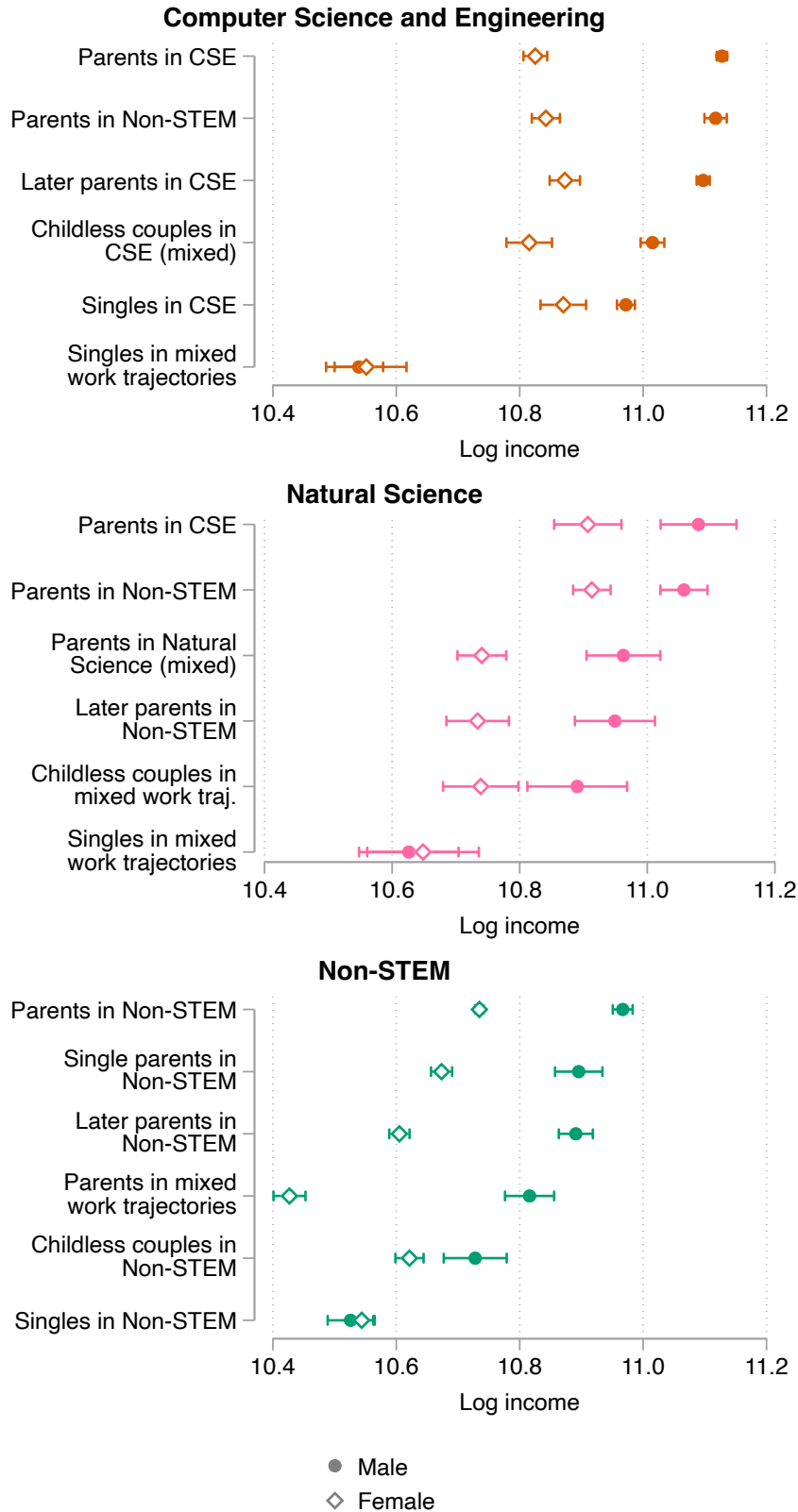


Fig. 3 Gender earnings gaps across majors and clusters.

Note: Figures provide the estimated earnings from Equation 1. Adjusted predictions are reported. Regressions are estimated separately for computer science and engineering (CSE), natural science, and non-STEM majors. Coefficients and standard errors are provided in Table A3. Data from authors' calculations based on Finnish register data 1987–2022.

Sensitivity analysis

We ran sensitivity analyses excluding individuals on parental leave anytime in ages 41–43 (Figure A5). They revealed similar patterns to those presented in the main analysis, although gender earnings gaps were not statistically significant for singles in CSE and childless couples in mixed work trajectories.

We also ran the main analysis focusing on the first three birth cohorts, in order to assess whether our results capture earnings shocks related to the COVID-19 pandemic (Figure A6). The results reveal similar patterns, though some gender earnings gaps that were small in the main analysis, are not statistically significant.

Finally, we assessed individuals' earned income from employment in ages 41–43, rather than relying on individuals' total taxable income (Figure A7). The results reveal similar gender differences, although the overall values are lower because earned income from employment excludes social benefits.

Discussion and conclusion

This study has assessed gender differences in the longer-term work trajectories of college educated computer science and engineering majors, and how they are linked to family formation. Exploiting longitudinal Finnish register data, we used multi-channel sequence analysis to identify individuals' joint work (employment status and occupation) and family trajectories (couple and children) in ages 30–40. We further assessed gender differences in lifetime earnings by comparing men and women with similar work-family trajectories, and within-gender differences.

The analysis revealed three main findings. First, we found that women are able to combine a career in computer science and engineering and having children. This suggests that family constraints related to having children are not the main deterring factor that keeps

women from pursuing a career in computer science and engineering. This could be facilitated by the fact that the technology industry provides work flexibility (Goldin 2014). Notably, we found that women are more strongly underrepresented in computer science and engineering careers when following non-normative (later parenthood and staying single between 30 and 40) rather than normative family trajectories (parenthood). Strong cultural norms that promote stable marriage with children may pose significant challenges for individuals who do not follow these traditional pathways in Finland, and may be particularly pronounced for those in gender-mismatched occupations (Jalovaara and Fasang 2020; Thomson, Winkler-Dworak, and Kennedy 2013).

Yet, women are strongly overrepresented among parents in non-STEM, whereas they are proportionally represented among parents in computer science and engineering. This suggests that work flexibility promotes mothers in computer science and engineering occupations, but only to a certain extent. Societal gender pressures, a lack of female role models, a chilly climate for women in STEM, and gender discrimination, among others, likely present barriers that keep women out of these male dominated sectors (Blickenstaff 2005). Our findings thus provide mixed support for the leaky pipeline hypothesis (H1), according to which women, and particularly mothers, are underrepresented in computer science and engineering occupations (Calhoun, Jayaram, and Madorsky 2022; Glass et al. 2013). On the one hand, we did find that women tend to be underrepresented in computer science and engineering occupations, which goes in line with prior evidence from the United States (Sassler, Michelmore, and Smith 2017; Sassler, Smith, and Michelmore 2023). On the other hand, our findings point to important variation across family trajectories. Whereas mothers proportionally pursue computer science and engineering careers, non-normative family trajectories are more clearly linked with an underrepresentation in computer science and engineering careers.

Second, the returns to combining a career in computer science and engineering with parenthood are much lower for women than for men. In broader terms, we found that the gender earnings gap is largest for parents and consistently so across occupations, corroborating H2, which posits that parents exhibit larger gender earnings gaps than non-parents and that these gaps are consistent in magnitude across occupations. This result qualifies the CSE gender gap scenario (H3) following the specialization theory (Becker 1985; 1991) and suggests that mothers face similar earnings gaps in male dominated and gender mixed occupations. It further suggests that work flexibility enables women to combine work with family, but does not reduce the earnings gap between fathers and mothers in computer science and engineering as these industries are simultaneously characterized by a high prevalence of “greedy jobs” (Goldin 2021).

Third, we found that, even though larger gender gaps observed for parents are consistent across occupations, they stem from different underlying within-gender differences. Distinct mechanisms may consequently be at play. The larger gender gaps observed for parents were expected to result from men earning more when they become fathers (H4). Consistent with this expectation and past research (Jalovaara and Fasang 2020; Bygren, Gähler, and Magnusson 2021; Ludwig and Brüderl 2018), our findings confirm this expectation: men’s earnings differ considerably by family status and indicate a clear fatherhood premium. Conversely, work trajectories appear less important for men’s earnings.

For women, patterns are more heterogeneous and indicate distinct rewards for pursuing a career in computer science and engineering. Among computer science and engineering majors, women’s earnings remain constant across work and family trajectories. Mothers in computer science and engineering experience neither motherhood premiums nor child related career costs. This finding paints a more pessimistic picture than prior evidence from the United States, which indicates a positive association between motherhood and

earnings in the STEM sector (Buchmann and McDaniel 2016; Michelmore and Sassler 2016; Beutel and Schleifer 2022). These differences might reflect that we distinguish computer science and engineering from natural science (in the latter, we observe indications of a motherhood premium).

By contrast, among natural science and engineering majors women's earnings vary across work trajectories. Women with a STEM major earn considerably less when they follow mixed work trajectories as compared to other career paths. This is likely due to the fact that women are more often homemakers in this cluster. Even though men also experience a reduction in earnings in this cluster, it is less severe than for women.

Among natural science majors, women earn more when they move into computer science and engineering and non-STEM careers, while we do not observe the same rewards among computer science and engineering majors. This distinction may be due to differences in how women select into computer science and engineering occupations across these two majors. They may also be related to differences in the subfield and work activity pursued (Goldin 2014). Women tend to be segregated into the less core technical subfields and social work activities, and this seems to be particularly the case for women who major in the field (White and Smith 2022). Conversely, women with a major in natural science may be more likely to pursue "greedy jobs" within these occupations, entering more prestigious and higher-paid positions (Goldin 2021). This will be important to explore further in future research.

Our study has some limitations that future research could help address. First, we are unable to address selection. Individuals select into their education fields of study and subsequent work-family trajectories. We expect that selection into fatherhood plays a non-negligible role in understanding observed parent gaps but were unable to examine this directly. Still, here we aimed at comparing individuals across different trajectories. Second, we assess individuals' earnings in ages 41–43. We would ideally follow individuals over a

longer time period, but are restricted by the statistical years available. Third, we analyze men and women, but do not capture individuals' partners. This will be pertinent for gaining a better understanding of gender inequalities at the individual versus the family level in future research.

In conclusion, we make three key contributions. First, we extend STEM research by adopting a longitudinal perspective to assess joint work and family trajectories in later stages of adulthood, revealing that women are able to combine employment in computer science and engineering and parenthood. Second, we assess individuals' earnings and show that, despite combining work and family, women earn considerably less than their male counterparts. Third, in addition to uncovering gender gaps, we show that a major mechanism underlying parental gaps is that men receive notable fatherhood premiums across education fields of study and work trajectories. For women, findings reveal more heterogeneous patterns. Among computer science and engineering majors, women have similar earnings across trajectories. In natural science and non-STEM, women gain from pursuing computer science and engineering and non-STEM careers.

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Appendix

We have further explored two sets of descriptive statistics to assess our categorization of CSE, natural science, and non-STEM occupations: the top ten occupations of computer science and engineering majors, and the top ten occupations by gender.

Tables A1 and A2 show that about half of computer science and engineering majors work in three occupations: (1) architects and engineering science professionals, (2) physical, chemical, and engineering science technicians, and (3) computing professionals (2001 classification), and (1) engineering professionals, (2) software and applications developers and analysts, and (3) physical and engineering science technicians (2010 classification). By contrast, natural science majors are often teachers and administrative professionals, besides life science, physical, and earth science professionals.

Given that men and women pursue distinct occupations, we also provide the top ten occupations by gender for CSE, natural science, and non-STEM majors in Figures A2 (2001 classification) and A3 (2010 classification). Gender differences are relatively small among CSE majors, although men are more often physical, chemical, and engineering science technicians (Figure A2). Women are instead more often architects, planners, surveyors, and designers (Figure A3). Among non-STEM majors, gender differences are more notable. About 15% of women are in nursing compared with about 4% of men (Figures A2 and A3), whereas men are most often finance and sales associate professionals and business professionals (2001 classification), or sales and purchasing agents and brokers (2010 classification).

Table A1 List of computer science and engineering and natural science occupations and the fraction of computer science and engineering and natural science majors working in each occupation, based on Statistics Finland's classification of occupations 2001 (relied on for years 2004-2009)

Occupation code	Occupation name	Fraction of CSE majors ¹	Fraction of natural science majors ²
Computer Science and Engineering			
213	Computing professionals	0.14	0.02
214	Architects and engineering science professionals	0.24	0.05
311	Physical, chemical, and engineering science technicians	0.24	0.06
312	Computer associate professionals	0.04	0.01
711	Miners, shotfirers, stone cutters and carvers	0.01	0.00
712	Building frame and related trades workers	0.01	0.00
713	Building finishers and related trades workers	0.01	0.00
714	Painters, building structure cleaners and related trades workers	0.01	0.00
721	Metal moulders, sheet-metal workers, structural metal preparers, and related trades workers	0.01	0.00
722	Blacksmiths, tool-makers and related trades workers	0.01	0.00
723	Machinery mechanics and fitters	0.01	0.00
724	Electrical, electronic and telecommunications equipment mechanics and fitters	0.01	0.01
811	Mining and mineral-processing-plant operators	0.01	0.00
812	Metal-processing plant operators	0.01	0.00
814	Wood-processing- and papermaking-plant operators	0.01	0.01
816	Power-production and related plant operators	0.01	0.01
817	Industrial robot operators	0.01	0.00
821	Metal- and mineral-products machine operators	0.01	0.00
823	Rubber- and plastic-products machine operators	0.01	0.00
824	Wood-products machine operators	0.01	0.00
Natural Science, Mathematics and Statistics			
211	Physicists, chemists, and related professionals	0.01	0.11
212	Mathematicians, statisticians and related professionals	0.01	0.02
221	Life science professionals	0.01	0.08
321	Life science technicians and related associate professionals	0.01	0.01
813	Glass, ceramics and related plant operators	0.01	0.00
815	Chemical-processing-plant operators	0.01	0.01
822	Chemical-products machine operators	0.01	0.00
Top Ten Occupations for Computer Science and Engineering Majors			
214	Architects and engineering science professionals	0.24	
311	Physical, chemical, and engineering science technicians	0.24	
213	Computing professionals	0.14	
341	Finance and sales associate professionals	0.05	
312	Computer associate professionals	0.04	
247	Public service administrative professionals	0.03	
123	Other specialist managers	0.02	
241	Business professionals not elsewhere classified	0.02	
522	Shop, stall and market salespersons and demonstrators	0.01	
122	Production and operations managers	0.01	
Top Ten Occupations for Natural Science Majors			
232	Secondary education teaching professionals	0.23	
247	Public service administrative professionals	0.16	
211	Physicists, chemists and related professionals	0.11	
221	Life science professionals	0.08	
311	Physical, chemical and engineering science technicians	0.06	
214	Architects and engineering science professionals	0.05	
231	College, university and higher education teaching professionals	0.04	
222	Health professionals (except nursing)	0.02	
322	Health associate professionals (except nursing)	0.02	
213	Computing professionals	0.02	

Notes: The prevalence of the occupation at age 30 is reported. Data are from authors' calculations. Data are from authors' calculations based on Finnish register data 1987-2022.

¹ Individuals who studied and majored in computer science and engineering (CSE).

² Individuals who studied and majored in natural science.

Table A2 List of computer science and engineering and natural science occupations and the fraction of computer science and engineering and natural science majors working in each occupation, based on Statistics Finland's classification of occupations 2010 (following the structure of ISCO-08, relied on for years 2010 and onwards)

Occupation code	Occupation name	Fraction of CSE majors ¹	Fraction of natural science majors ²
Computer Science and Engineering			
132	Manufacturing, mining, construction, and distribution managers	0.04	0.01
133	ICT service managers	0.02	0.01
214	Engineering professionals (excl. electrotechnology)	0.16	0.04
215	Electrotechnology engineers	0.08	0.01
216	Architects, planners, surveyors and designers	0.02	0.01
251	Software and applications developers and analysts	0.15	0.03
252	Database and network professionals	0.02	0.01
311	Physical and engineering science technicians	0.12	0.04
312	Mining, manufacturing, and construction supervisors	0.01	0.00
313	Process control technicians	0.01	0.01
351	ICT operations and user support technicians	0.03	0.01
352	Telecommunications and broadcasting technicians	0.01	0.00
711	Building frame and related trades workers	0.01	0.00
712	Building finishers and related trades workers	0.01	0.00
713	Painters, building structure cleaners and related trades workers	0.01	0.00
721	Sheet and structural metal workers and moulders and welders, and related workers	0.01	0.00
722	Blacksmiths, toolmakers and related trades workers	0.01	0.00
723	Machinery mechanics and repairers	0.01	0.00
741	Electrical equipment installers and repairers	0.01	0.00
811	Mining and mineral processing plant operators	0.01	0.00
812	Metal processing and finishing plant operators	0.01	0.00
814	Rubber, plastic and paper products machine operators	0.01	0.00
817	Wood processing and papermaking plant operators	0.01	0.00
818	Other stationary plan and machine operators	0.01	0.00
Natural Science, Mathematics and Statistics			
211	Physical and earth science professionals	0.01	0.11
212	Mathematicians, actuaries, and statisticians	0.01	0.02
213	Life science professionals	0.01	0.11
314	Life science technicians and related associate professionals	0.01	0.01
813	Chemical and photographic products plant and machine operators	0.01	0.01
Top Ten Occupations for Computer Science and Engineering Majors			
214	Engineering professionals (excl. electrotechnology)	0.16	
251	Software and applications developers and analysts	0.15	
311	Physical and engineering science technicians	0.12	
215	Electrotechnology engineers	0.08	
332	Sales and purchasing agents and brokers	0.04	
243	Sales, marketing, and public relations professionals	0.04	
132	Manufacturing, mining, construction, and distribution managers	0.04	
351	ICT operations and user support technicians	0.03	
242	Administration professionals	0.03	
216	Architects, planners, surveyors, and designers	0.02	
Top Ten Occupations for Natural Science Majors			
233	Secondary education teachers	0.19	
213	Life science professionals	0.11	
211	Physical and earth science professionals	0.11	
242	Administration professionals	0.05	
311	Physical and engineering science technicians	0.04	
231	University and higher education teachers	0.04	
214	Engineering professionals (excl. electrotechnology)	0.04	
234	Primary school and early childhood teachers	0.03	
251	Software and applications developers and analysts	0.03	
235	Other teaching professionals	0.03	

Notes: The prevalence of the occupation at age 40 is reported. Data are from authors' calculations based on Finnish register data 1987-2022.

¹ Individuals who studied and majored in computer science and engineering (CSE).

² Individuals who studied and majored in natural science.

Table A3 Coefficients from ordinary least squares regressions on the average earnings of computer science and engineering, natural science, and non-STEM majors in ages 41-43 across clusters and gender

	Computer Science and Engineering		Natural Science		Non-STEM			
	(1)	(2)	(1)	(2)	(1)	(2)		
<i>Cluster (ref. Parents in CSE)</i>			<i>Cluster (ref. Parents in CSE)</i>		<i>Cluster (ref. Parents in Non-STEM)</i>			
Parents in Non-STEM	-0.01 (0.01)	-0.01 (0.01)	Parents in non-STEM	-0.09* (0.03)	-0.02 (0.04)	Single parents in Non-STEM	-0.08*** (0.02)	-0.07*** (0.02)
Later parents in CSE	-0.04*** (0.01)	-0.03*** (0.01)	Parents in Natural Science (mixed)	-0.12*** (0.04)	-0.12** (0.04)	Later parents in Non-STEM	-0.10*** (0.02)	-0.08*** (0.02)
Childless couples in CSE (mixed)	-0.14*** (0.01)	-0.11*** (0.01)	Later parents in Non-STEM	-0.24*** (0.04)	-0.13** (0.05)	Parents in mixed work trajectories	-0.12*** (0.02)	-0.15*** (0.02)
Singles in CSE	-0.19*** (0.01)	-0.16*** (0.01)	Childless couples in mixed work trajectories	-0.25*** (0.05)	-0.19*** (0.05)	Childless couples in Non-STEM	-0.30*** (0.03)	-0.24*** (0.03)
Singles in mixed work traj.	-0.70*** (0.02)	-0.59*** (0.01)	Singles in mixed work traj.	-0.57*** (0.05)	-0.45*** (0.05)	Singles in Non-STEM	-0.54*** (0.02)	-0.44*** (0.02)
<i>Gender (ref. Male)</i>			<i>Gender (ref. Male)</i>		<i>Gender (ref. Male)</i>			
Female	-0.37*** (0.01)	-0.30*** (0.01)	Female	-0.22*** (0.04)	-0.17*** (0.04)	Female	-0.32*** (0.01)	-0.23*** (0.01)
<i>Cluster × Female (ref. Parents in CSE × Female)</i>			<i>Cluster × Female (ref. Parents in CSE × Female)</i>		<i>Cluster × Female (ref. Parents in Non-STEM × Female)</i>			
Parents in Non-STEM × Female	-0.01 (0.02)	0.03 (0.02)	Parents in Non-STEM × Female	-0.01 (0.04)	0.03 (0.04)	Single parents in Non-STEM × Female	0.01 (0.03)	0.01 (0.02)
Later parents in CSE × Female	0.11*** (0.02)	0.08*** (0.02)	Parents in Natural Science (mixed) × Female	-0.12* (0.05)	-0.05 (0.05)	Later parents in Non-STEM × Female	-0.04 (0.02)	-0.05** (0.02)
Childless couples in CSE (mixed) × Female	0.11*** (0.02)	0.10*** (0.02)	Later parents in Non-STEM × Female	-0.02 (0.06)	-0.04 (0.05)	Parents in mixed work traj. × Female	-0.23*** (0.03)	-0.16*** (0.02)
Singles in CSE × Female	0.25*** (0.02)	0.20*** (0.02)	Childless couples in mixed work traj. × Female	-0.03 (0.06)	0.02 (0.06)	Childless couples in Non-STEM × Female	-0.18*** (0.03)	0.13*** (0.03)
Singles in mixed work traj. × Female	0.38*** (0.04)	0.31*** (0.04)	Singles in mixed work traj. × Female	0.21** (0.07)	0.20** (0.07)	Singles in Non-STEM × Female	0.31*** (0.03)	0.25*** (0.02)
<i>Education (ref. Lower tertiary education)</i>			<i>Education (ref. Lower tertiary education)</i>		<i>Education (ref. Lower tertiary education)</i>			
Upper tertiary education	0.22*** (0.01)	0.17*** (0.01)	Upper tertiary education	0.36*** (0.05)	0.23*** (0.05)	Upper tertiary education	0.32*** (0.01)	0.22*** (0.01)
<i>Age finish education (ref. below age 25)</i>			<i>Age finish education (ref. below age 25)</i>		<i>Age finish education (ref. below age 25)</i>			
25-29	-0.03*** (0.01)	-0.03*** (0.01)	25-29	-0.10** (0.04)	-0.07 (0.04)	25-29	-0.02*** (0.01)	-0.01 (0.01)
30+	-0.03** (0.01)	-0.03** (0.01)	30+	-0.07 (0.04)	-0.07 (0.04)	30+	0.07*** (0.01)	0.03 (0.01)
Swedish speakers (ref. Finnish speakers)	0.01 (0.02)	0.01 (0.02)	Swedish speakers (ref. Finnish speakers)	0.09* (0.04)	0.07 (0.04)	Swedish speakers (ref. Finnish speakers)	0.02 (0.02)	0.02 (0.02)
Region of residence FE	Yes	Yes	Region of residence FE	Yes	Yes	Region of residence FE	Yes	Yes
Occupation FE		Yes	Occupation FE		Yes	Occupation FE		Yes
Constant	10.93*** (0.06)	10.76*** (0.06)	Constant	10.96*** (0.09)	10.60*** (0.15)	Constant	10.85*** (0.06)	10.65*** (0.05)
R ²	0.20	0.29	R ²	0.14	0.27	R ²	0.19	0.32
N ¹	38,746	38,746	N ²	5,328	5,328	N ³	39,854	39,854

Notes: Robust standard errors in parentheses. Time varying characteristics (region of residence and occupation) are measured at age 41. Data are from authors' calculations based on Finnish register data 1987-2022.

¹Observations with zero income are excluded from the total of 38,860 (N=114).

²Observations with zero income are excluded from the total of 5,364 (N=36).

³Observations with zero income are excluded from the total of 40,000 (N=146).

* p < 0.05; ** p < 0.01; *** p < 0.001 (two-tailed).

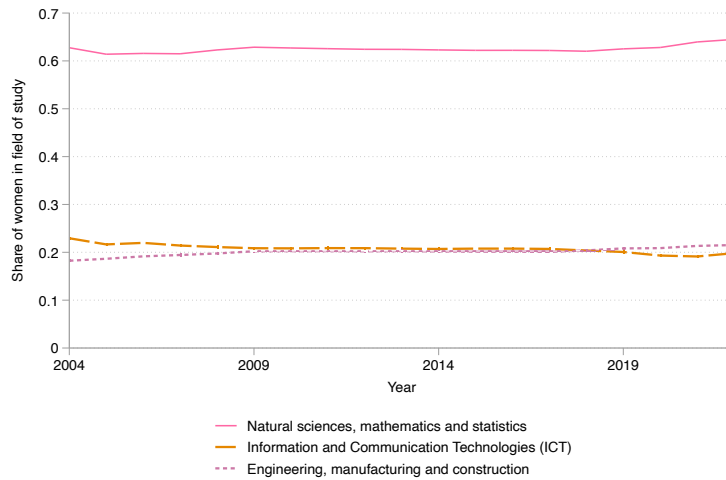


Fig.A1 Share of women across STEM fields in Finland in the analytical population.
Notes: Data from authors' calculations based on Finnish register data 1987–2022.

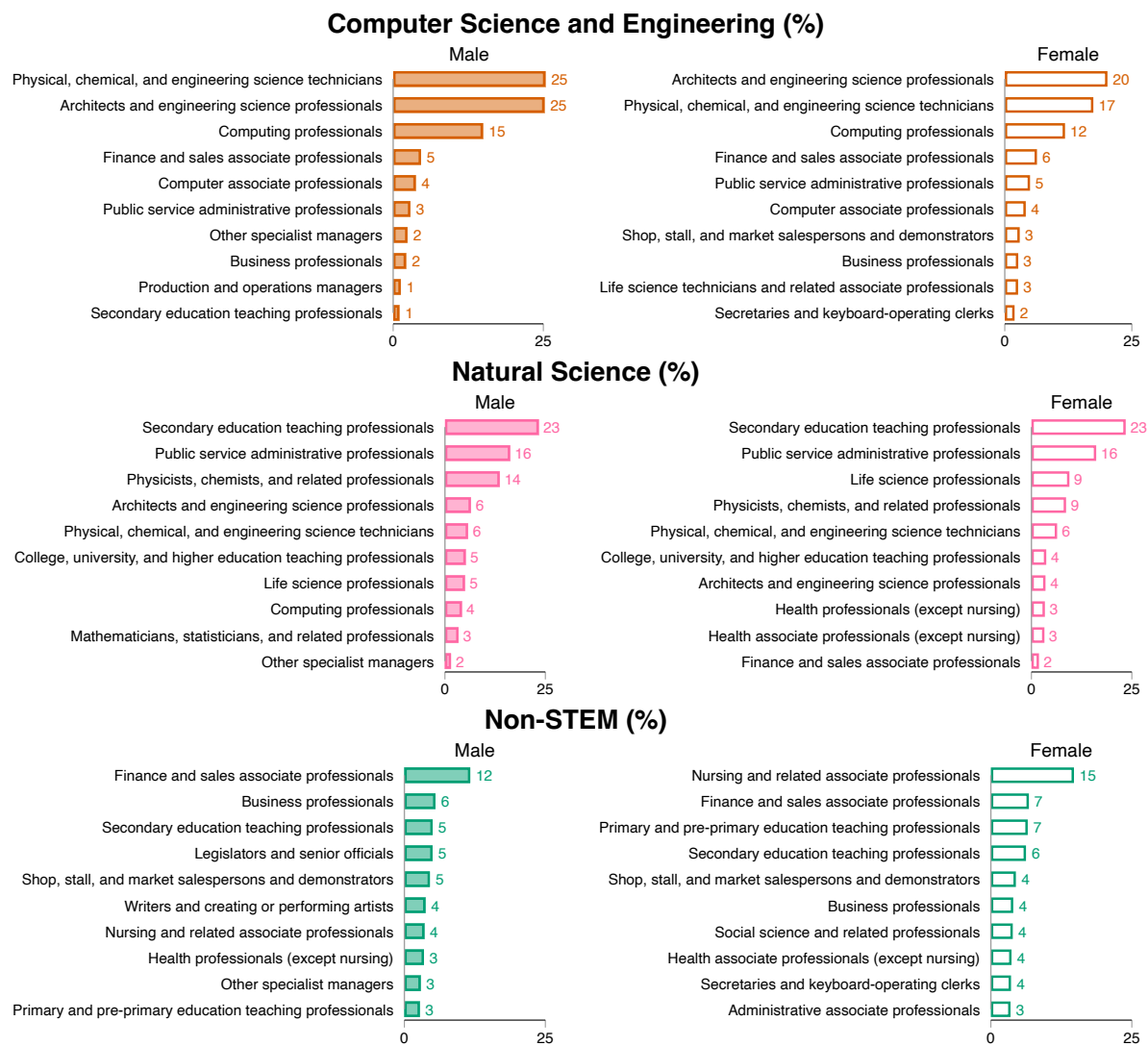


Fig.A2 Top ten occupations for men and women with computer science and engineering, natural science, and non-STEM majors at age 30.

Notes: Based on Statistics Finland's classification of occupations 2001 (relied on for years 2004-2009). Data from authors' calculations based on Finnish register data 1987–2022.

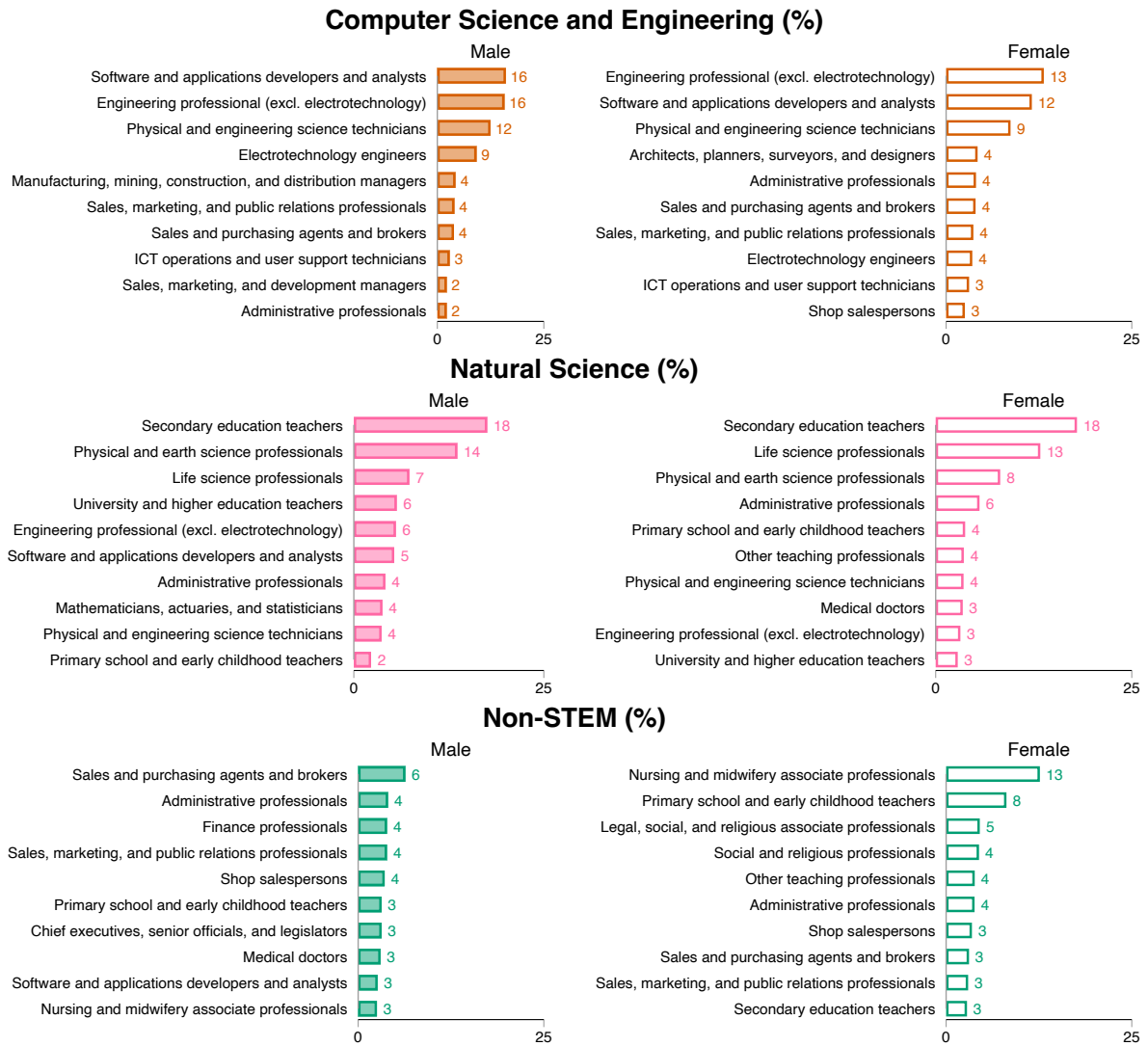


Fig.A3 Top ten occupations for men and women with computer science and engineering, natural science, and non-STEM majors at age 40.

Notes: Based on Statistics Finland's classification of occupations 2010 (following the structure of ISCO-08, relied on for years 2010 and onwards). Data from authors' calculations based on Finnish register data 1987–2022.

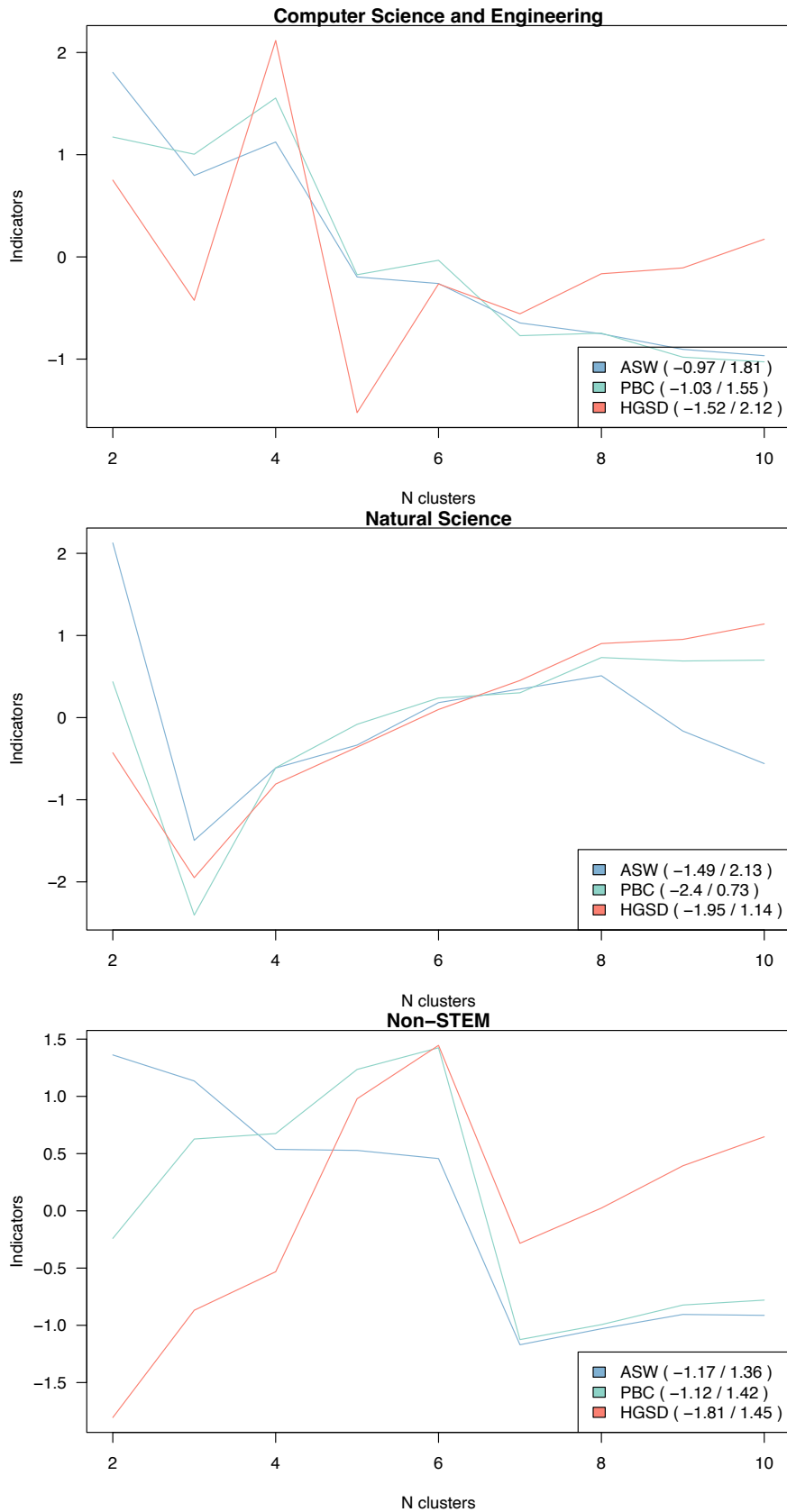


Fig.A4 Cluster cut-off criteria for Ward's cluster analysis derived from multi-channel sequence analysis.

Notes: ASW = Average Silhouette Width; PBC = Point Biserial Correlation; HGSD = Hubert's gamma (Sommer's D). Data from authors' calculations based on Finnish register data 1987–2022.

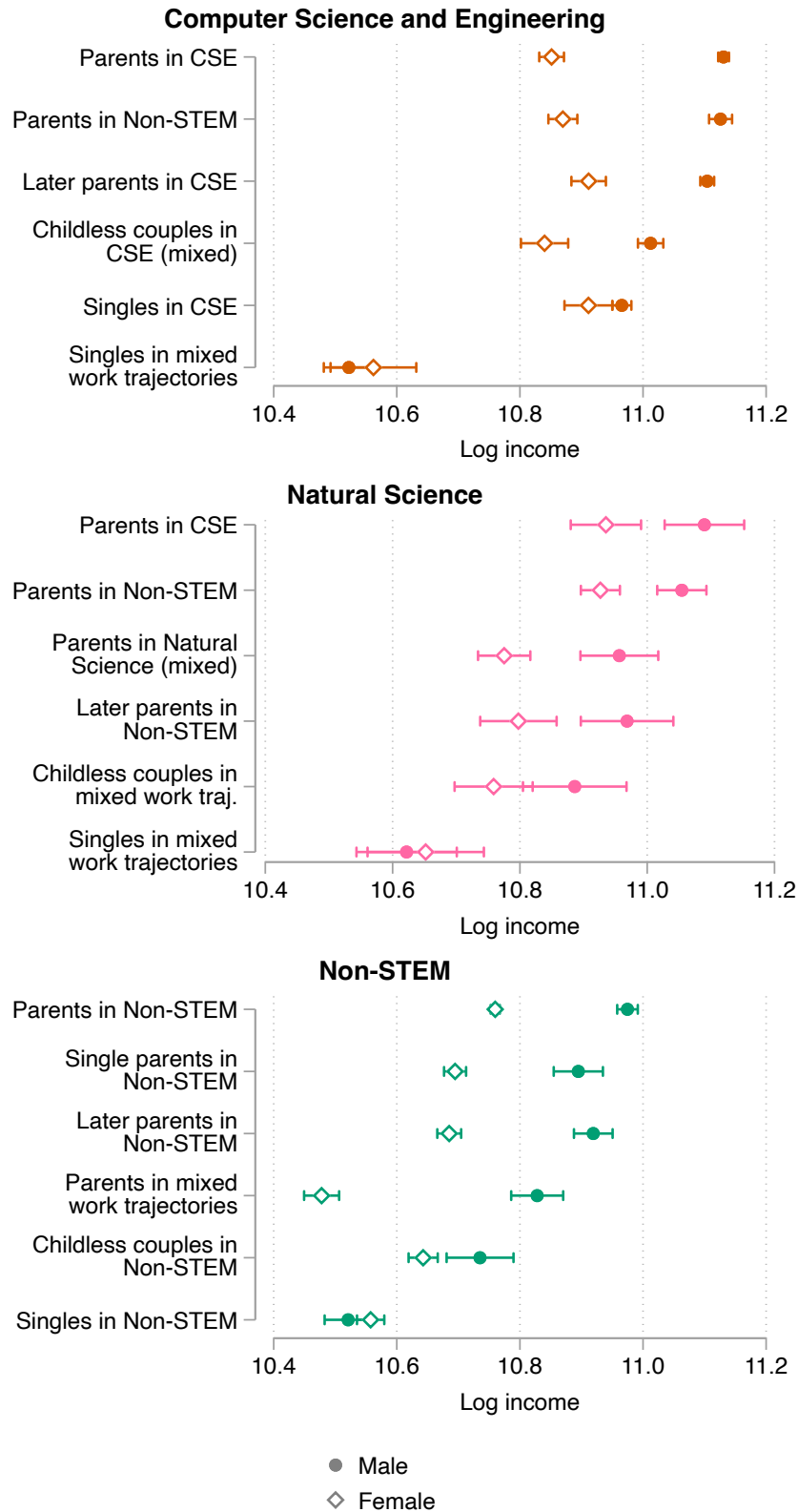


Fig.A5 Gender earnings gaps across majors and clusters, excluding individuals who are on parental leave anytime in ages 41–43.

Notes: Figures provide the estimated earnings from Equation 1. Adjusted predictions are reported. Regressions are estimated separately for computer science and engineering (CSE), natural science, and non-STEM majors. Data from authors' calculations based on Finnish register data 1987–2022.

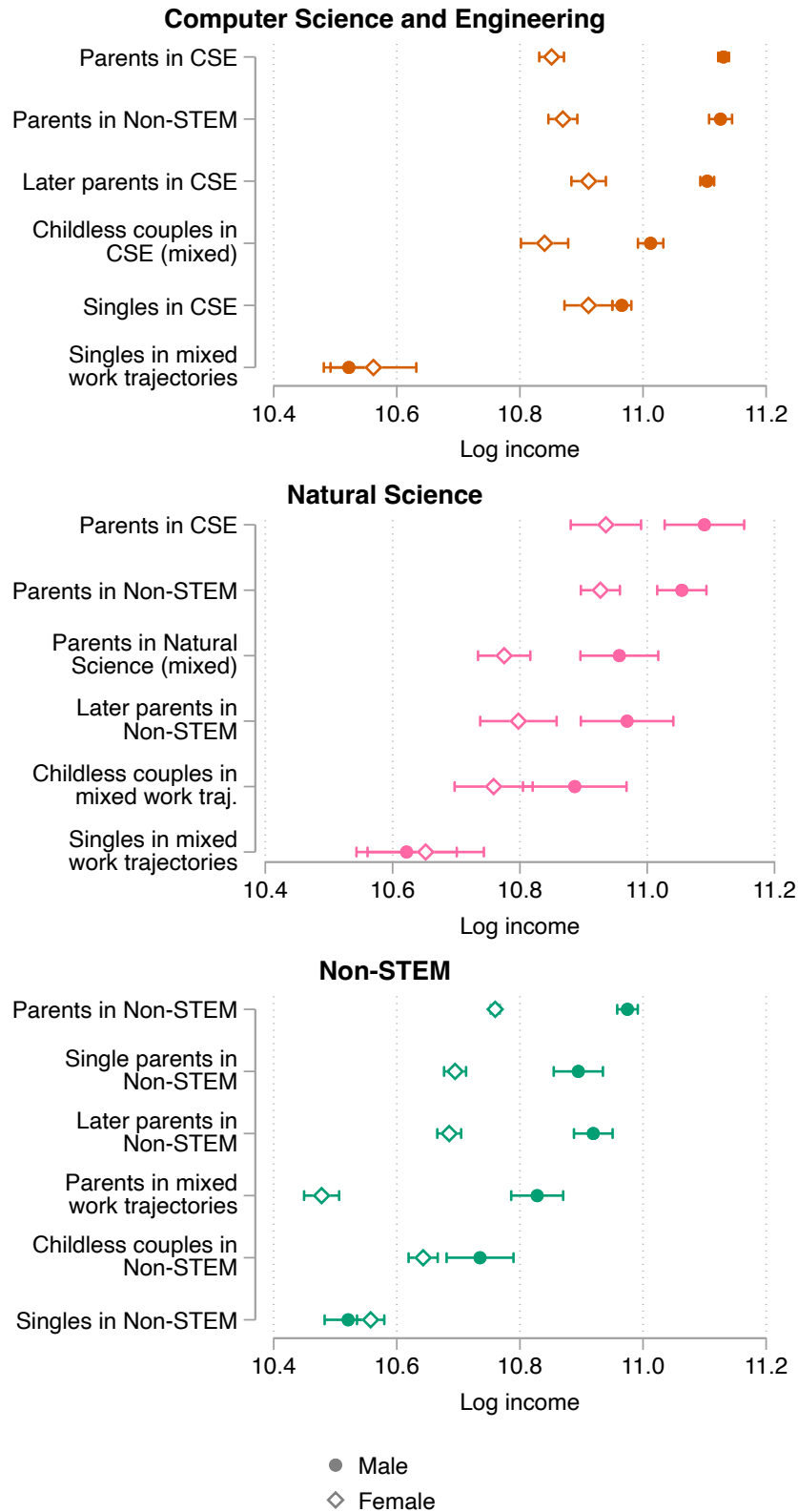


Fig.A6 Gender earnings gaps across majors and clusters, focusing on the first three cohorts (1974–1976).

Notes: Figures provide the estimated earnings from Equation 1. Adjusted predictions are reported. Regressions are estimated separately for computer science and engineering (CSE), natural science, and non-STEM majors. Data from authors' calculations based on Finnish register data 1987–2022.

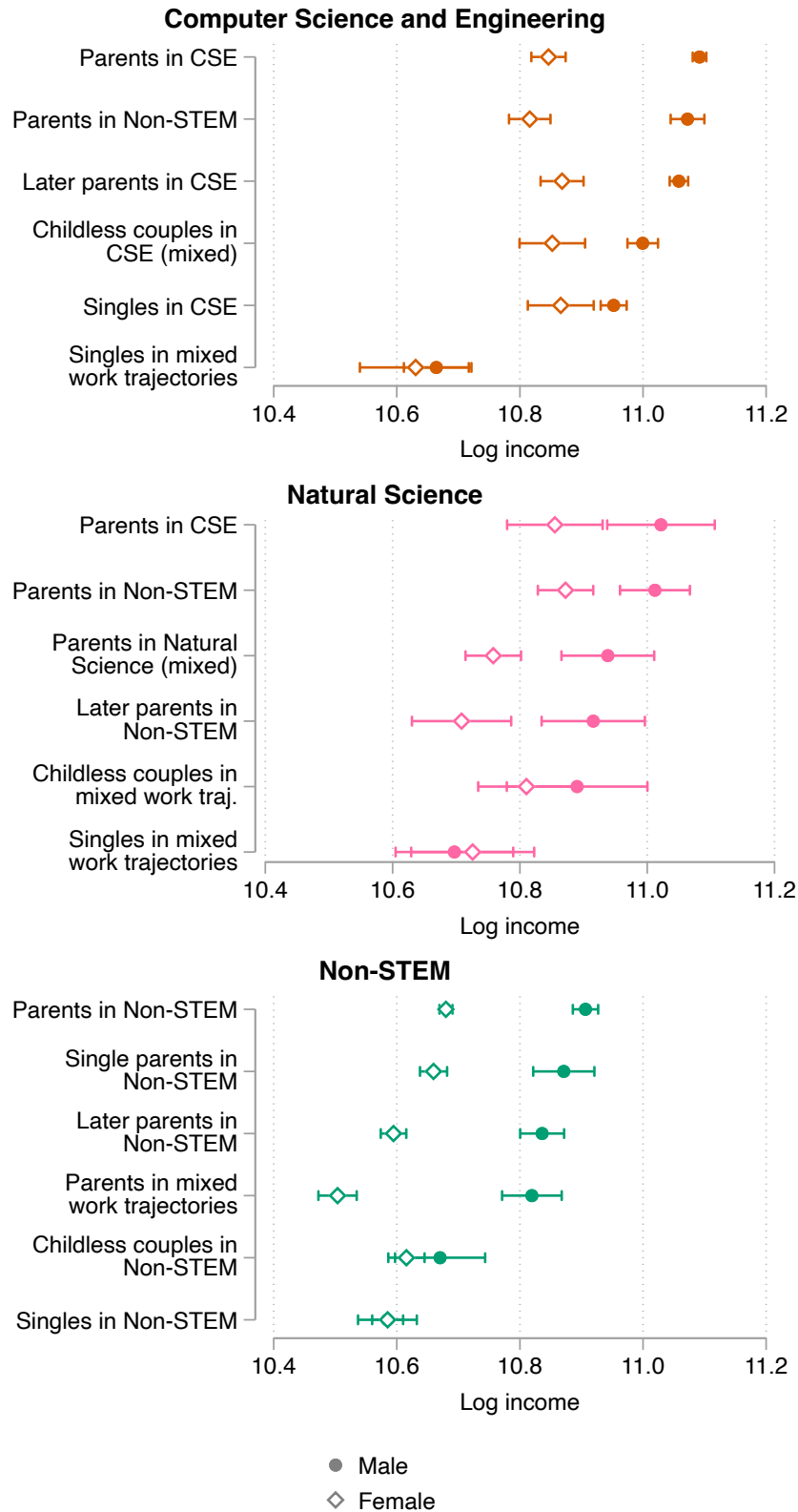


Fig.A7 Gender earnings gaps across majors and clusters, based on earned income rather than total taxable income.

Notes: Figures provide the estimated earnings from Equation 1. Adjusted predictions are reported. Regressions are estimated separately for computer science and engineering (CSE), natural science, and non-STEM majors. Data from authors' calculations based on Finnish register data 1987–2022.