Discussion Paper Series

IZA DP No. 19056

October 2026

How Is AI Affecting College Major and Course Choices? Evidence from Finland

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IZA@LISER NETWORK
ISSN: 2365-9793

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Abstract

Have concerns about the potential job displacement effects of artificial intelligence affected the education choices of students? We analyze administrative data on the university applications and course choices of Finnish students. We find, after the launch of ChatGPT 3.5 in November 2022, a persistent drop in applications to fields of study classified as more exposed to AI under several different measures. The drop is particularly large in computer science and other ICT fields. Examining the elective course choices of non-ICT students, we find declining enrollment in programming and algorithms courses, particularly among students who had not taken mathematics as part of their high school exit exam. At the same time, non-ICT students enrolled more in AI/ML courses, and this increase was relatively larger among men.

JEL classification

I21, J24, J64, O33

Keywords

artificial intelligence, college major choice, higher education, unemployment

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* The authors would like to thank participants at the Helsinki GSE lunch seminar for useful comments and suggestions.

1 Introduction

Students respond to cyclical economic conditions when choosing college majors. This conclusion comes from a body of work which has analyzed variation in unemployment rates in the economy across cohorts or regions (Liu et al. [2019], Han and Winters [2020], Ersoy [2020], Foote and Grosz [2020], Blom et al. [2021], Acton [2021], Weinstein [2022], Leibing [2026]). Students exposed to a higher risk of unemployment may choose more lucrative majors, which have tighter major-occupation links, or may switch away from university studies and pursue vocational education. More generally, while heterogeneous tastes remain quantitatively important in explaining college major choices (Altonji et al. [2016]), students may change their intended majors in response to information about expected earnings.[1] The rapid diffusion of generative AI has raised the prospect of worker displacement, particularly for young workers. How are students reacting to these concerns in their college major choices and their choice of elective courses?

An online survey conducted in October 2025 among US higher education students (Lumina Foundation and Gallup [2026]) found that 16% of undergraduates reported already having changed their major and 47% reported having reconsidered their major due to the impact of AI. Students were likely responding to widely publicized early evidence of the displacement effects of generative AI. Brynjolfsson et al. [2025] found the employment of young workers in the most AI-exposed occupations has fallen by roughly 13 percent relative to their less-exposed peers, while employment of older workers in the same occupations has remained stable. Subsequent work has qualified these findings: job postings in exposed occupations began declining months before the release of ChatGPT, and the divergence attenuates once correlated shocks such as remote work are accounted for (Iscenko and Curto Millet [2026], Frank et al. [2026], Lambert and Schindler [2026]). Brynjolfsson et al. [2026] updated their analysis and found statistically significant declines starting from 2024. While the exact magnitude of the disemployment effects of AI are an empirical matter, the concerns persist, particularly for students and young workers.

Finland is one of the leading European adopters of artificial intelligence, ranking second after Denmark in the share of enterprises using AI technologies in 2025.[2] Descriptively, the Finnish employment patterns

[1] Many studies have found students respond to information about expected earnings, for example Beffy et al. [2012], Wiswall and Zafar [2015], Ruder and Van Noy [2017], Baker et al. [2018], although some researchers report null findings, e.g. Pekkala Kerr et al. [2020].

[2] Eurostat. (2026). Artificial intelligence by size class of enterprise (`isoc_eb_ai`) [Data set]. European Commission. https://doi.org/10.2908/isoc_eb_ai

resemble the patterns in the US: employment of young workers diverges from that of older peers after late 2022 (Figure 1), particularly in occupations classified as highly exposed to AI (Figure 2). The drop is particularly large for software developers, one of the most AI-exposed occupations (Figure A1).

Recent Finnish graduates have experienced rising unemployment and decreasing employment rates, particularly among ICT graduates.[3] To understand how these labor market developments may be affected by AI, we classify majors based on their AI exposure, by establishing a mapping between measures of occupational exposure to AI technologies (Handa et al. [2025]) and university majors. The mapping uses the distribution of occupations held by graduates in each major in Finland. Using this exposure measure at the degree level, we conduct event studies that analyze changes in overall employment and unemployment of recent university graduates by quartile of AI exposure. Figure 3 reveals a drop in employment and a rise in the unemployment rate for recent graduates in the most AI-exposed fields of study. Complementary descriptive evidence in Figures A2 and A3 show graduates in the most-exposed AI fields, particularly ICT, have experienced the slowest wage growth since 2022.

Our preferred measure of AI college major exposure is based on the Handa et al. [2025] measure, which relies on actual user use of genAI. This measure distinguishes between AI's potential to automate or augment tasks performed by workers. The automation risk is directly relevant for students' calculations about changing prospects to different occupations, compared to measures which calculate theoretical exposure of occupations to genAI, which do not distinguish between labor displacement and productivity-raising complementarities. We examine the robustness of our findings across a variety of exposure measures, described in more detail in section 3.1, including Eloundou et al. [2023], Frey and Osborne [2017], and Garg et al. [2026].

To understand whether students respond to these short-run labor market developments and to the broader discourse surrounding the long-run effects of AI, we examined several margins of adjustment: choice of field of study at the time of university application, choice of course electives for students already enrolled, and college major switching behavior.

First, we use administrative data on university applications and examine whether these choices have fundamentally shifted after the launch of ChatGPT 3.5 on November 30th, 2022. The announcement gen-

[3] See Figure A4, which indicates decreasing employment rates particularly in ICT fields and rising unemployment rates across most fields.

erated significant media attention and shed new light on the possibilities of artificial intelligence, especially as ChatGPT was easily accessible online. Most Finnish students apply to universities in the March joint application, for programs beginning in the fall.[4] As such, applicants in March 2023 may have already been exposed to generative AI through media coverage and/or personal use. The first survey data on AI usage collected by Statistics Finland indicates that 45% of those aged 16-24 had used generative artificial intelligence in the last three months of 2024.[5] In event studies, we find a decline in applications to fields in the top quartile of AI exposure, notably in Computer Science and Information Technology majors. As shown in Figure 4, applicant demand for fields of study classified in the top quartile of exposure is the only one to decrease, while applications in the third quartile are stable and applications in the lower two quartiles of AI exposure have been on the rise. Among the top quartile of exposure, computer science majors and foreign language majors saw the largest decreases (Figure A5).

Beyond the effects of artificial intelligence, one alternative explanation for these declines is that fields more exposed to AI may also be on a different path in terms of employment opportunities for young workers. Controlling for measures of occupational exposure to remote work (Dingel and Neiman [2020]) does little to change the magnitude of degree AI exposure on applications. More broadly, controlling for changes in unemployment for graduates in each field of study in our event study specification induces only small changes in our estimates. This suggests students may be reacting to long-run expectations about disemployment as opposed to short-run changes in labor market conditions. In other robustness checks, we additionally control for changes in university study places allocated by the Finnish government[6] and find very small changes in our estimates. While our descriptive evidence of declining applications in the majors most exposed to AI is robust to a series of controls, our estimates are not causal, as other economic developments in the post-pandemic recovery may influence student choices in the same direction as the threat of AI automation. We also do not observe all changes in program quality, curricula, or marketing.

Second, for students already enrolled, we examine how the launch of ChatGPT and subsequent fast

[4] A smaller January round covers foreign-language programs, which mainly attract international applicants, and certain arts programs. We include Finnish applicants from both spring application rounds to retain the arts programs on offer in January. The autumn joint application round, for studies beginning the following spring, offers few first-cycle university programs.

[5] Population's use of information and communication technology [online publication].Reference date : 31.12.2024 . ISSN= 2341-8699 . Helsinki : Statistics Finland [Referenced : 27.8.2026]. Access method : https://stat.fi/fi/julkaisu/cm42fjq642e9507vyca4lko1r

[6] Virtually all higher education in Finland is public, and universities post a number of starting places based on quotas decided in consultations with the government.

growth in generative AI use has affected elective course choices. Course selection can be flexibly made until the start date of the course, therefore students could have been influenced by the public discourse about generative AI as early as Spring 2023. We focus on the choice of Information Technology course electives by students from other disciplines. For many students in Business, Social Sciences or other scientific disciplines, computer science courses can bring a useful set of basic programming skills. We hypothesized that in the light of the increasing coding capabilities of generative AI, students may have substituted away from courses such as 'Introduction to Programming'. We therefore distinguish, among computer science elective courses, between 'classic' computer science courses such as programming and algorithms, data science courses as well as machine learning and artificial intelligence courses. We find declining enrollment in programming elective courses and rising interest in courses on artificial intelligence and machine learning. Interest in programming electives was on a downward trend before the launch of chatGPT 3.5, while enrollment in AI electives was relatively flat but picked up after 2023. We explore heterogeneity in these course choice responses by interacting a post-genAI coefficient with a series of individual characteristics. We find that students who had not taken math as a subject in the high school exit exam are less likely to sign up for programming courses post-genAI. At the same time, AI courses see a sustained increase, but women lag behind men in the choice of AI or ML electives.

Finally, we have found little evidence that undergraduate students are switching majors. Finnish students apply to specialized university programs, and switching majors is equivalent to re-applying and re-enrolling in a different program.

Understanding student responses to the rise of generative AI is important for mapping out the aggregate effects of AI: fast-changing student field of study choices may have large implications for future effects of genAI on employment. Mapping out student choices is also important for decision-makers adapting allocations of university seats of study across fields, or changing curricula. Our results indicate strong responses away from fields perceived to be exposed to AI. The magnitude of the response exceeds the observed employment losses, as we would expect if students anticipated larger long-term declines in employment in exposed occupations. Students are also less likely to take basic programming courses, perhaps as the tasks they could accomplish after completing such courses are now easily achieved by generative AI. This raises questions about whether students should be required to take certain basic coursework such as introduction to programming or whether they can rely on the coding help of genAI to pursue more advanced topics.

Our paper is the first to bring evidence on the potential effects of AI on college application data and course choices from administrative records for university students. Our finding that students are less likely to apply to majors with high AI exposure are in line with findings that shortly after the launch of Chat GPT 3.5, applications to apprenticeship programs in Switzerland declined more in programs leading to routine cognitive occupations compared to routine manual ones (Goller et al. [2025]). Our findings on reductions in IT coursework are similar to evidence from Light [2026], who finds declining computer science enrollment in the US in 2025/2026 but flat or growing enrollment in data science and AI programs. We also contribute to the broader literature tracking the effect of AI on the labor market outcomes of recent college graduates (Hosseini Maasoum and Lichtinger [2025], Klein Teeselink [2025], Nordström Skans and Sokolow Romin, Dodini and Smith [2026], Demirev [2026], Lodefalk et al. [2026], Orr et al. [2026]). We also update the analysis in Kauhanen and Rouvinen [2026] to March 2026 in Finland and find little evidence of economy-wide aggregate disemployment effects, in line with evidence from other Nordic countries (Facius and Iacono [2026], Hernæs and Kostøl [2026], Humlum and Vestergaard [2025], Nordström Skans and Sokolow Romin).

In the next section, we provide institutional background on the Finnish higher education system. In section 3, we detail our data sources on exposure measures, employment, applications and course choices and provide summary statistics. We lay out the empirical strategy in section 4, present results in Section 5 and conclude in section 6.

2 Institutional background

Our analysis focuses on applicants to Finnish universities, which provide academically-oriented tertiary education leading to a master's degree.[7] Universities are largely publicly funded, and Finnish students pay no tuition fees. Universities determine the number of study places for each program, within the framework of degree targets and funding agreed upon with the government.

Finnish students choose majors by directly applying to degree programs at specific universities. Most

[7]Students in most programs complete a three-year bachelor's followed by a two-year master's degree. Only a small fraction of students enter the labor market with just an intermediate bachelor's degree. Besides universities, Universities of Applied Sciences provide more professionally-oriented shorter duration bachelor's degrees which may allow for more flexible mixing of work and studies.

Finnish students apply in the March joint application round for studies beginning in the fall. Applicants may rank up to six programs and are offered a seat at the highest-ranked program for which they qualify. Students have two routes into most programs: they may apply using the scores on their high school matriculation exam,[8] or they may take an entrance exam in subjects related to the field they are applying for. This latter modality is particularly helpful for older students who may return to academia many years after having taken their high school matriculation exam, or for students who performed poorly on the high school exit exam.

In 2025, universities introduced nine national entrance exams covering most programs in the March application round, replacing approximately 120 separate written exams. A single exam can now be used to apply to several fields and universities. Announced in 2024, the reform reduced overlaps between exam dates. By reducing the need to prepare for several separate exams, the reform may have affected which fields applicants consider. We examine changes in applicants' first choice, which are unlikely to have been significantly affected by the 2025 reform, which lowered the application costs (mainly the need to take multiple exams) across all fields.

In joint applications, universities reserve a fraction of starting places for first-time applicants, with quotas varying across programs. First-timers have neither completed a Finnish higher education degree nor accepted a study right for studies beginning in autumn 2014 or later. The remaining places are open to both first-time and other applicants. Accepting a place therefore means forfeiting this advantage in subsequent applications. In our analysis we focus on first-time applicants, and we examine major switching behavior separately.

Changing degree fields generally requires a new application and enrollment in another program, through ordinary admission or a transfer procedure. Transfer admission may also require previous coursework in the new field and good grades. Previously completed courses can count toward the new degree, but differences in degree requirements can leave credits unused and require additional coursework. These requirements make switching fields costly.

Students usually begin major-specific coursework in their first year, but degree programs also allow elective studies, including courses outside the student's own field. The amount of elective coursework and the courses available vary substantially across programs, and individual courses may have prerequisites or

[8] Grades in the high school matriculation examination are converted into admission points using subject weights that vary by field.

limits on participation. Students can adjust these choices while continuing in their existing degree program, without having to secure a new study right. Electives therefore provide a more flexible margin of adjustment for enrolled students.

3 Data and Summary Statistics

3.1 Occupational exposure measures

Our primary measure of occupational AI exposure is derived from the Anthropic Economic Index [Handa et al., 2025], which allocates observed usage of a large language model across occupational tasks. We reproduce Anthropic's task-allocation methodology from their March 2025 data release and crosswalk the resulting occupation-level measures from SOC-2010 to ISCO-08 following Hardy et al. [2018], splitting one-to-many mappings equally across destination codes. Occupations are grouped into quartiles of exposure, with quartile cutpoints computed unweighted across occupations, as in Brynjolfsson et al. [2025].

The Anthropic data distinguish automation, where a task is handed off to an AI, from augmentation, where the AI supports the user's work. This distinction is important, because occupations with similar overall exposure may face different different labour market consequences depending on whether the technology replaces or augments what workers do. For the application analysis, we use the occupation-level automation measure. We aggregate it to the degree level using the occupational distribution of each degree's graduates, as described below. Higher values of the measure indicate that a degree's graduates tend to work in occupations in which observed large-language-model use is more automation-oriented.

We also consider three alternative measures of automation. The first uses the GPT-4 task labels from Eloundou et al. [2023], based on task descriptions in the 2023 O*NET release. We measure the share of an occupation's tasks classified as highly or fully automatable. This includes the tasks that LLMs and related software could perform almost entirely with human oversight, or fully without oversight. The second is the probability of computerization estimated by Frey and Osborne [2017], a pre-LLM benchmark for automation potential. They classify occupations using expert assessments of 70 occupations and 2010 O*NET measures of occupational requirements for perception and manipulation, creativity, and social intelligence. The third is the Finland-specific substitution measure from the Global Automation Atlas [Garg et al., 2026]. The

authors use the Gemini 3.1 Flash-Lite language model to assess what AI, conventional software, and robotics could automate under Finnish production conditions in 2026, drawing on the 2024 O*NET release. We use the share of all tasks in each occupation classified as exposed to substitution-only automation, where technology can reduce human input. These measures capture assessed automation potential rather than observed adoption or displacement. We aggregate these occupational measures at the degree level using the same graduate–occupation mapping described above, and standardize each across degree codes.

The alternative measures are highly correlated with each other but much less strongly with our main measure of automation from [Handa et al., 2025]. Appendix Table A5 shows correlations between Handa and the alternative measures ranging from 0.15 to 0.40, while correlations among Eloundou, Frey-Osborne, and ATLAS range from 0.82 to 0.94. The higher correlations likely reflect their similar measurement approach, relying on expert- or AI-based assessments of task automatability, whereas the Handa measure is based on observed real-world AI use.

3.2 Employment data

Our employment data come from the Finnish Incomes Register (Tulorekisteri), a national administrative database maintained by the Tax Administration that records every wage payment in the economy at the level of individual payment reports, identifying both the worker and the paying firm. We aggregate these reports into a worker–firm–month panel covering January 2021 through March 2026. We restrict to private-sector wage employees with non-zero wage income. We assign each worker–firm–month an occupation using the three-digit ISCO-08 code reported in the register, and drop observations with no reported occupation from the analysis sample. We group workers into six age bands from 22–25 to 50 and above, following Brynjolfsson et al. [2025].

3.3 Application data

We use university application statistics from Vipunen, the Finnish education administration's statistical service. The data cover applications by Finnish citizens to first-cycle university programs beginning in the fall of 2018–2026, including both the January and March application periods. Observations are at the level of individual admission units (*hakukohde*) by year. Applicants rank their programs in order of preference. Our

main outcome is the count of applicants naming a given program as their first choice. We restrict to first-time applicants, who have not previously accepted a Finnish degree place, since they face the choice without the constraints of existing enrollment and switching costs. Applications for intake year t are submitted in the spring of year t, so the 2022 applications predate the release of ChatGPT, making 2023 the first post-release application year.

We assign each six-digit degree[9] an AI exposure score by mapping its holders to the occupations in which they are observed working. Using the Incomes Register for 2021–2022, restricted to full-time employees under 45, we compute for each degree code the mean of the occupation-level exposure measures over the occupations its holders work in, weighted by employment months. The exposure of a degree therefore describes the labour market its graduates entered before the release of ChatGPT, and is fixed over the application window.[10]

3.4 Coursework data

For coursework choices, we use the Virta higher education register, which records every course completion at every Finnish university, including the course name, credits and completion date. We link completions to study rights and to degree program codes, and merge in information on demographics and parental background from FOLK, and matriculation examination grades from the Matriculation Examination Board. Mathematics is optional in the matriculation examination and can be taken at either an advanced ('long') or basic ('short') level. The panel covers Finnish university students who complete at least 30 credits in a given year,[11] over 2018–2025. We restrict our analysis to universities rather than universities of applied sciences, which follow a more prescribed curriculum with little elective discretion, and to Finnish students, since international students are a selected group enrolled mostly in English-language programs, with those from outside the EU/EEA also paying tuition fees. For the purpose of analyzing enrollment in ICT elec-

[9] Degrees are identified by the six-digit codes of Statistics Finland's *Koulutusluokitus* 2025. Finnish degree codes were renumbered during our window and a program may report either a bachelor-level or a master-level code in different years. We harmonized codes to a single master-level code per program before counting. For specifications that require a consistent panel we restrict to degree $\times$ institution units observed in all nine years, which account for 92 per cent of 2026 first-choice applicants.

[10] For our main automation measure, we exclude Military Science (degree code 782603), because less than 50 per cent of the underlying employment observations have nonmissing automation scores. The Handa et al. automation score is unavailable for the military occupations accounting for most of these observations.

[11] Students are normally expected to complete 60 credits during a year.

tives, we further restrict the sample to students in non-ICT degree programs, and to years 2021–2025. An observation is a student × study right × year, where a study right is a student's seat at a degree program at a given university. A student may hold more than one at a time.

We classify courses as ICT using the field code of the course itself (ISCED-F 2013 broad field 06), which is assigned in the VIRTA register and imputed for unclassified courses from the modal field of the coursetakers. Within ICT courses we assign content categories by keyword matching on course names, in Finnish, Swedish and English. The categories are AI/ML (e.g. *artificial intelligence*, *machine learning*), programming (e.g. *programming*, *Python*), algorithms, and data science. Appendix Table A6 lists the most commonly taken courses in each category. For the analysis, we further group these into *modern* ICT, combining AI/ML with data science, and *traditional* ICT, combining programming and algorithms.

Our outcomes are elective courses taken outside the student's own field. Information on elective status is not available and we impute it assuming the course is elective if 1) it is taken by fewer than 20 per cent of the cohort, and 2) the course's field differs from the student's degree's field. We apply this restriction to isolate the margin where students have discretion over their coursework: within-field courses are largely mandated by the degree. In robustness checks, we relax condition 1) and find it does not meaningfully change the observed patterns.

Table A7 describes the estimation sample. Just under two-thirds of observations are female, and 92.4 per cent report Finnish as their mother tongue against 6.0 per cent Swedish. Parental income averages 96,705 euros and 44.4 per cent of students have a parent with a master's degree or higher. Most have completed the matriculation examination (85.9 per cent); among all students, 48.7 per cent took long mathematics, 27.8 per cent short mathematics and 9.4 per cent no mathematics at all. Liberal arts is the largest field at 39.3 per cent, followed by STEM at 27.8 per cent, business, law and administration at 19.3 per cent, and health at 11.7 per cent. Students complete 46.5 credits in an average year, of which 3.4 are outside-field electives, and 36.5 per cent take at least one outside-field elective. ICT electives are a small share of overall electives: 5.6 per cent of students take at least one in a given year, and ICT accounts for 11.8 per cent of outside-field elective credits. Among those who take any, ICT electives amount to 6.7 credits, or roughly two courses. Long mathematics and parental education both rise across the two periods, while the share with no matriculation mathematics falls; the degree program and year fixed effects in equation 4 absorb composition shifts of this kind.

4 Empirical Strategy

4.1 Employment

We begin by examining whether the employment and unemployment trends among university master's degree holders under 30 vary with field-level automation exposure. Separately for each outcome, we estimate

$$y_{gt} = \sum_{\tau \neq 2022} \beta_\tau E_g \times \mathbb{1}\{t = \tau\} + \alpha_g + \delta_t + \varepsilon_{gt}, \tag{1}$$

where y_{gt} is the employment or unemployment rate in three-digit ISCED field g and year t, and E_g is the standardized field-level automation exposure. The terms α_g and δ_t are field and year fixed-effects. We estimate by weighted least squares, weighting each field-year observation by the number of degree holders for employment and the corresponding labor force for unemployment. Standard errors are clustered by field. The coefficients capture differential changes relative to 2022, expressed in percentage points per standard deviation of AI exposure.

Our economy-wide employment analysis follows Kauhanen and Rouvinen [2026]'s, who adapt the design of Brynjolfsson et al. [2025] to Finnish register data. We aggregate the worker–firm–month panel to headcounts by firm, exposure quartile, age band, and month, filling unobserved cells with zeros within each firm's observed lifespan. Separately for each age band, we estimate the Poisson model

$$\log \mathbb{E}\left[y_{fqt}\right] = \sum_{\tau \neq \tau_0} \beta_{q\tau}\, \mathbb{1}\{\tau(t) = \tau\} + \gamma_{fq} + \delta_{ft}, \tag{2}$$

where y_{fqt} is the headcount of firm f in exposure quartile q in month t, $\tau(t)$ denotes event months relative to the release of ChatGPT, and γ_{fq} and δ_{ft} are firm-by-quartile and firm-by-month fixed effects. The firm-by-month effects absorb all firm-level shocks, so that the coefficients of interest, $\beta_{q\tau}$, are identified from within-firm changes in the occupational composition of employment across exposure quartiles. The omitted categories are the lowest exposure quartile ($q = 1$) and the month preceding the release (τ_0). We estimate the model by Poisson pseudo-maximum likelihood with high-dimensional fixed effects [Correia et al., 2020] and cluster standard errors by firm.

4.2 University applications

For the education margin our outcome is the count of first-choice applicants to a degree program. We estimate Poisson models of these counts at the degree × institution × year level, allowing the effect of AI exposure to vary by application year. The specification is

$$\log \mathbb{E}\left[a_{dit}\right] = \sum_{\tau \neq 2022} \beta_\tau E_d \times \mathbb{1}\{t = \tau\} + \gamma E_d + \lambda_{f(d)t} + \mu_i, \tag{3}$$

where a_{dit} is the number of first-choice applicants to degree d at institution i in year t, E_d is the degree's standardized AI exposure, $\lambda_{f(d)t}$ are broad field × year effects and μ_i are institution effects. The 2022 application year, the last to close before the release of ChatGPT, is the omitted category. Because field × year effects are absorbed, the β_τ are identified from differences in exposure between degrees within the same broad field. Standard errors are clustered on degree code.

We estimate the same specification replacing the continuous exposure measure with an indicator for ICT degrees. ICT is the field where the application response is largest. In that version institution and year effects are absorbed rather than field × year effects, since ICT is itself a broad field.

4.3 Coursework choices

For coursework choices, we use a student × study right × year panel. Let y_{ijt} indicate that student i in degree program j completes at least one elective of a given type in year t, and let X_i be a student characteristic. We estimate

$$y_{ijt} = \beta \left(\text{Post}_t \times X_i\right) + \gamma X_i + \alpha_j + \delta_t + \varepsilon_{ijt}, \tag{4}$$

where Post_t equals one for 2023–2025, α_j collects degree program, university and year-of-study fixed effects, and δ_t are year effects, which absorb the main effect of Post_t. Standard errors are clustered by university × entry cohort. Because every student is exposed at the same date, there is no untreated comparison group. Hence β measures how the gap between groups defined by X_i changes after the release rather than the effect of the release itself. Identification rests on those gaps being stable absent the shock.

5 Results

5.1 Employment

Descriptively, employment of young workers decreased faster than that of older workers between 2021 and 2026 (Figure 1), and within the youngest age band the decline is concentrated in the most AI-exposed occupations (Figure 2). Software developers, an occupation which has been commonly identified as highly exposed, show a similar clear pattern by age (Figure A1).

Conducting the event study specification in equation 1, we find the employment decreased (and unemployment increased) for graduates of majors with higher AI exposure. By 2026, a one-standard deviation increase in AI exposure (Handa et al. [2025]) was associated with a one percentage point lower employment rate, and about a 0.7 percentage point increase in the unemployment rate. Turning to the economy-wide analysis, we estimate equation 2 with firm-by-month fixed effects. In this specification, the differential trends across exposure quartiles largely disappear (see Figure A6), and we replicate the null result of Kauhanen and Rouvinen [2026] with data up to March 2026 (compared to October 2025 in their analysis). This suggests the disemployment effects observed in the descriptive evidence and in the event study for young graduates are not driven by within-firm reallocation across occupations, but are likely caused by changes across firms in the hiring of young workers.

5.2 University Applications

Applications to ICT programs saw a significant decline. Between the 2022 and 2026 rounds, first-choice applicants to ICT fell 38.0 per cent while applicants to all other fields rose 16.5 per cent (Figure 5, Panel A). The supply of seats of study in ICT was largely unchanged over the same period (see Figure A15), therefore the decline reflects applicant demand rather than a contraction in supply. The contrast across fields is stark: business, administration and law grew 39.8 per cent, engineering 24.8 per cent and health and welfare 8.0 per cent (Figure 5, Panel B). It is important to note that the drop in university applications did not translate into a generalized decrease in enrollment, as ICT programs, just as most university programs in Finland, receive more applications than starting places.[12] However, while in 2019 ICT programs were oversubscribed by a

[12] One exception was registered in 2026, when the University of Eastern Finland had 112 unfilled seats in computer science and data technology programs and organized a supplemental application round. Source: Kainulainen [2026].

ratio of about 2:1 in the Spring application round for all applicants, by 2026 the ratio is close to 1 (see Figure A21). In contrast, in the United States, where most students choose majors after admission to a four-year college, actual enrollment in Computer and Information Sciences at four-year colleges decreased 8.1% year over year in the fall of 2025 (National Student Clearinghouse Research Center [2026]).

We examine the change in ICT applications in Figure A11, which plots event study estimates (Equation 3). The 2023 coefficient is close to zero while a small statistically significant decline is registered in 2024. Significant declines appear in 2025 (-34.36 per cent relative to other programs) and deepen in 2026 (-45.34 per cent). Because treatment is assigned to four degree codes within a single broad field, the cluster-robust standard errors rest on few treated clusters and we report them for reference. In Appendix Figure A12 we conduct a randomization inference analysis, treating every degree as treated, one at a time. The ICT programs stand out in the lower tail of the declines in applications.

The response is not confined to ICT. Grouping degrees by degree-level automation exposure, first-choice applicants to the top (most exposed) quartile fell 16.6 per cent between 2022 and 2026, while the bottom three quartiles together grew 20.3 per cent (Figure 4). The quartiles move similarly before 2022, but the most automation-exposed quartile begins to diverge in 2024 and falls sharply by 2026. The pattern is not driven by a few programs: 15 of the 20 degree codes in the top quartile decline, with a median per cent change of -15.38% (see Table A1).

To quantify the effects of exposure across all degrees, we estimate the event study in equation 3 using the degree-specific AI exposure measures. Figure 6 shows that a one standard deviation increase in AI exposure is associated with a 8.79 per cent decline in first-choice applicants in 2025 and a 14.02 per cent decline in 2026, with no pre-period coefficient distinguishable from zero. Because field $\times$ year effects are absorbed, these estimates are identified from differences between degrees within the same broad field. Excluding ICT degrees leaves the gradient essentially unchanged: the corresponding coefficients are -8.789 in 2025 and -13.929 in 2026. Results are plotted in Figure A13.

We also examined whether the drop in applications is robust under alternative measures of AI exposure. We report event study estimates using the Eloundou et al. [2023] measure in Figure A8, the Frey and Osborne [2017] occupational probability of computerization risk in Figure A9, and the Finland-specific substitution-only task share from the Global Automation Atlas (Garg et al. [2026]) in Figure A10. We observe declines in applications to AI-exposed fields are in all three event studies, more clearly in 2025 and 2026. Magnitudes

of the effect are about half or less of the magnitudes we observe using the Handa et al. [2025] measure and stand at about a five percentage point decline per standard deviation of automation exposure. The lower magnitudes are due to theoretical and expert-based task-automamatibility measures classifying large and fast-growing majors such as Business Economics among the top-automation exposed degrees, whereas the Handa et al. [2025] measure does not.

One interpretation for the observed effects is that students are responding to the prospect of generative AI leading to worse labor market outcomes in exposed fields. A rival explanation is that AI exposure may be higher in fields in which employment prospects were already weakening for other reasons, so that applicants are responding to declining employment rather than to expectations about AI. Given the rise of remote work in recent years, graduates may be facing competition from a broader pool of applicants. Occupations where remote work is common may also be more exposed to potential AI automation. In Figure A22 we report estimates included controls for the exposure of each major (degree program) to remote work, using measures of occupation-specific exposure (Dingel and Neiman [2020]) and the occupational distribution of graduates in the Finnish labor market in 2021-2022. The addition of these controls did not produce meaningful changes in our baseline estimates. We also attempt to more broadly control for other potential correlates of AI exposure that may be affecting the outcomes of recent graduates. Figure A4 plots unemployment rates for holders of Finnish university master's degrees under 30, by broad field of degree. Unemployment rises in every field after 2022, including in engineering and ICT, from 2.1 to 6.4 and 2.7 to 5.6 per cent respectively. But ICT remains mid-ranked in level among fields, below arts and humanities at 14.2 per cent, natural sciences at 8.6 and social sciences at 7.5. As such, the most exposed fields are not those with the weakest graduate labor markets. The 2.9 percentage point rise in ICT unemployment is also small set against the 38 per cent fall in first-choice applicants to ICT. We nevertheless include a control for field-specific unemployment in the event study. Results are reported in Figure A14: the 2025 coefficient moves from –8.879 to –8.423, so the field labour-market control leaves the gradient essentially unchanged. The application response therefore may be driven by expectations about future employment rather than the labor market conditions experienced by recent graduates.

Another possible explanation for the observed decline is that changes in the admission modalities may have influenced applicant's choices. A reform in 2025 introduced a smaller number of national entrance exams which displaced approximately 120 university-specific exams. This reform made it easier for students

to apply across fields and universities. It is unlikely that this reform caused the significant decline in ICT applications, as ICT programs in engineering schools had already been sharing entrance exams with other engineering programs since an earlier admissions reform in 2018. Studying the 2018 expansion of joint admissions, Murto et al. [2023] found that the increase in applications was concentrated in programs ranked second through fifth by applicants, with little change in applicant's first choice.

We find no corresponding increase in field switching among students already enrolled in highly AI-exposed degrees: switching rates one year after entry do not increase differentially in the most exposed quartile after 2022 (Appendix Figure A19). This suggests that adjustment is concentrated at the entry margin, potentially because switching is relatively costly and requires students to go through another application round.

5.3 Course Choices

While applications to ICT programs were seeing large declines, did already enrolled students change their choices of ICT electives? In Table A7 we report summary statistics on the ICT course-taking behavior of non-ICT students. Overall participation rates in ICT courses declined slightly, from 5.8 per cent of students in 2021–2022 to 5.5 per cent in 2023–2025. The ICT share of outside-field overall elective credits fell from 0.128 to 0.113. But while the overall decrease is small, we observe significant compositional changes in Figure 7. Programming courses have been steadily declining as a fraction of overall elective credits taken by students, and the decline continues after the launch of ChatGPT 3.5. At the same time, AI/ML and Data Science courses were not registering significant trends before 2022 but see sustained growth every year thereafter. Take-up of AI/ML electives among all students rises from 0.3 per cent to 0.7 per cent (Figure A18).

Table 1 reports estimates of equation 4, which allows us to descriptively quantify how the characteristics of ICT elective course takers change after the launch of GPT 3.5. Students who did not take math as a high school exam subject reduce overall ICT elective take-up by 0.79 percentage points relative to students taking the advanced curriculum math. The post-2022 change in AI/ML or data science take-up was 0.36 percentage points lower for women than men.

6 Conclusion

We hypothesized that to the extent artificial intelligence will impact employment and labor market returns to certain fields of study, students may react and switch away from more exposed majors. We found large shifts in applications away from majors classified in the top quartile of exposure to AI, in particular computer science. This evidence is not causal, as other economic developments correlated with AI exposure, or small changes in admission mechanisms, program quality or curriculum may impact student application behavior. Nevertheless, our evidence, based on administrative applications data, is consistent with survey evidence (Lumina Foundation and Gallup [2026]) that students are actively weighing the impact of AI when choosing majors. The decrease in ICT applications in Finland is in line with evidence on declining ICT enrollment in the US (National Student Clearinghouse Research Center [2026]). However, in Finland, ICT programs remain, with few exceptions, oversubscribed, and as such the drop in applications has not yet led to a generalized decrease in ICT enrollment.

We complemented the evidence on applications with data from course elective choices among already enrolled students. We found students switching their elective coursework away from programming courses, extending a decline already underway in student interest in such courses. This switch was particularly large for students who had not taken a math exam in high school. At the same time, ML and AI elective courses have seen increases in enrollment among non-ICT students.

The magnitude of college application responses to AI in Finland is likely influenced by the institutional setup. Students submit most of their applications through a centralized system and they rank programs. But once admitted and enrolled in their preferred major, students are exposed to a curriculum that is very concentrated in their specific field of study, and switching costs are high, essentially involving another application cycle. We therefore expect the magnitude of the responses to genAI to be mediated by the flexibility of the tertiary education system in terms of when students are required to specialize. Indeed, we find no evidence of relatively higher major switching behavior in AI-exposed fields.

Overall, our findings indicate fast and large responses in field of study choices in response to generative AI. Such responses are likely to be quantitatively important when estimating medium and long-run disemployment effects of genAI. Smeets et al. [2025] simulate the effects of widespread AI adoption in a model in which forward-looking students choose fields of study. They point out that allowing students flexibility

in field of study choices significantly changes the aggregate effects of technological disruption. Our results are consistent with their observation, as we see a rapid and significant shift towards less exposed majors. The applicants in the 2025 and 2026 rounds seem to have accounted for significant potential disemployment risks in AI-exposed fields. However, actual enrollment in these fields did not decrease, as most programs in Finland are oversubscribed. We also did not find evidence of students switching majors, likely given the high costs of re-applying to another program. University systems where switching costs across majors are high are likely to experience slower and potentially costlier adjustments to the labor market impacts of genAI.

Several extensions to this analysis are currently in progress. Our data on applications is based on publicly available counts at the degree and university level. In ongoing work, we are incorporating new evidence on the changing background characteristics of applicants to university programs as the microdata on individual applicant choices for more recent rounds becomes available. Preliminary evidence indicates that while the number of applicants to ICT programs dropped considerably, students who eventually enroll in ICT are more likely to take an advanced math exam in the high school exit exam, and their scores on this exam are higher (Figures A23 and A24). One hypothesis that could explain this pattern is that the marginal students who switched away from ICT, possibly out of concern about the effects of AI, had lower math skills. We will also expand the analysis to other tertiary education institutions. Preliminary evidence indicates the application trends we observe for universities are similar among applicants to Universities of Applied Sciences (see Figure A20). We are also examining the choice of minor fields of study, the elective choices of university students more broadly, and the coursework and matriculation exam choices of high school students. Regardless of the magnitude and timing of AI impacts on employment and wages, students may be responding to the perceived future effects of AI across many different stages of their human capital accumulation.

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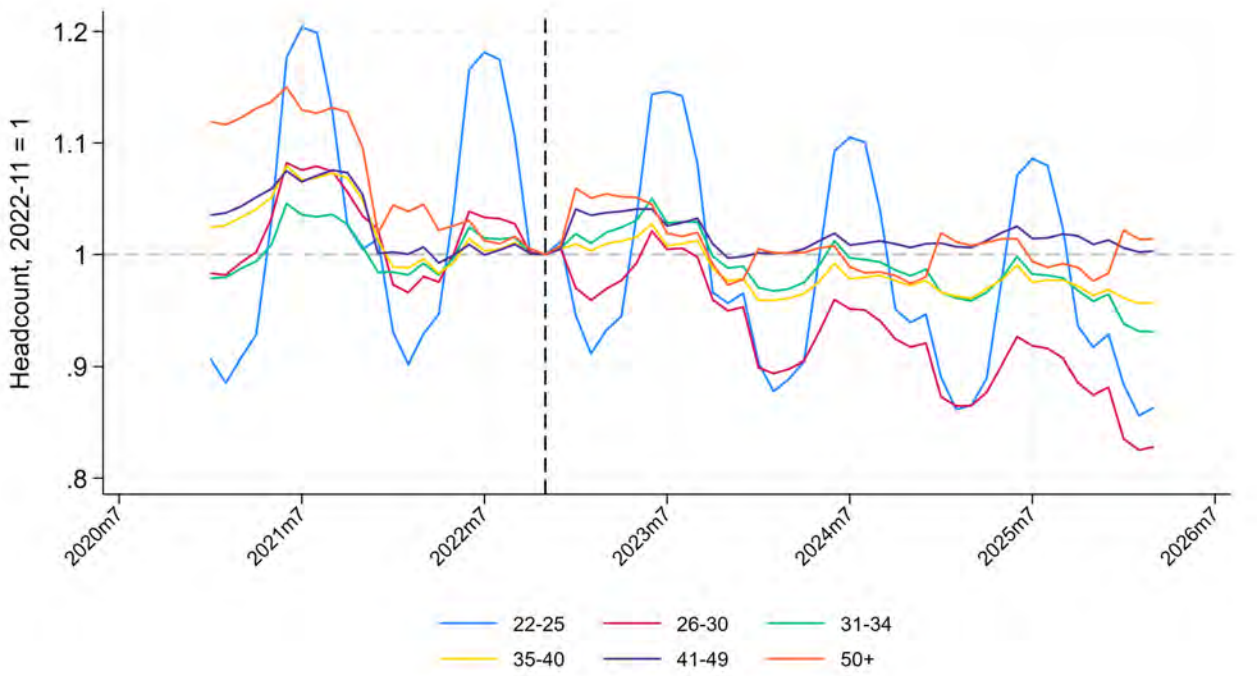
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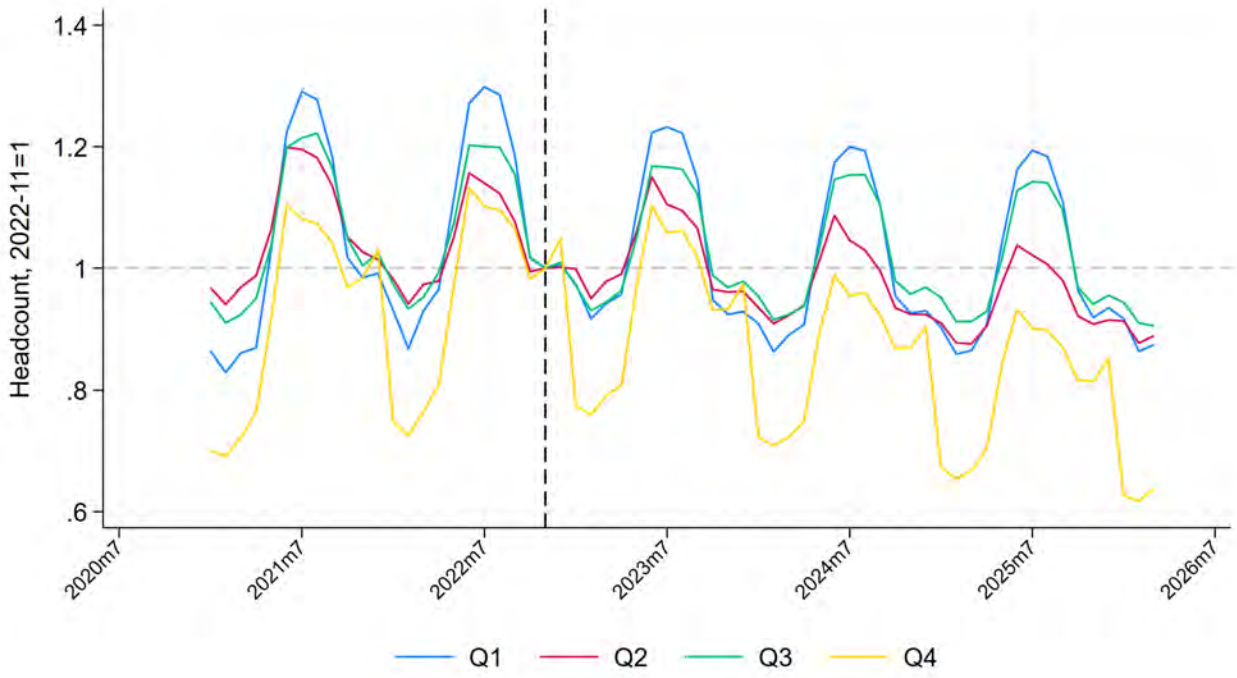
Figures and Tables

Figure 1: Employment by age band, 2022m11 = 1



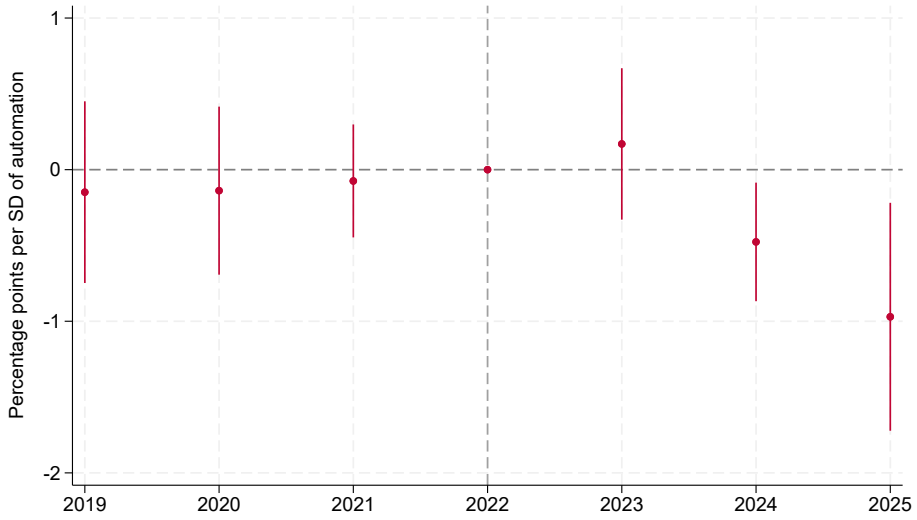
Notes: Employed persons by age band, normalized to one in November 2022. Sample: private-sector employees aged 22 and above. Source: Finnish Incomes Register, Statistics Finland FOLK.

Figure 2: Employment of 22-25 year-olds by AI exposure quartile

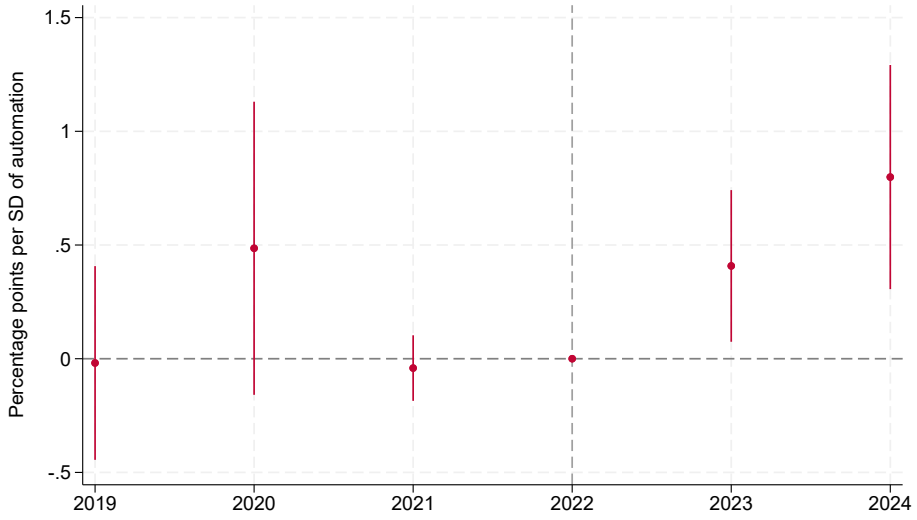


Notes: Employment of workers aged 22–25 by AI exposure quartile, normalized to one in November 2022. Exposure quartiles calculated using the Anthropic Economic Index [Handa et al., 2025], described in Section 3.1; Q4 is most exposed. Source: Finnish Incomes Register.

Figure 3: Graduate employment, unemployment and automation exposure



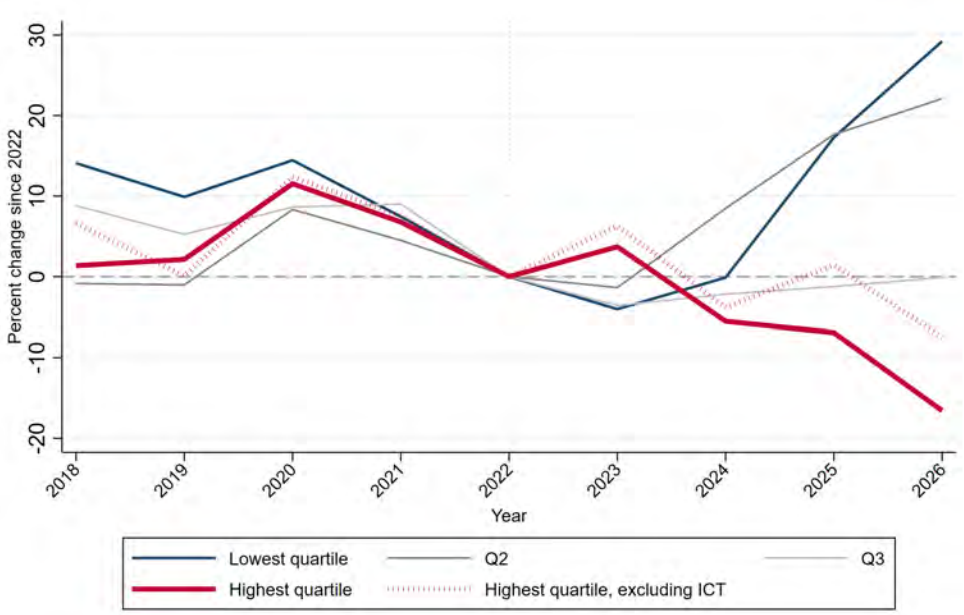
(A) Employment



(B) Unemployment

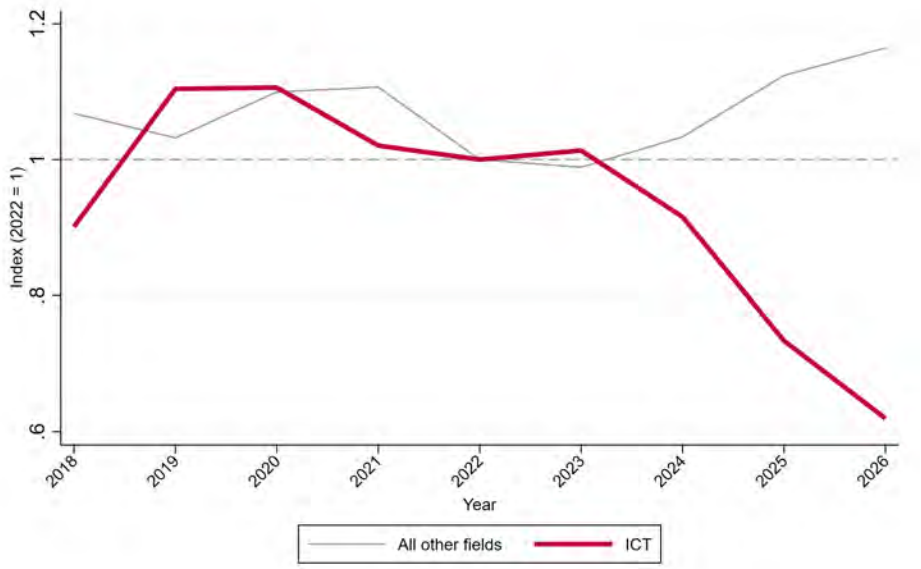
Notes: Event-study coefficients on a one-standard-deviation increase in field-level automation exposure (indicator based on Handa et al. [2025]), base year 2022. Sample: degree holders aged under 30 whose highest recorded qualification is a university master's degree or equivalent. The field-specific employment rate is calculated as the share of graduates with at least one wage payment during the calendar year. The field-specific unemployment rate is the number of unemployed jobseekers divided by the field's labor force at year-end. Observations are aggregated at the level of ISCED-F 2013 three-digit field of study codes. Regressions are estimated by weighted least squares on the field $\times$ year panel, with field and year fixed effects. Employment observations are weighted by the number of degree holders and unemployment observations by the field's labour force. Coefficients are in percentage points; bars are 95 per cent confidence intervals, with standard errors clustered at the 3-digit field level.

Figure 4: Change in university applicants, by quartile of automation exposure of the field of study

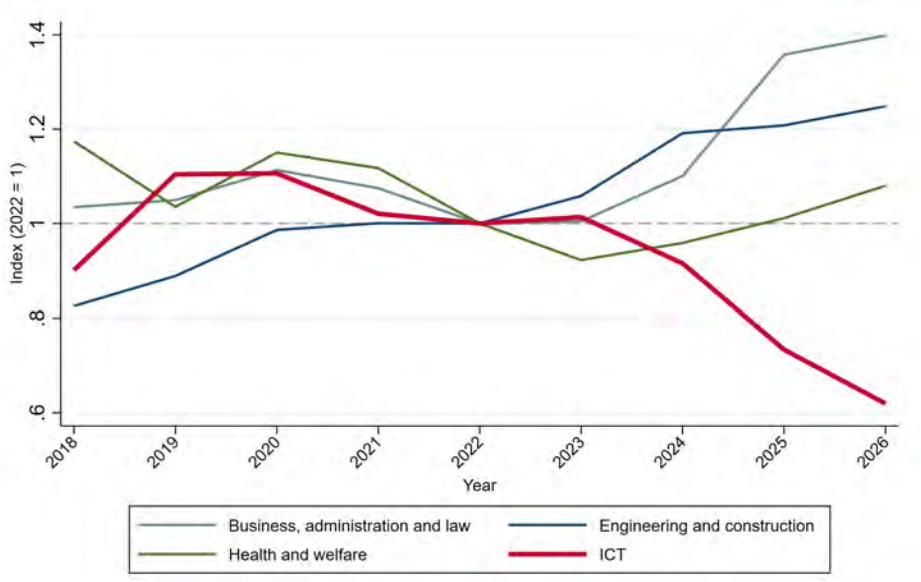


Notes: First-choice applicants by quartile of degree-level automation exposure, shown as percentage changes relative to the 2022 round. Sample: First-time applicants (individuals not previously enrolled). Automation exposure is described in Section 3.1 and aggregated at the degree code level as described in Section 3.3, based on the Handa et al. [2025] measure. The panel is restricted to degree $\times$ institution units observed in all nine years, which account for 92 per cent of 2026 first-choice applicants; applicants are summed within each quartile and the sum is indexed to 2022. The dotted red line shows the highest automation quartile after excluding ICT degrees, retaining the original quartiles.

Figure 5: First-choice field of study applicants, 2022 = 1



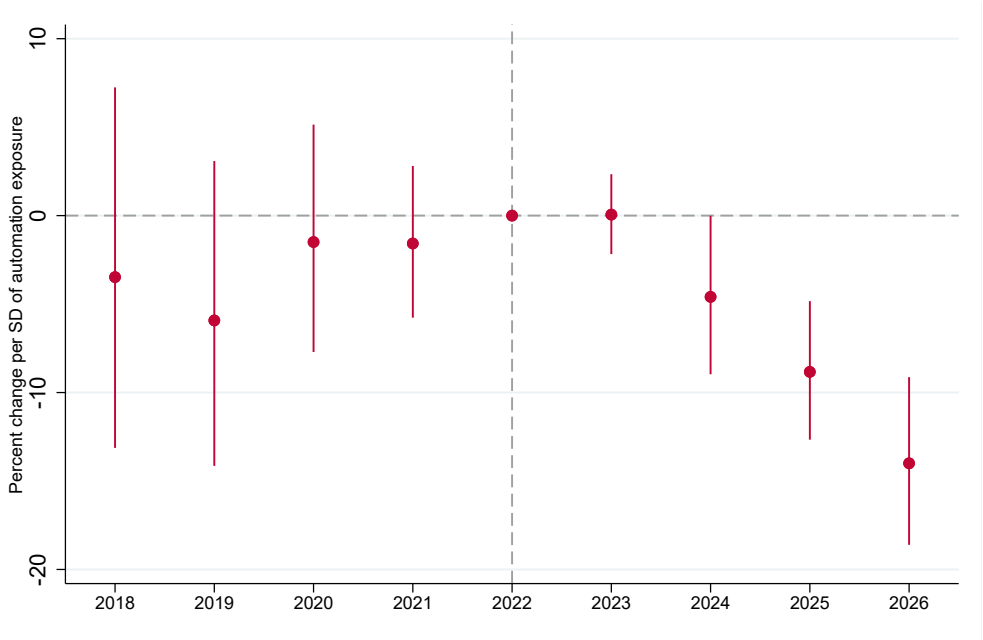
(A) ICT and all other fields



(B) Four broad fields

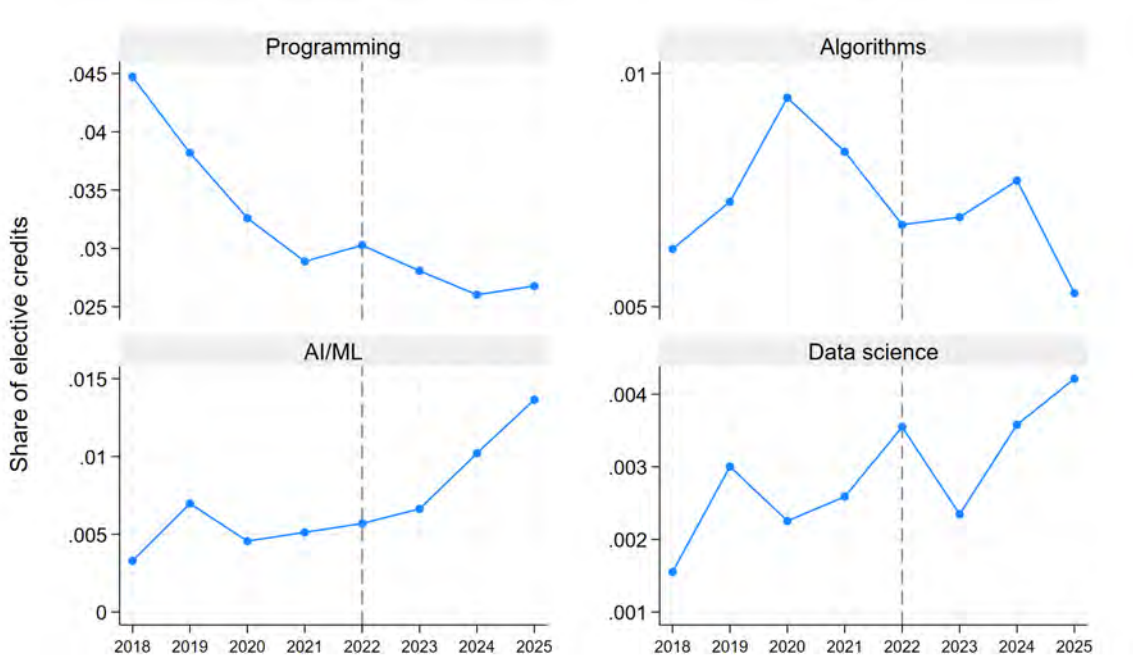
Notes: Number of applicants whose first-ranked programme is in the field, indexed to the 2022 intake round, for ISCED-F 2013 broad fields. Source: Vipunen (Finnish Ministry of Education and Culture), report *Haku ja valinta, korkeakoulu*. Sample: autumn intake, joint application, main round, first-cycle university programmes, Finnish citizens. Panel A plots ICT against the university sector total excluding ICT. Panel B plots ICT, engineering, health and welfare, and business, administration and law separately.

Figure 6: Applications and automation exposure



Notes: Event-study coefficients from equation 3 on a one-standard-deviation increase in degree-level automation exposure (based on the Handa et al. [2025] measure), base year 2022; 2,169 cells covering 89 degree codes, first-time applicants (individuals who were not previously enrolled in higher education). The automation exposure measure is described in Section 3.1, aggregated to the degree level as set out in Section 3.3, and standardized across degree codes. Since field $\times$ year effects are absorbed, the coefficients are identified from differences in automation exposure between degrees within the same broad field of study. The 2026 coefficient is –14.015 and the 2025 coefficient is –8.789.

Figure 7: Composition of ICT electives chosen by students in non-ICT programs, 2018–2025



Notes: Share of outside-field elective credits going to each ICT course type, by year. Sample: Finnish university students in non-ICT degree programmes, 2018–2025, who completed at least 30 credits within a study right in the year, with non-missing information on high school exit exam mathematics track and parental income, and at least one outside-field elective in the year. Course types are keyword classifications of ICT course names (see Table A6). The dashed line marks the release of ChatGPT 3.5 in November 2022.

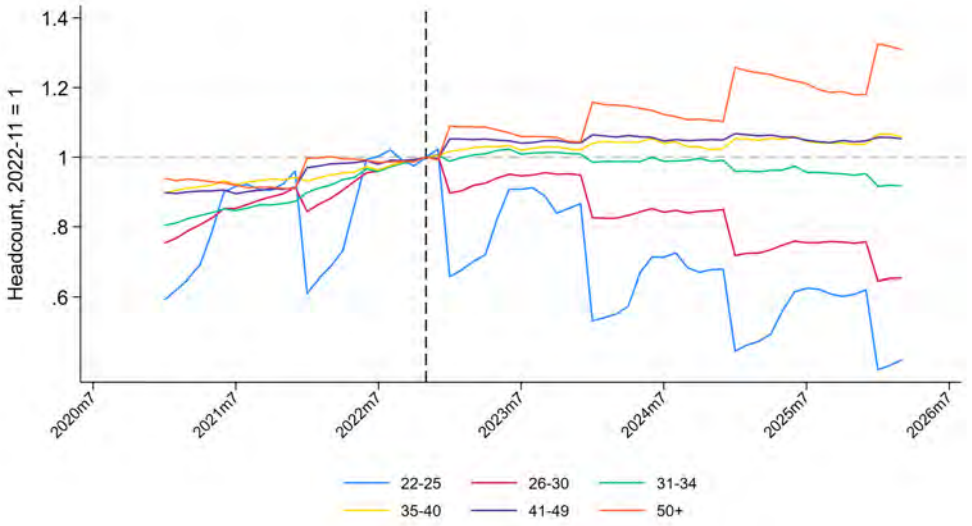
Table 1: Differential changes in ICT elective take-up among non-ICT students after the launch of ChatGPT 3.5

Selected coefficients	Any ICT	Programming and Algorithms	AI/ML+ Data science	AI/ML
Post × Female	−0.0040	0.0002	−0.0036***	−0.0026**
	(0.0053)	(0.0037)	(0.0013)	(0.0011)
Post × No matriculation exam in math	−0.0079*	−0.0041*	−0.0004	−0.0004
	(0.0041)	(0.0023)	(0.0011)	(0.0008)
Post × Math, basic curriculum	−0.0056	−0.0017	−0.0003	−0.0009
	(0.0050)	(0.0021)	(0.0013)	(0.0010)
Post × Parental income, top quartile	−0.0031	0.0000	−0.0007	−0.0001
	(0.0034)	(0.0017)	(0.0011)	(0.0009)
Observations	232,885	232,885	232,885	232,885
$\bar{Y}$	0.0560	0.0198	0.0075	0.0057

Notes: Coefficients on Post × X from equation 4, estimated by OLS on the student × study right × year panel, 2021–2025. All four characteristics enter a single regression per outcome. Mathematics coefficients are relative to long mathematics; the omitted income category is the bottom three quartiles, ranked within entry cohort. Specifications include year, degree programme, university and year-of-study fixed effects. Standard errors clustered by university × entry cohort. Eleven observations are dropped as singleton fixed-effect groups, so the sample is slightly smaller than in Table A7. Modern ICT combines AI/ML with data science, traditional ICT combines programming with algorithms, and any ICT covers all ICT-field electives (see Table A6). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

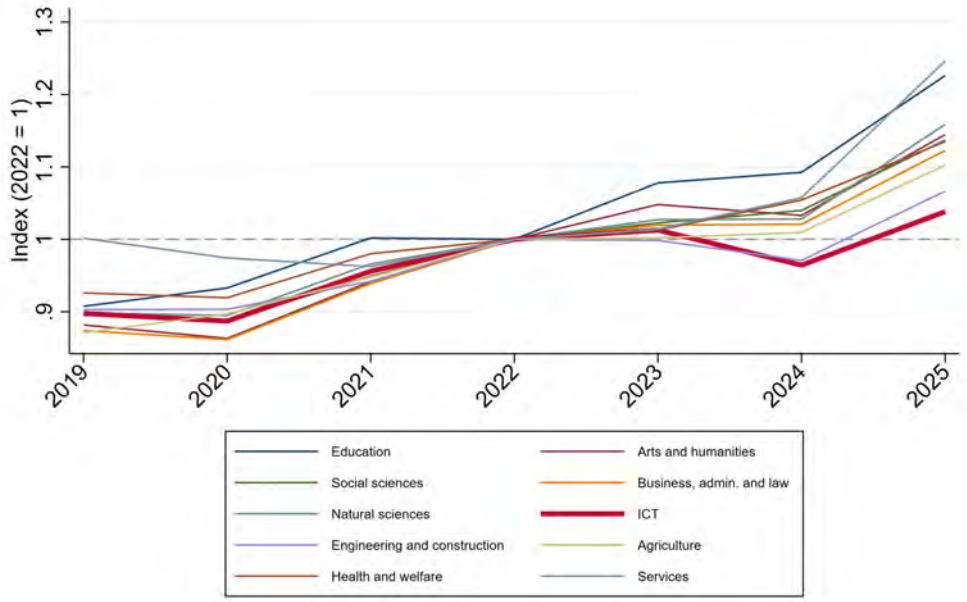
A Additional Figures and Tables

Figure A1: Employment of software and applications developers (ISCO 251) by age band



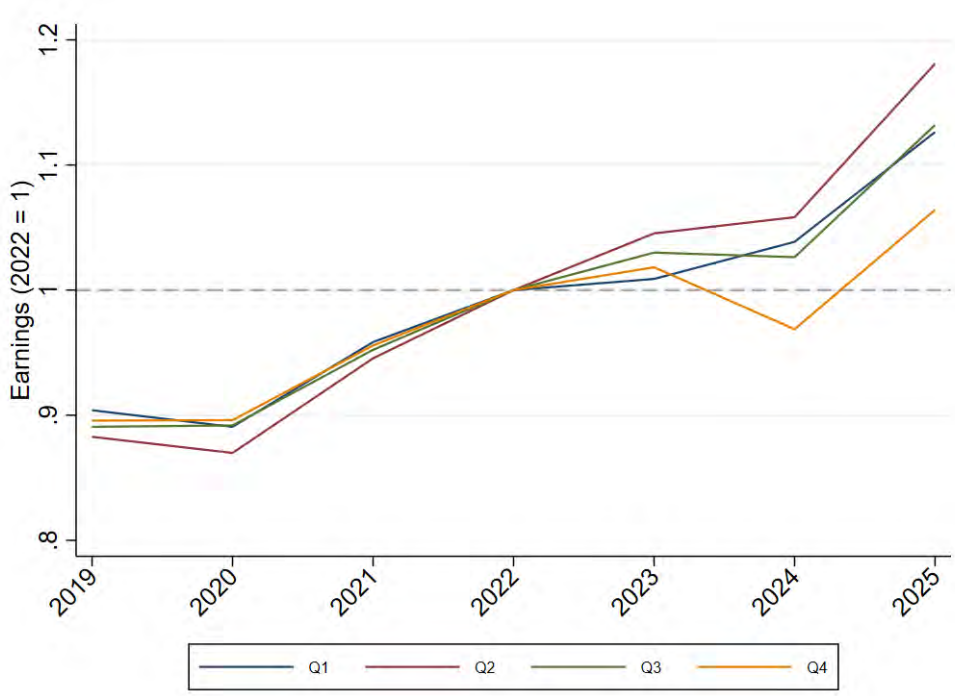
Notes: Employment of software developers, by age band, normalized to one in November 2022. Private sector employees aged 22 and above. Source: Finnish Incomes Register.

Figure A2: Earnings of university graduates under 30, by field of study



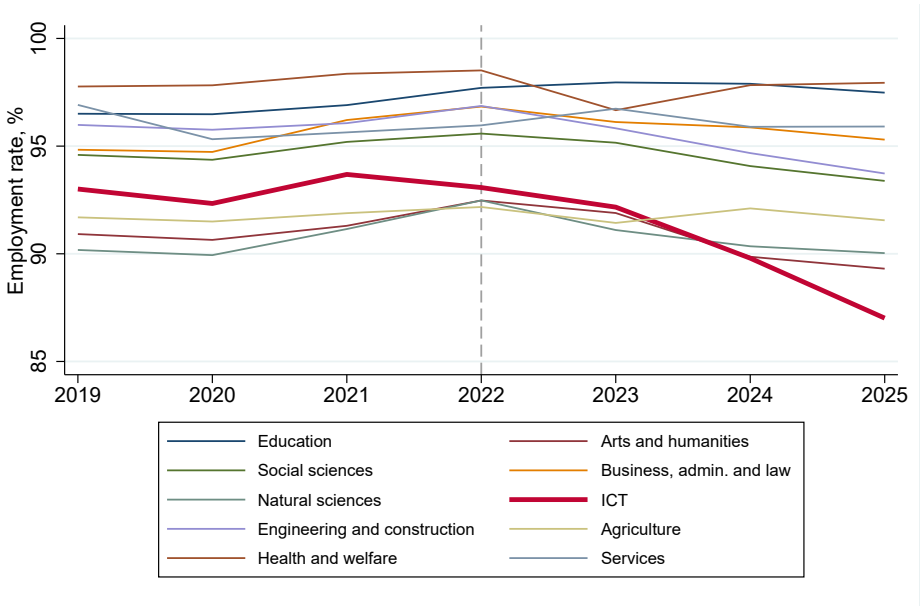
Notes: Mean annual nominal wage earnings by ISCED-F 2013 broad field of degree, 2019–2025, indexed to one in 2022. Sample: degree holders aged under 30 whose highest recorded qualification is a university master's degree or equivalent. Annual earnings are summed across employers and months, including zero earnings for degree holders without wage payments. Degree information for 2025 is taken from 2024. ICT is shown in red. Source: Finnish Incomes Register and Statistics Finland FOLK.

Figure A3: Graduate earnings by automation exposure quartile

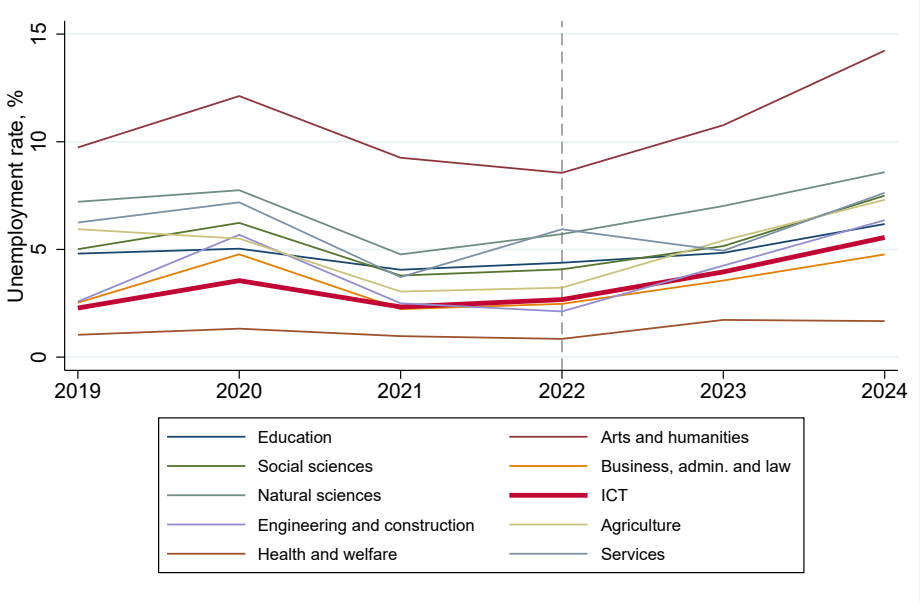


Notes: Mean annual nominal wage earnings by automation exposure quartile, indexed to one in 2022. Sample and earnings construction are as in Figure A2, restricted to narrow fields with non-missing automation exposure. Quartiles are formed across ISCED-F 2013 narrow fields (three-digit codes) in the earnings sample and held fixed over time; Q4 is most exposed. Automation exposure is the narrow-field equivalent of the degree-level measure described in Section 3.3.

Figure A4: Employment and unemployment of university graduates under 30, by field of study



(A) Employment



(B) Unemployment

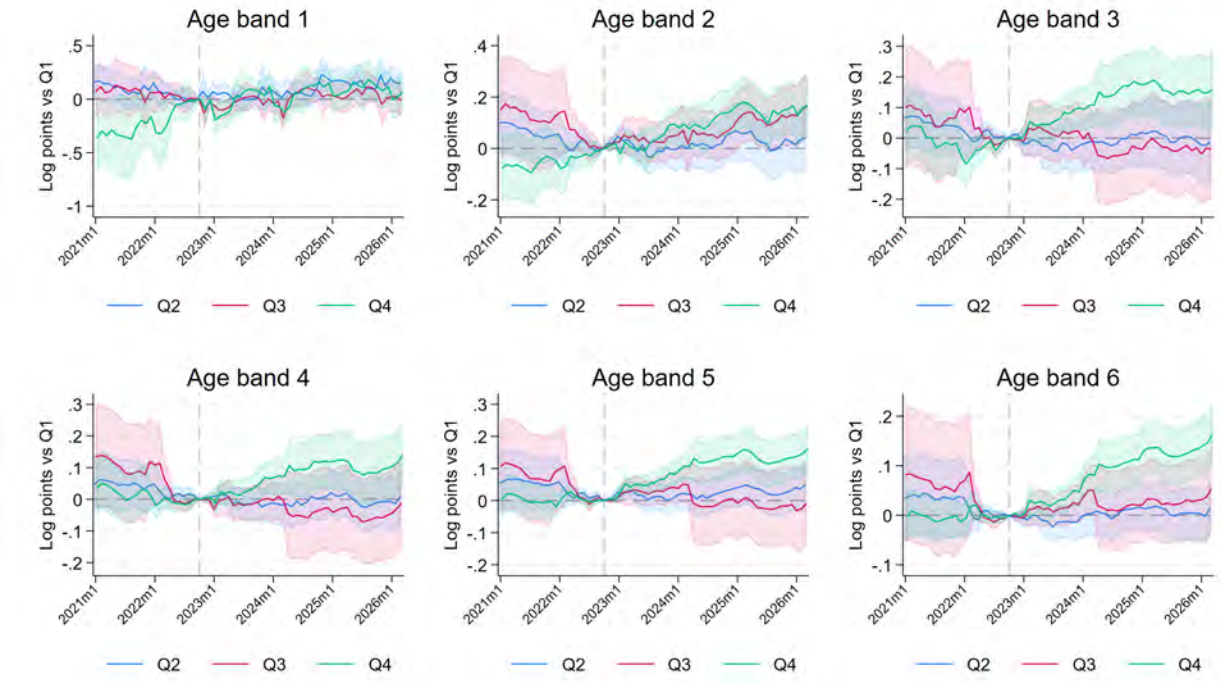
Notes: Employment and unemployment rates by ISCED-F 2013 broad field of degree. Sample: degree holders aged under 30 whose highest recorded qualification is a university master's degree or equivalent. Employment is the share with at least one wage payment during the calendar year. Unemployment is the number of unemployed jobseekers divided by the field's labour force at year-end. The unemployment series ends in 2024, the latest available FOLK year. ICT is shown in red; the dashed line marks 2022. Source: Finnish Incomes Register and Statistics Finland FOLK.

Figure A5: Degrees ranked by change in first-choice applicants, 2022–2026



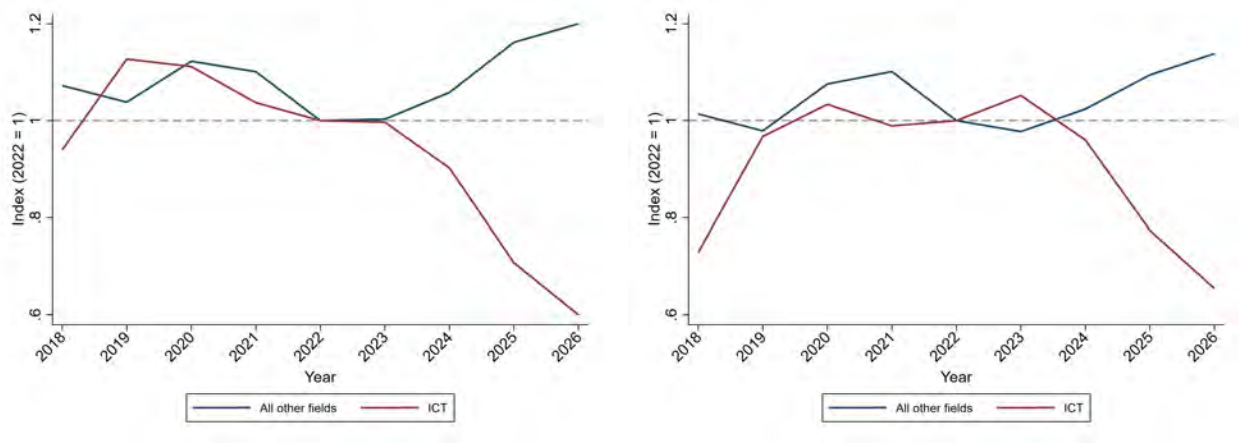
Notes: Each line is one degree code, ordered by the percent change in first-choice applicants between the 2022 and 2026 rounds. Sample: first-time applicants, i.e. applicants who have not previously accepted a Finnish degree place, at the 67 degree codes with at least 50 first-choice applicants in 2022. ICT degrees are shown in red and rank first, seventh and eighth of 67: Computer Science, Information Systems Science and Information Technology. Telecommunications Technology, the fourth ICT degree, had 48 first-choice applicants in 2022 and falls below the floor.

Figure A6: Within-firm employment by AI exposure quartile and age band



Notes: Event-study coefficients from equation 2, estimated separately for each age band by Poisson pseudo-maximum likelihood with firm × quartile and firm × month fixed effects. Age bands 1–6 correspond to ages 22–25, 26–30, 31–34, 35–40, 41–49, and 50 and above, respectively. Each line is the log change in headcount of one exposure quartile relative to the lowest quartile within the same firm and month, relative to October 2022, the last full month before the release of ChatGPT. Shaded regions are 95 per cent confidence intervals, standard errors clustered by firm. Exposure quartiles from the Anthropic Economic Index [Handa et al., 2025], as in Section 3.1. Sample: private-sector wage employees with a reported occupation, January 2021 to March 2026. Following Brynjolfsson et al. [2025] and Kauhanen and Rouvinen [2026], each age band's regression is restricted to firms with at least ten workers in that age band in every month of the window and at least 100 cumulative worker-months in each exposure quartile;Source: Finnish Incomes Register, Statistics Finland FOLK.

Figure A7: First-choice applicants to ICT and all other fields, by gender



(A) Men (B) Women

Notes: First-choice applicants to ICT and all other university fields, separately for men and women, indexed to 1 in the 2022 application round. Sample and construction are as in Figure 5. Source: Educational Administration Statistics Service, vipunen.fi

Table A1: Top 20 Degrees by Automation Exposure (Handa et al., 2025)

Code	Degree	ISCED Broad Field	Automation Exposure	Appl. 2022	Appl. 2026	% Change
725111	Master of Arts (Theatre and Drama)	Arts and Humanities	52.9	879	690	-21.5
723111	Master of Music	Arts and Humanities	47.0	241	222.5	-7.7
751301	Master of Science (Technology), Information Technology	ICT	45.4	1116	750	-32.8
742201	Master of Science, Computer Science	ICT	45.4	580	272	-53.1
754101	Master of Science (Architecture)	Engineering, Manuf. & Const.	45.1	513	516	0.6
754201	Master of Science (Landscape Architecture)	Engineering, Manuf. & Const.	43.6	30	45	50.0
733206	Master of Social Sciences, Communication Sciences	Social Sciences & Journalism	43.3	213	198	-7.0
732115	Master of Science (Econ. & Bus. Admin.), Info. Systems	ICT	42.8	81	57	-29.6
722101	Master of Arts (Art and Design)	Arts and Humanities	42.0	1161	963	-17.1
726501	Master of Arts, Art History and Art Education	Arts and Humanities	41.4	39	33	-15.4
726601	Master of Arts, Communication and Information Sciences	Social Sciences & Journalism	41.4	89.5	60	-33.0
751202	Master of Science (Technology), Automation Engineering	Engineering, Manuf. & Const.	41.2	195	327	67.7
726116	Master of Arts, Scandinavian Languages	Arts and Humanities	40.8	23.5	24	2.1
724101	Master of Fine Arts	Arts and Humanities	40.8	342	288	-15.8
712109	Master of Arts (Education), Music Teacher	Education	40.7	12	6	-50.0
742101	Master of Science, Mathematics	Natural Sciences & Maths	40.7	114	102	-10.5
751203	Master of Science (Technology), Engineering Physics	Engineering, Manuf. & Const.	40.6	183	279	52.5
726502	Master of Arts, Musicology and Music Education	Arts and Humanities	40.5	39	33	-15.4
726402	Master of Arts, Cultural Research	Arts and Humanities	40.4	346.5	309	-10.8
726105	Master of Arts, French Language	Arts and Humanities	40.4	33	24	-27.3

Notes: Sample: First-time applicants, 2022 and 2026 rounds. Automation measure from Handa et al. [2025].

Table A2: Top 20 Degrees by Automation Exposure (Eloundou et al., 2023)

Code	Degree	ISCED Broad Field	Automation Exposure	Appl. 2022	Appl. 2026	% Change
732105	Master of Science (Econ. & Bus. Admin.), Social Sciences	Social Sciences & Journalism	48.1	35.5	39	9.9
732101	Master of Science (Econ. & Bus. Admin.), Business Economics	Business, Admin. & Law	47.4	7933.5	10170	28.2
733102	Master of Social Sciences, Economics	Social Sciences & Journalism	45.9	105	138	31.4
732115	Master of Science (Econ. & Bus. Admin.), Info. Systems	ICT	43.9	81	57	-29.6
733206	Master of Social Sciences, Communication Sciences	Social Sciences & Journalism	43.6	213	198	-7.0
726601	Master of Arts, Communication and Information Sciences	Social Sciences & Journalism	43.5	89.5	60	-33.0
733211	Master of Social Sciences, Tourism	Services	42.2	21	12	-42.9
733101	Master of Social Sciences, Political Sciences	Social Sciences & Journalism	41.8	885	1122	26.8
742201	Master of Science, Computer Science	ICT	41.4	580	272	-53.1
733301	Master of Administrative Sciences, Administrative Sciences	Social Sciences & Journalism	40.8	113	114	0.9
751301	Master of Science (Technology), Information Technology	ICT	40.7	1116	750	-32.8
733201	Master of Social Sciences, Political Sciences	Social Sciences & Journalism	39.9	146.5	201	37.2
751601	Master of Science (Technology), Industrial Management	Engineering, Manuf. & Const.	39.8	891	1137	27.6
762301	Master of Food Sciences	Agriculture, Forestry & Vet.	39.0	66	99	50.0
712202	Master of Arts (Education), Adult Education	Education	38.9	113.5	90	-20.7
734101	Master of Laws	Business, Admin. & Law	36.9	2778	4469	60.9
726402	Master of Arts, Cultural Research	Arts and Humanities	36.5	346.5	309	-10.8
751502	Master of Science (Technology), Surveying Technology	Engineering, Manuf. & Const.	35.7	89	99	11.2
733107	Master of Social Sciences, Philosophy	Arts and Humanities	35.6	45	33	-26.7
751202	Master of Science (Technology), Automation Engineering	Engineering, Manuf. & Const.	35.2	195	327	67.7

Notes: First-time applicants, 2022 and 2026 rounds. Automation measure from Eloundou et al. [2023].

Table A3: Top 20 Degrees by Automation Exposure (Frey-Osborne)

Code	Degree	ISCED Broad Field	Automation Exposure	Appl. 2022	Appl. 2026	% Change
732105	Master of Science (Econ. & Bus. Admin.), Social Sciences	Social Sciences & Journalism	54.2	35.5	39	9.9
733211	Master of Social Sciences, Tourism	Services	52.5	21	12	-42.9
732101	Master of Science (Econ. & Bus. Admin.), Business Economics	Business, Admin. & Law	52.0	7933.5	10170	28.2
762301	Master of Food Sciences	Agriculture, Forestry & Vet.	51.6	66	99	50.0
733102	Master of Social Sciences, Economics	Social Sciences & Journalism	50.3	105	138	31.4
762201	Master of Science (Agriculture and Forestry), Agriculture	Agriculture, Forestry & Vet.	48.0	54	42	-22.2
742702	Master of Science, Biosciences, Biochemistry	Natural Sciences & Maths	46.5	477	543	13.8
726501	Master of Arts, Art History and Art Education	Arts and Humanities	45.2	39	33	-15.4
733101	Master of Social Sciences, Political Sciences	Social Sciences & Journalism	44.6	885	1122	26.8
726402	Master of Arts, Cultural Research	Arts and Humanities	44.3	346.5	309	-10.8
733301	Master of Administrative Sciences, Administrative Sciences	Social Sciences & Journalism	44.0	113	114	0.9
733201	Master of Social Sciences, Political Sciences	Social Sciences & Journalism	42.8	146.5	201	37.2
751401	Master of Science (Technology), Chemical Engineering	Engineering, Manuf. & Const.	42.7	42	69	64.3
712202	Master of Arts (Education), Adult Education	Education	42.5	113.5	90	-20.7
724101	Master of Fine Arts	Arts and Humanities	42.5	342	288	-15.8
733107	Master of Social Sciences, Philosophy	Arts and Humanities	42.1	45	33	-26.7
762202	Master of Science (Agriculture and Forestry), Forestry	Agriculture, Forestry & Vet.	41.6	135	104.5	-22.6
726106	Master of Arts, Russian Language	Arts and Humanities	41.4	32.5	17	-47.7
751409	Master of Science (Technology), Biotechnology	Engineering, Manuf. & Const.	40.8	171	165	-3.5
751601	Master of Science (Technology), Industrial Management	Engineering, Manuf. & Const.	40.7	891	1137	27.6

Notes: First-time applicants, 2022 and 2026 rounds. Automation measure from Frey and Osborne [2017].

Table A4: Top 20 Degrees by Automation Exposure (ATLAS)

Code	Degree	ISCED Broad Field	Automation Exposure	Appl. 2022	Appl. 2026	% Change
732105	Master of Science (Econ. & Bus. Admin.), Social Sciences	Social Sciences & Journalism	32.6	35.5	39	9.9
733211	Master of Social Sciences, Tourism	Services	31.8	21	12	-42.9
732101	Master of Science (Econ. & Bus. Admin.), Business Economics	Business, Admin. & Law	31.4	7933.5	10170	28.2
733102	Master of Social Sciences, Economics	Social Sciences & Journalism	30.9	105	138	31.4
762301	Master of Food Sciences	Agriculture, Forestry & Vet.	30.2	66	99	50.0
733101	Master of Social Sciences, Political Sciences	Social Sciences & Journalism	27.3	885	1122	26.8
712202	Master of Arts (Education), Adult Education	Education	26.6	113.5	90	-20.7
726402	Master of Arts, Cultural Research	Arts and Humanities	26.6	346.5	309	-10.8
726106	Master of Arts, Russian Language	Arts and Humanities	26.4	32.5	17	-47.7
733301	Master of Administrative Sciences, Administrative Sciences	Social Sciences & Journalism	26.2	113	114	0.9
762201	Master of Science (Agriculture and Forestry), Agriculture	Agriculture, Forestry & Vet.	26.0	54	42	-22.2
726601	Master of Arts, Communication and Information Sciences	Social Sciences & Journalism	25.9	89.5	60	-33.0
733107	Master of Social Sciences, Philosophy	Arts and Humanities	25.6	45	33	-26.7
733201	Master of Social Sciences, Political Sciences	Social Sciences & Journalism	25.5	146.5	201	37.2
726501	Master of Arts, Art History and Art Education	Arts and Humanities	25.0	39	33	-15.4
762202	Master of Science (Agriculture and Forestry), Forestry	Agriculture, Forestry & Vet.	24.5	135	104.5	-22.6
751601	Master of Science (Technology), Industrial Management	Engineering, Manuf. & Const.	23.9	891	1137	27.6
732115	Master of Science (Econ. & Bus. Admin.), Info. Systems	ICT	23.1	81	57	-29.6
724101	Master of Fine Arts	Arts and Humanities	23.0	342	288	-15.8
726108	Master of Arts, Italian Language	Arts and Humanities	22.8	21	12	-42.9

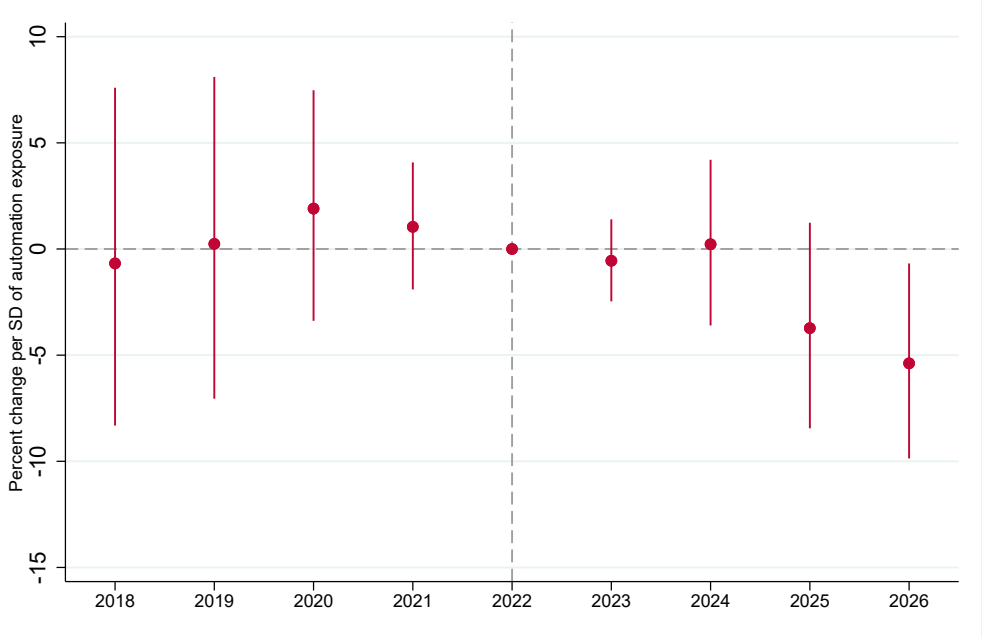
Notes: First-time applicants, 2022 and 2026 rounds. Automation measure is a Finland-specific substitution measure from Garg et al. [2026].

Table A5: Correlations among degree-level automation measures

	Handa	Eloundou	Frey–Osborne	ATLAS
Handa	1.000	0.404	0.151	0.242
Eloundou	0.404	1.000	0.816	0.854
Frey–Osborne	0.151	0.816	1.000	0.935
ATLAS	0.242	0.854	0.935	1.000

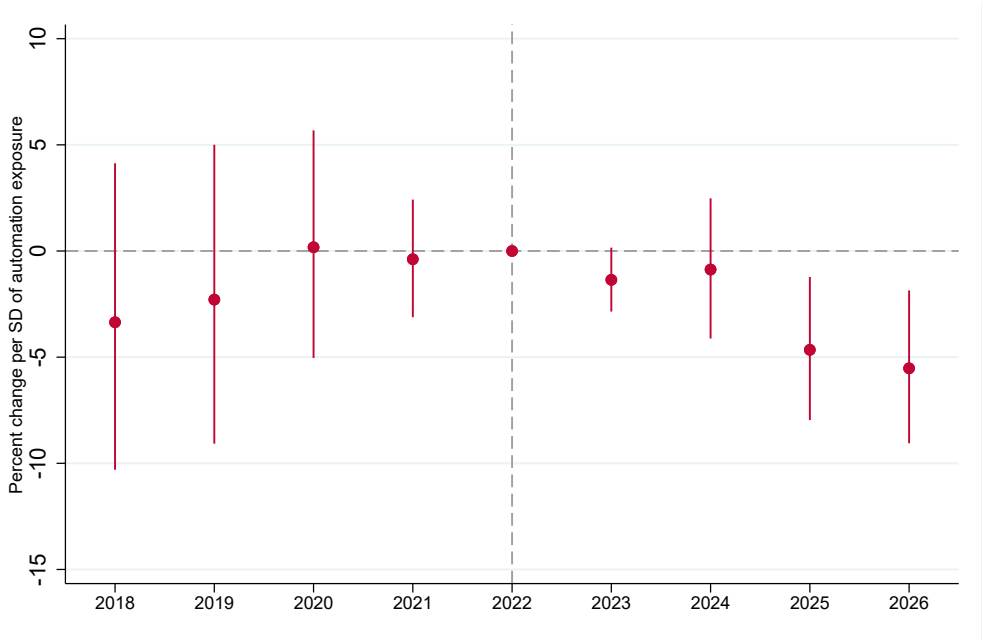
Notes: Pearson correlations among the four degree-level automation measures used in the applications analysis, computed across 87 degree codes in the balanced application sample with nonmissing data for all four measures. Each degree code weighted equally.

Figure A8: Applications and automation exposure, Eloundou GPT-4 task labels



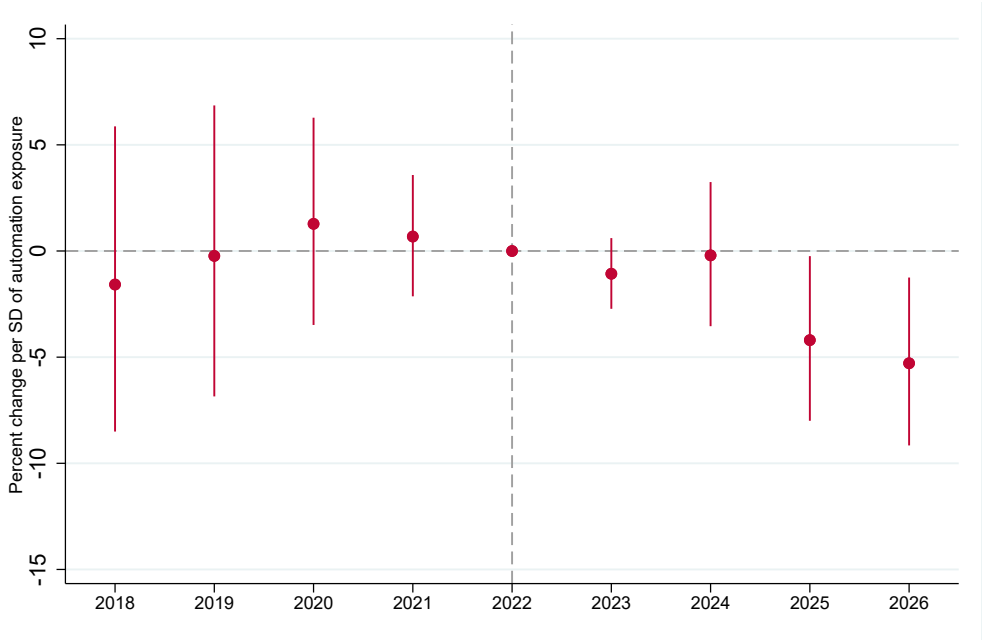
Notes: As in Figure 6, replacing the Handa et al. automation share with the share of occupational tasks classified by GPT-4 as highly or fully automatable [Eloundou et al., 2023]. High automation (T3) means that LLM-based software could perform 90–100 per cent of a task's components with human oversight. Full automation (T4) means complete, high-quality task performance that normally requires no human oversight.

Figure A9: Applications and automation exposure, Frey–Osborne computerisation risk



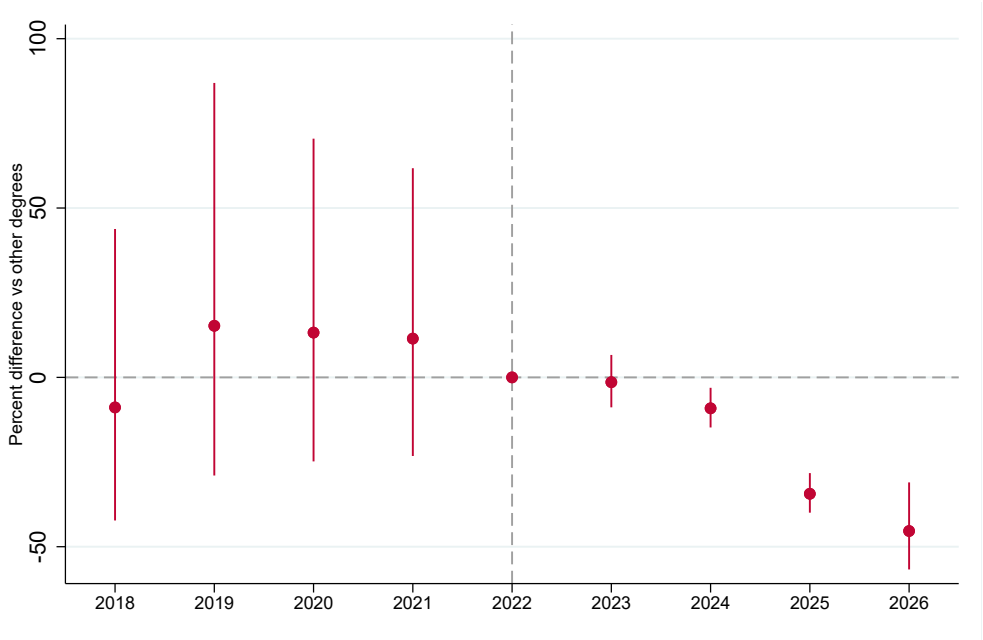
Notes: As in Figure 6, replacing the Handa et al. automation share with the occupational probability of computerisation estimated by Frey and Osborne [2017]. The measure assesses whether an occupation could be automated, using expert assessments and occupational requirements for skills that limit automation, such as dexterity, creativity and social interaction.

Figure A10: Applications and automation exposure, ATLAS Finland substitution-only measure



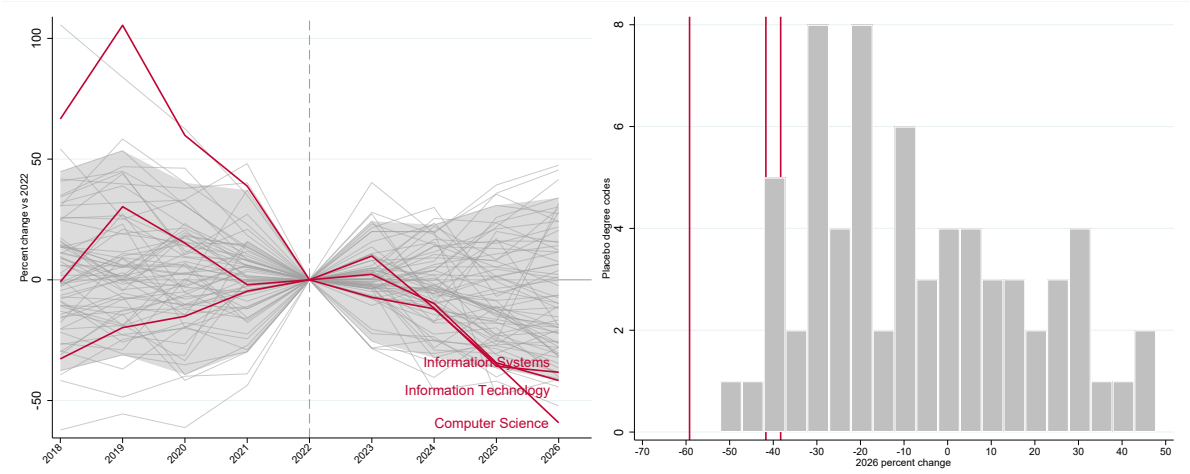
Notes: As in Figure 6, replacing the Handa et al. automation share with the Finland-specific substitution-only task share from the Global Automation Atlas [Garg et al., 2026]. The measure captures the scope for technology to reduce human labour input across occupational tasks in Finland, covering AI, conventional software and robotics.

Figure A11: ICT applications relative to all other degrees



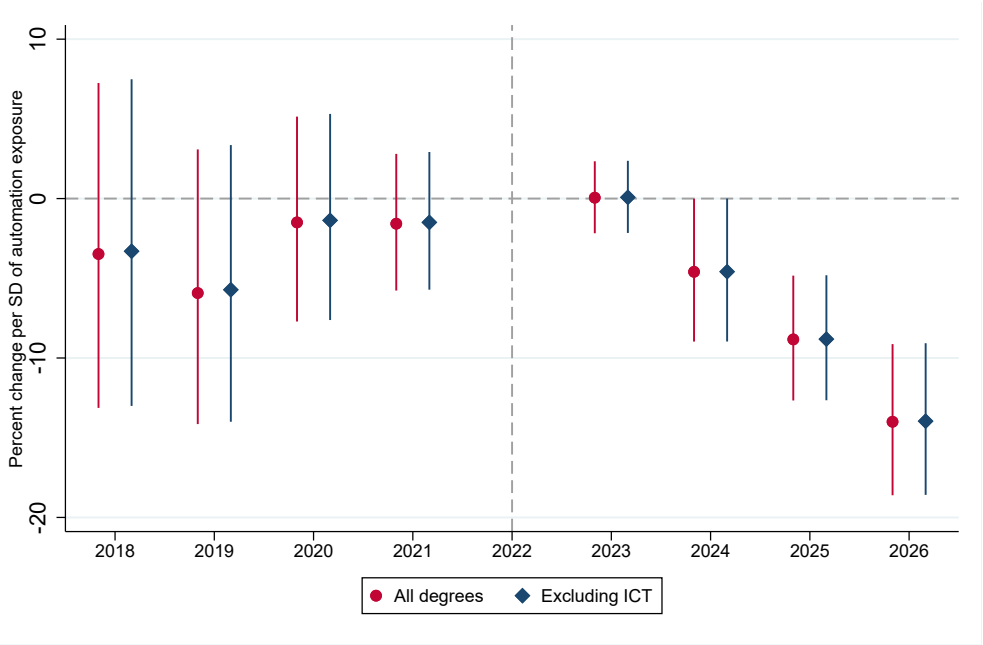
Notes: Event-study coefficients from equation 3, estimated with an indicator for ICT degrees in place of the continuous exposure measure, base year 2022. The unit of observation is the degree code × institution × year cell, with year and institution fixed effects absorbed and standard errors clustered on degree code. Sample: first-time applicants to university programmes, 2018–2026, 2,627 cells covering 105 degree codes at 14 institutions. ICT comprises four degree codes – Computer Science, Information Technology, Telecommunications Technology and Information Systems Science – offered at nine institutions. The 2026 coefficient is –45.338 and the 2025 coefficient –34.361; Since treatment is assigned to four degree codes in a single broad field, the cluster-robust standard errors rest on few treated clusters and are shown for reference.

Figure A12: Placebo exercise for ICT applications



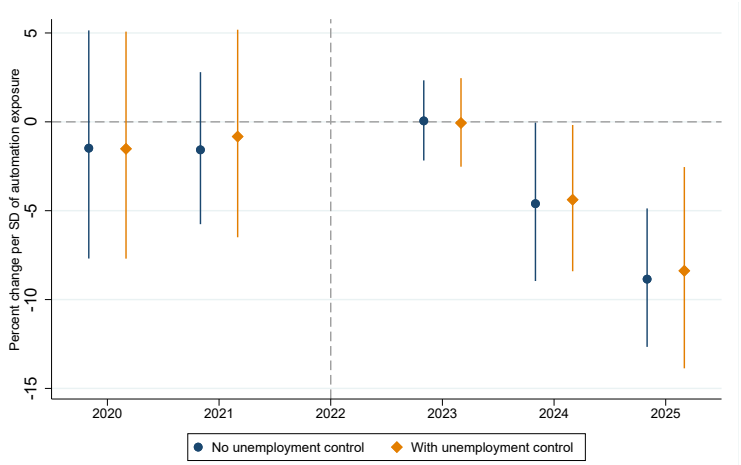
Notes: Placebo exercise for the ICT specification in Figure A11. The sample is restricted to degree–institution units observed in every year from 2018 to 2026 and to degree codes with at least 50 first-choice applicants in the 2022 round within this balanced panel, leaving 70 eligible degree codes. For each eligible degree code in turn, we re-estimate the PPML event-study specification, treating that code alone against all other eligible codes, with year and institution fixed effects. The left panel plots the resulting event-study paths. Thin gray lines correspond to non-ICT degree codes and red lines to the three eligible ICT degree codes. The shaded region gives the 5th–95th percentile range across all 70 single-degree estimates in each year. The right panel shows the distribution of the 2026 estimates from the non-ICT placebo assignments; vertical red lines indicate the corresponding ICT estimates. Telecommunications Technology is excluded because it is not observed before 2022. The 2022 round is the omitted base year. Estimates are expressed as percentage changes. Sample: first-time applicants to university programmes.

Figure A13: Applications and automation exposure, excluding ICT degrees



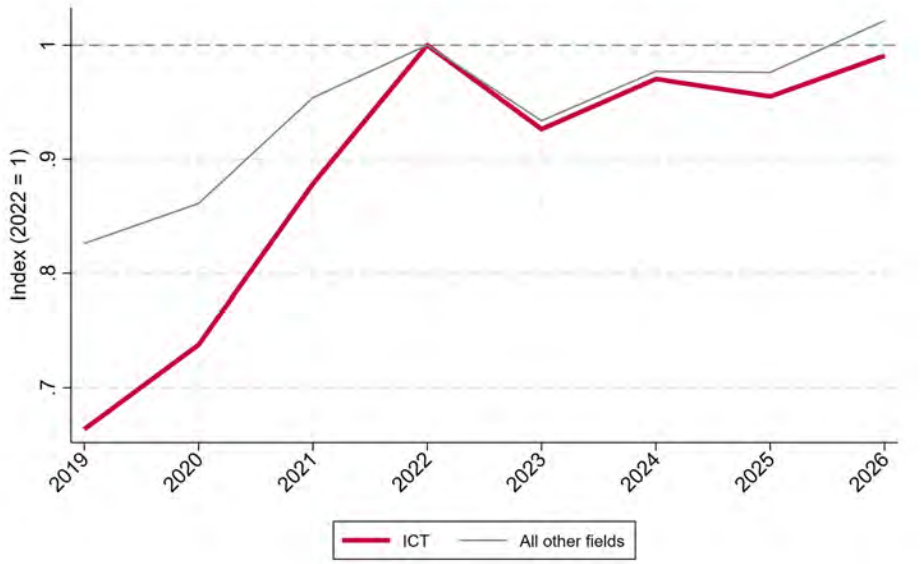
Notes: Event-study coefficients from equation 3, as in Figure 6. The first specification uses all degrees and reproduces the main estimate; the second re-estimates the same specification after excluding ICT degrees. Both specifications use the balanced panel of degree × institution units observed in every year, with field × year and institution fixed effects and standard errors clustered on degree code. Automation exposure is standardized on the full set of degree codes in both specifications, so the coefficients are on the same scale. The 2022 round is the omitted base year.

Figure A14: Applications and automation exposure, with and without a control for unemployment among graduates of the field

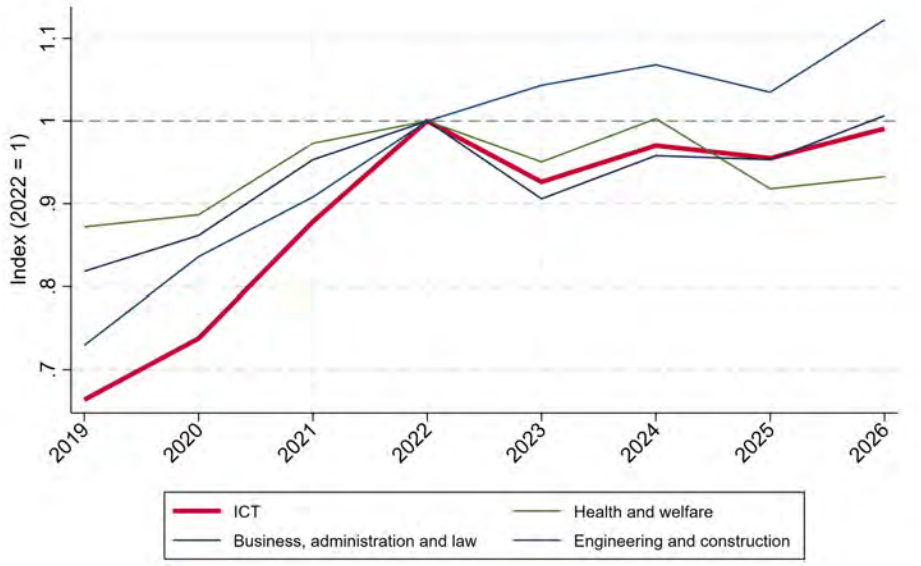


Notes: Event-study coefficients from equation 3 on a one-standard-deviation increase in degree-level automation exposure, estimated with and without a control for the unemployment rate of the corresponding field, base year 2022. The specification is that of Figure 6. The control is the field unemployment rate defined in the notes to Figure A4, lagged one round, since applicants in round t can only have observed year $t-1$. The unemployment series ends in 2024, so the lagged control is unavailable for the 2026 round. The estimation window is 2020–2025. The final-year coefficient is –8.879 without the control and –8.423 with it; the control itself enters at –6.667 with a t-statistic of –0.28. Because broad field $\times$ year effects are absorbed, a broad-field control is collinear with them and the control is measured at the detailed ISCED-F four-digit level. Standard errors clustered on degree code.

Figure A15: Study seats available for bachelors students in various fields



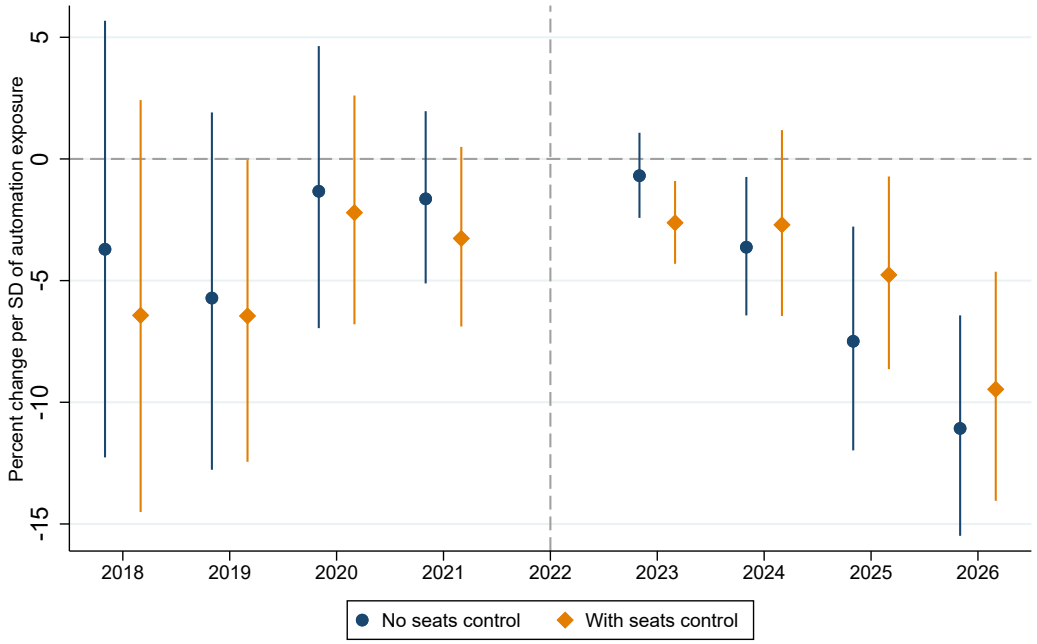
(A) ICT and all other fields



(B) Four broad fields

Notes: Normalized to 2022 = 1. Data from the Educational Administration Statistics Service (vipunen.fi)
Sample: autumn intake, joint application, main round, first-cycle university programmes.

Figure A16: Applications and automation exposure, with and without a control for planned study places



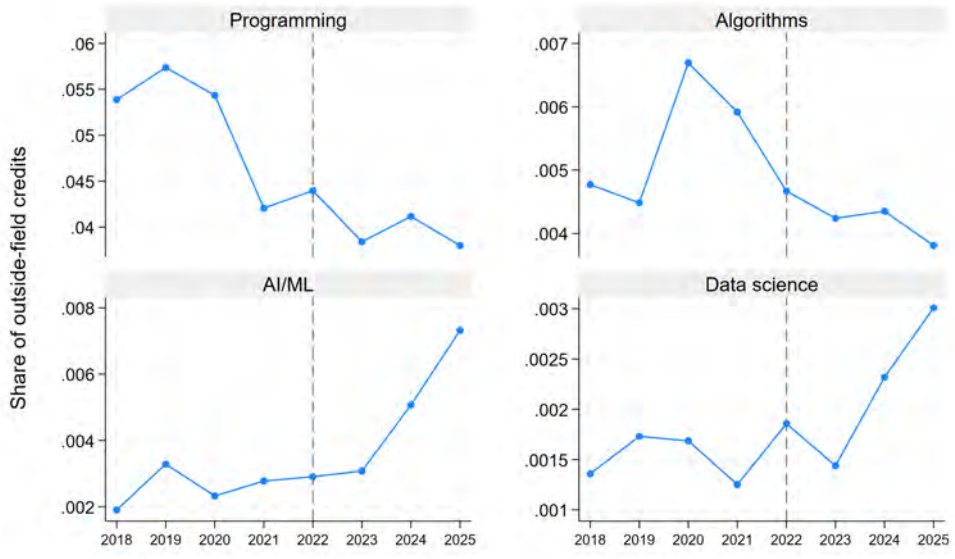
Notes: Event-study coefficients on a one-standard-deviation increase in degree-level automation exposure, estimated with and without a control for the log of planned study places, base year 2022. Planned places are set programme by programme, so both series replace the institution fixed effects of equation 3 with degree × institution fixed effects; the control is then identified from changes in planned places within a programme over time rather than from differences in programme size. Field × year effects and the balanced panel are as in Figure 6. Sample: the 2,160 cells with planned places reported. The 2026 coefficient is –11.1 per cent without the control and –9.5 per cent with it, and the 2025 coefficient –7.5 and –4.8 per cent. Applicants rise by 0.45 per cent per one per cent increase in planned places ($t = 7.69$). Standard errors clustered on degree code.

Table A6: Most commonly taken courses by category

Category	Course	Completions
Programming		
	Programming 1 (T)	1,013
	Introduction to programming (T)	782
	Basic programming course Y2 (T)	696
	Basic programming course Y1 (T)	678
	Programming 2: structures (T)	397
	Programming 1: introduction to programming (T)	390
	Basic course in C programming	369
	Elements of programming (T)	322
	Introduction to object-oriented programming (T)	305
	Introduction to Python programming (T)	265
Algorithms		
	Data structures and algorithms (T)	650
	Data structures and algorithms Y (T)	502
	Data structures and algorithms 1 (T)	401
	Introduction to algorithmic thinking (T)	319
	Data structures and algorithms	213
	Data structures and algorithms I (T)	168
	Principles of algorithmic techniques	116
	Algorithms 1 (T)	112
	Basic course in algorithms and programming (T)	106
	Algorithms and programming project (T)	73
AI/ML		
	Introduction to artificial intelligence* (T)	794
	Introduction to artificial intelligence** (T)	471
	Artificial intelligence	384
	Introduction to artificial intelligence*** (T)	174
	Introduction to machine learning	167
	Methods of artificial intelligence (T)	157
	Machine learning: basic principles	147
	Computer vision	142
	Elements of artificial intelligence (T)	128
	Supervised machine learning	73
Data science		
	Bayesian data analysis	370
	Towards data mining (T)	180
	Business intelligence	116
	Introduction to data science	103
	MySQL, data analytics and data management (T)	85
	Introduction to programming and data analytics (T)	78
	Data analytics in business (T)	70
	Introduction to data analytics (T)	41
	Business intelligence: applications and projects	38
	Statistical data analysis	32

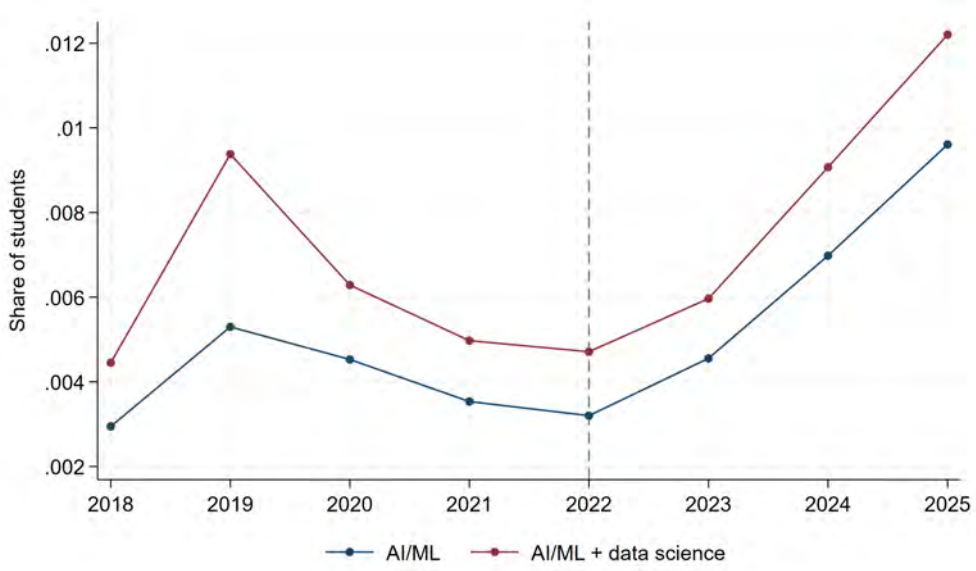
Notes: The ten most frequently completed courses in each keyword category, counted as outside-field elective completions by students in non-ICT degree programmes, 2018–2025. Course names are as recorded in the Virta register, with capitalisation restored and delivery-mode suffixes removed; (T) marks titles translated from Finnish or Swedish. Courses recorded under different implementation modes of the same name are combined. *, **, *** Different courses with the same translated name in English may have a slightly different Finnish course name.

Figure A17: Composition of outside-field ICT coursework, without the elective restriction



Notes: As in Figure 7, but without restricting courses to those taken by fewer than 20 percent of the student's degree-programme cohort. The denominator is all credits completed outside the student's own field, and the numerators are credits in ICT-field courses classified as programming, algorithms, AI/ML, or data science by course-name keywords. The sample is restricted to non-ICT students with at least one outside-field course in the year. Panels have separate vertical scales. The dashed line marks the release of ChatGPT in November 2022.

Figure A18: AI/ML elective take-up



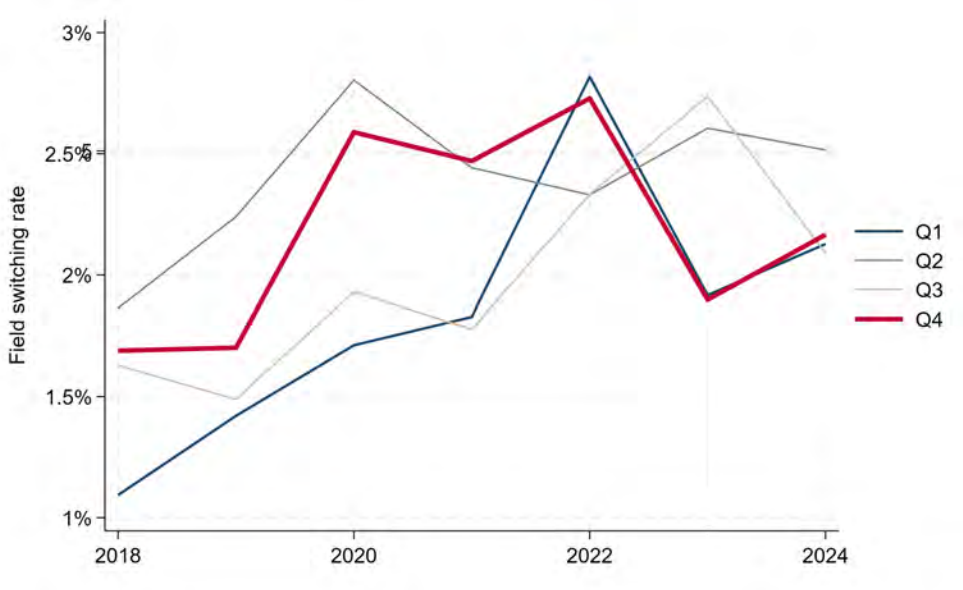
Notes: Share of all students completing at least one AI/ML elective, and at least one AI/ML or data science elective, by year. The sample is as in Figure 7, but includes students with no outside-field electives; the denominator contains all students in the sample. The dashed line marks the release of ChatGPT in November 2022.

Table A7: Summary statistics

	2021–2022	2023–2025	Total
Female	0.648	0.645	0.646
Mother tongue: FIN	0.924	0.924	0.924
Mother tongue: SWE	0.062	0.059	0.060
Mother tongue: OTHER	0.013	0.017	0.016
Parental income (2025 EUR)	94,502	98,013	96,705
Parent with MA or higher	0.429	0.452	0.444
Matriculated (passed HS exit exam)	0.826	0.879	0.859
Chose Long mathematics HS exit exam	0.447	0.511	0.487
Chose Short mathematics HS exit exam	0.272	0.282	0.278
Did not choose mathematics in HS exit exam	0.108	0.086	0.094
Field: Lib Arts	0.402	0.387	0.393
Field: Business, law & admin	0.190	0.195	0.193
Field: STEM	0.270	0.283	0.278
Field: Health	0.118	0.116	0.117
Total credits	46.555	46.525	46.536
Outside-field elective credits	3.196	3.524	3.402
Any outside-field electives?	0.352	0.373	0.365
Any ICT elective?	0.058	0.055	0.056
Any programming elective?	0.017	0.016	0.017
Any AI/ML elective?	0.003	0.007	0.006
At least 5 credits in ICT elec.	0.042	0.043	0.043
ICT elective credits	0.374	0.376	0.375
ICT elective credits if any	6.460	6.856	6.704
ICT share of outside-field electives	0.128	0.113	0.118
Observations (study right $\times$ year)	86,792	146,104	232,896

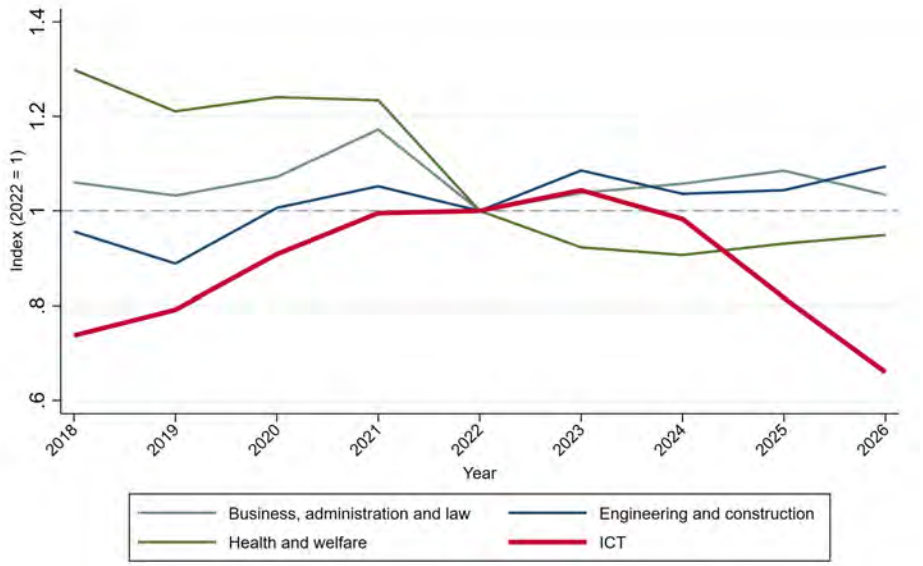
Notes: Characteristics of university students in non-ICT degree programmes. The unit of observation is the study right $\times$ year. The sample is restricted to students who completed at least 30 credits within a study right, 2021–2025, with non-missing information on high school exit exam mathematics track and parental income. Parental income is the mean of combined parental earnings over the student's ages 0–17, deflated to 2025 euros.

Figure A19: Field switching by automation exposure quartile



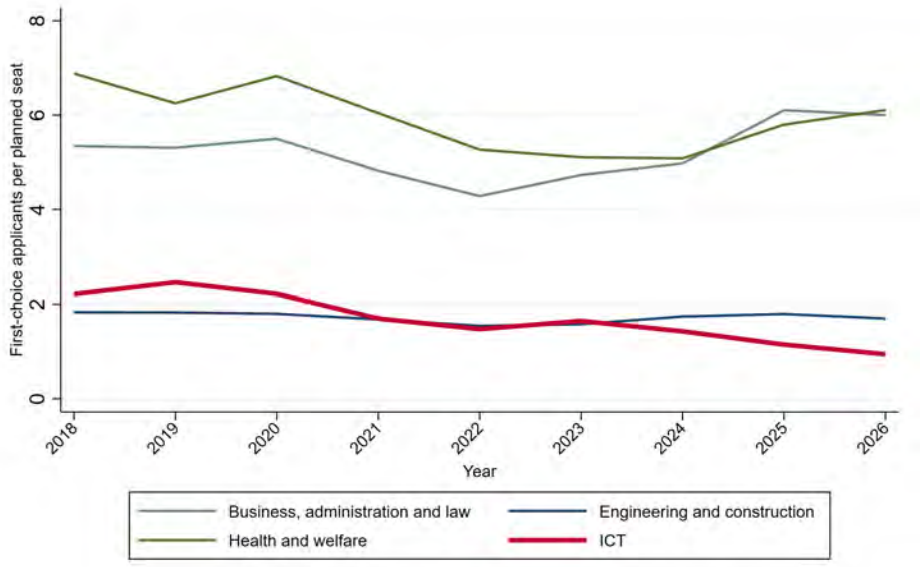
Notes: Share of first-cycle university students who, one year after entry, start a new first-cycle degree in a different narrow field from their initial degree. Students are grouped by the automation exposure quartile of their initial field of study; Q4 is most exposed. Year denotes the observation year one year after entry, so 2023 corresponds to the 2022 entry cohort. The vertical line marks the first post-ChatGPT year. Source: Statistics Finland OPISK register.

Figure A20: Applications to University of Applied Sciences bachelor's programs



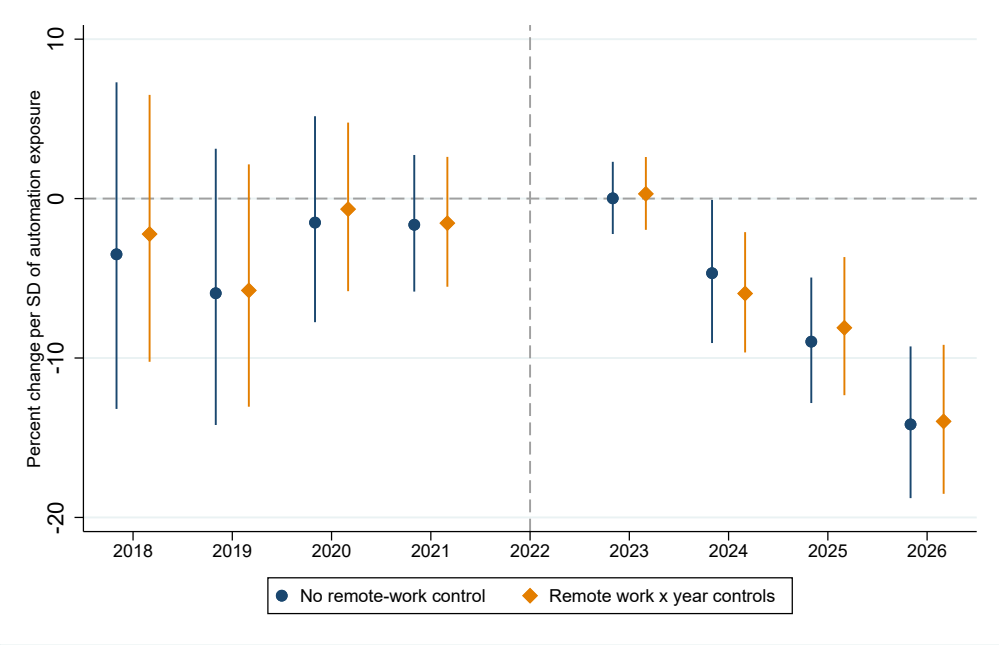
Notes: First-choice applicants to universities of applied sciences by broad field, indexed to one in 2022. Sample: Finnish citizens in the joint application for studies beginning in autumn, 2018–2026, including both first-time and other applicants. Source: Vipunen.

Figure A21: Ratio of applicants to starting seats



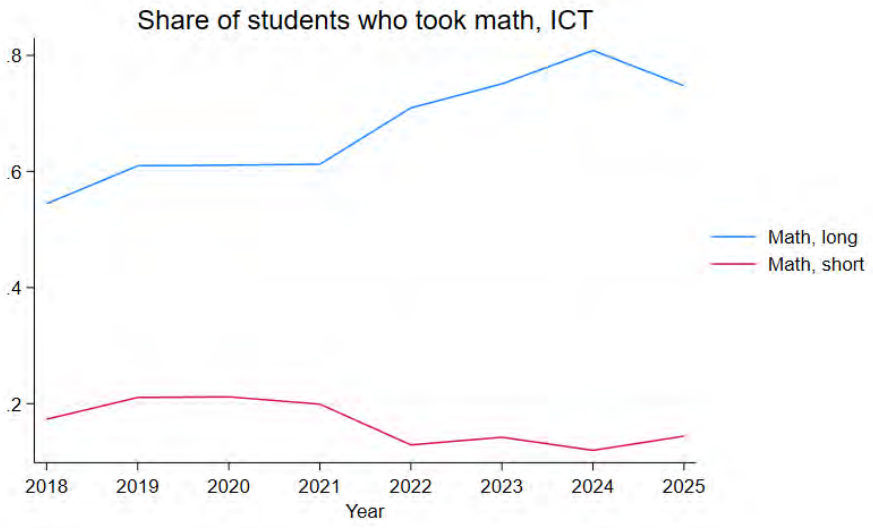
Notes: First-choice applicants per planned study place in first-cycle university programmes, by broad field. Sample: Finnish citizens in the joint application for studies beginning in autumn, 2018–2026, including both first-time and other applicants. Applicants and places are summed over the same programmes reporting positive planned places; the denominator includes all planned places. Source: Education Administration Service, Vipunen.fi.

Figure A22: Applications and automation exposure, with and without a control for remote work



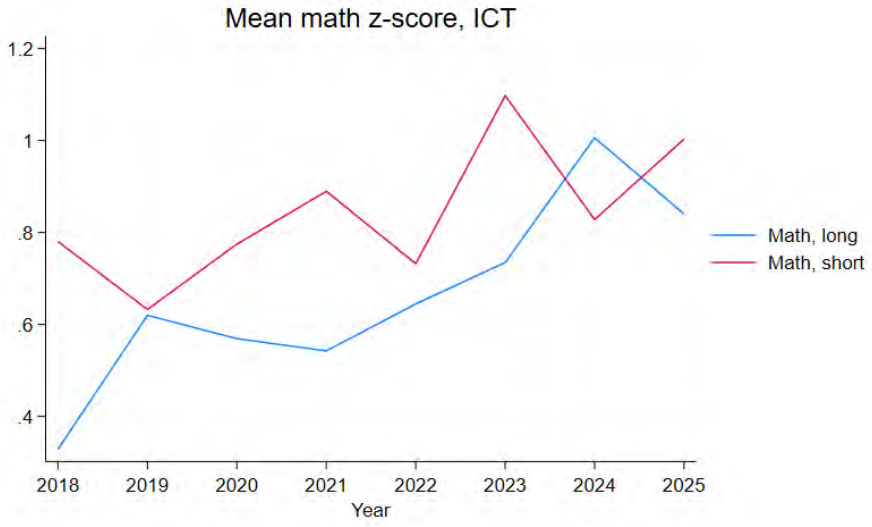
Notes: Remote work controls at the degree level have been aggregated based on the remote work measure in Dingel and Neiman [2020] and the occupational distribution of Finnish graduates in 2021-2022.

Figure A23: Share of new ICT students who took a matriculation exam in Mathematics



Notes: Long and short refer to the advanced or basic curriculum students may choose when taking the exam. See section 2 for background about the matriculation exam and how points on this exam count towards admission to higher education.

Figure A24: Standardized matriculation exam score in Mathematics, newly enrolled ICT students



Notes: The figure plots the standardized matriculation exam scores of newly enrolled students in ICT programs. Long and short refer to the advanced or basic curriculum students may choose when taking the exam. See section 2 for background about the matriculation exam and how points on this exam count towards admission to higher education.