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Has AI Widened Employment Gaps? Tracking Early-Career Employment by Occupational Exposure in Norway*

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Abstract

This paper uses data on the universe of private-sector employment in Norway up to February 2026 to examine whether AI exposure has contributed to a widening employment gap across occupations with varying AI exposure. Since October 2022, the month before ChatGPT's release, employment in the most exposed occupations has grown by 0.1 percent, against 0.3 percent in the least exposed occupations. We track this number on a monthly basis on the public dashboard *kiindeksen.no*. The dashboard updates the full-distribution comparison each month as new administrative data arrives, allowing differential employment growth by AI exposure to be tracked over time. We also show that when we compare young workers by complete occupation quintiles of exposure, the relative decline of the most exposed quintile is estimated as an imprecise zero.

JEL: J23, O33, J21

Keywords: artificial intelligence, labor market, employment, AI exposure, Norway

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1 Introduction

Artificial intelligence currently perform well at tasks that entry-level workers have often handled, such as coding, customer support, writing, and routine analysis. AI can automate tasks workers used to perform, but it can also raise the productivity of the tasks that stay human, and the net employment effect turns on the balance between displacement, productivity gains, and the creation of new tasks (Acemoglu, 2025).

The capabilities of AI models are improving rapidly, making the effect of AI a moving target. This paper introduces a public dashboard, *kiindeksen.no*, designed to track this target at a monthly rate for the Norwegian economy, a high-AI adoptoin setting. The dashboard shows monthly employment series for cells defined by occupation, age group, and AI-exposure, indexed to October 2022, the month before ChatGPT's public release. If AI is moving the labor market, users can track these dynamics on the dashboard. We validate the cell-level approach against within-firm estimates based on individual-level data and find that they give largely similar results.

Because hiring and entry adjust faster than the stock of incumbent workers, young workers are the margin on which a shift in labor demand should appear first: if AI displaces the entry-level tasks they specialize in, employment among young workers in exposed occupations would fall before aggregate employment moves. Using high-frequency US payroll data, Brynjolfsson et al. (2025) indeed show weaker employment growth in the period after the introcution of ChatGPT among young workers in occupations highly exposed to AI, with larger declines where AI automates rather than augments work.[1] The authors call this early-warning decline the "canary in the coal mine." Signs of negative employment effects for exposed young workers have also been found in the UK and Sweden,[2] and mixed results elsewhere.[3]

[1]Brynjolfsson et al. (2025) use ADP private payroll records on 3.5–5 million workers per month (January 2021–September 2025) and a Poisson event study with firm-by-quintile and firm-by-time fixed effects; workers aged 22–25 in the most AI-exposed occupational quintile decline by about 15 log points relative to the least-exposed quintile, the effect is concentrated in automation-exposed occupations under the Handa et al. (2025) classification, and wages show little divergence.

[2]Klein Teeselink (2025) finds, in UK Revelio Labs data, that a one-standard-deviation increase in LLM exposure is associated with 0.3 percent lower employment, concentrated in junior and high-wage positions, and Klein Teeselink and Carey (2026) report that AI exposure reduces job postings across 39 countries, more so where employment protection is stricter. Lodefalk et al. (2026) replicate Brynjolfsson et al. (2025)'s design on Swedish employer–employee data (January 2019–June 2025) with employer-by-quartile and employer-by-month fixed effects and the DAIOE generative-AI index of Engberg et al. (2024); workers aged 22–25 in the most-exposed quartile fall 5.5 percent by 2025H1 while the oldest gain 1.3 percent. The authors also analyze job-postings, and attribute part of the decline to monetary tightening after the April 2022 Riksbank interest rate hike.

[3]Humlum and Vestergaard (2026) compare AI-chatbot adopters to non-adopters in Danish registers merged with two surveys of around 25,000 individuals and find precise nulls on earnings and employ-

We make two contributions. First, inspired by the *Canaries Dashboard* of Stanford Digital Economy Lab and ADP Research (2026), we build a public monthly dashboard (kiindeksen.no) that updates employment by AI exposure and age for the complete private-sector in Norway. The headline number of this dashboard, the "AI index" is the employment growth of the most AI exposed occupations relative to the employment growth of the least AI exposed occupations since October 2022, the month before ChatGPT's release. The latest vintage, based on data until February 2026, shows that employment in the most AI-exposed occupations has grown by 0.1%, compared with 0.3% in the least exposed occupations, yielding an "AI index" of -0.2.

Second, we investigate whether we find any "canary" pattern of young AI-exposed employment decline in Norway. We find some evidence of this for selected high-exposed occuations such as software development, but when all occupations are ranked by exposure, youth employment in the group of all the most exposed occupations shows no comparable decline. Population data make this contrast possible, because selected-occupation case studies can be checked against the full exposure distribution and because net employment changes include firm entry, exit, and reallocation across firms, not only reallocation within continuing firms.

The paper proceeds as follows. Section 2 describes the Norwegian register data, the AI-exposure measures, and the crosswalk that assigns each occupation to an exposure quintile. Section 3 presents the employment evidence. Section 4 validates the cell-level results against within-firm estimates from individual-level administrative data. Section 5 tracks the most recent quintile gap and describes the companion dashboard. Section 6 concludes.

2 Data and Measurement

This section describes the data sources and how AI exposure is measured in the Norwegian data.

ment, ruling out effects above 2 percent. Though their Appendix D.2 documents aggregate early-career declines that mirror the US; their firm-level design shows workplace adoption does not drive these declines. Kauhanen and Rouvinen (2026) replicate Brynjolfsson et al. (2025)'s design on Finnish registers and find results consistent with earlier Finnish null effects (Kauhanen and Rouvinen, 2024, 2025). There are also two related studies on Norwegian data: Vatne et al. (2026) regress overall occupation-level unemployment growth on a Claude-based exposure measure for 2022–2025 and reports a positive gradient and no wage relationship. In independent and concurrent work to ours, Facius and Iacono (2026) examine generative AI and the Norwegian labor market with register data until March 2025.

2.1 Norwegian Labor Market Data

Our labor market data come from the *A-ordningen*, Norway's coordinated employer reporting system. Every Norwegian employer submits a monthly report of all employment relationships, including wages. The Norwegian Tax Administration administers the system on behalf of Statistics Norway and the Norwegian Labour and Welfare Administration. Statistics Norway compiles the reports into the ARBLONN register, which covers the universe of formal employment in Norway except self-employment and contains approximately 3.1 million employment records per month (Statistics Norway, n.d.a). We access the data through microdata.no, Statistics Norway's remote analysis platform, which provides programmatic access to population-level registers and exports aggregated cell-level tables. Two data-construction details matter for interpretation. First, the count outcomes are based on active employment relationships with positive reported cash earnings in the month, so employment should be read as paid payroll employment rather than every formal relationship recorded before this restriction. Second, the microdata.no exports suppress cells with fewer than 5 observations; in the count regressions we estimate on balanced occupation-by-month panels and code absent exported cells as zero, so this treatment combines true zero cells with suppressed small cells. The comparison with individual-level records below provides a check that this small-cell approximation does not drive the main Q5-vs-Q1 patterns.

Reference period and inclusion rules. ARBLONN is a monthly status register. The reference period is the week containing the 16th of each month, almost always week 3 (Statistics Norway, n.d.b). On microdata.no, every monthly observation is stamped to the 16th. An employment relationship is included in month t if its start date is on or before the last day of the reference week and either no end date is recorded or the end date is on or after the first day of the reference week. Two further rules apply. First, when cash earnings are reported for the calendar month but cannot be linked to a contemporaneous or prior-month employment relationship, Statistics Norway constructs a fictional employment relationship and classifies the worker as employed. Second, when wage is paid in the month after an employment relationship ends, the relationship is retained for the last month in which it covered the reference week. As a result, monthly counts cover slightly more workers than a strict snapshot on the 16th would.

Variables. The unit of observation is a person–firm pair in a given month. Statistics Norway aggregates wage components reported by the same employer for the same person into a single person–firm record (Statistics Norway, n.d.b). Table 1 lists the variables we use; all are measured at the 16th of the month.

Table 1: ARBLONN variables used in the analysis

Variable	Description
Occupation code	Four-digit STYRK-08 code for the employment relationship; STYRK-08 is based on the International Standard Classification of Occupations (ISCO-08) and shares codes for overlapping four-digit unit groups (Statistics Norway, 2011).
Cash earnings	Total cash compensation paid by the employer during the calendar month, gross of tax; includes base salary, fixed and irregular supplements, bonuses, overtime pay, and severance. Statistics Norway removes extreme outliers in the data available at microdata.no. When we use the individual-level data, we winsorize at the 99.9th percentile within each occupation-by-month cell, with a pooled fallback for small cells.
Overtime hours	Overtime hours reported by the employer for the calendar month.
Start date	Contractual start date of the employment relationship active on the 16th. We define a new-job indicator equal to one if the start date falls within the 30 days ending on the 16th of month t.
Institutional sector	Four-digit code from Statistics Norway's Business Register, used to restrict the sample to private-sector employment relationships.

For the decade age-group series we also index employment per capita, dividing headcount by the resident population in each age group (Statistics Norway table 07459, interpolated from annual to quarterly) to remove the mechanical effect of changing cohort sizes; these per-capita series are the raw twins in Appendix A, while the seasonally adjusted series shown in the main text index headcount directly. Population in the decade groups mostly changes slowly over the sample.

The Norwegian occupation coding is stable over 2021–2026 by design, but as AI-relevant occupations evolve, employers may shift how they classify ambiguous job titles, introducing a reclassification channel that runs in the opposite direction from the one we are after.

Sample. Age is computed at monthly precision by subtracting birth year from calendar year and decrementing by one if the birth month exceeds the current month. Workers are assigned to four decade age groups: 21–30 (early career), 31–40, 41–50, and 51–60 (senior). We exclude individuals under age 21, whose labor market attachment is dominated by education transitions, and those over 60, who are affected by retirement timing. The sample period is January 2021 through February 2026.

Normalization, quintiles, and outcomes. We construct normalized time series following the approach in Brynjolfsson et al. (2025), Figures 1–3. Each series is indexed to October 2022 = 1, the month immediately preceding ChatGPT's public release on November 30, 2022. For outcome y in cell c at month t, the normalized series is $\tilde{y}_{c,t} = y_{c,t}/y_{c,\text{Oct 2022}}$. Changes after October 2022 are expressed as proportional deviations from that pre-ChatGPT level.

For each AI exposure measure, we rank all four-digit STYRK-08 occupation codes by their exposure score and assign them to quintiles, from quintile 1 (least exposed) to quintile 5 (most exposed). Quintiles are formed on the occupation distribution (each four-digit code counts once, regardless of its employment share) rather than on the employment-weighted distribution. Quintile assignment is performed separately for each measure, so an occupation may fall in different quintiles under different measures. We then aggregate employment counts and other outcomes within each quintile-by-age-group cell and construct the normalized time series.

The primary outcome is employment indexed to October 2022, by decade age group and exposure quintile. We restrict the analysis to the private sector, where AI-exposed occupations cluster, and do not pool or compare with the public sector because the occupations in a given exposure quintile differ sharply across the two: among workers aged 21 to 30, the most-exposed quintile is mostly IT, sales, and finance jobs in the private sector but is dominated by public-administration roles in the public sector, so the same quintile does not describe the same work and a cross-sector comparison could be misleading. Secondary outcomes include monthly earnings, overtime hours, and the share of new jobs. Table 2 lists the five largest occupations in each exposure quintile.

Seasonal Adjustment Norwegian employment carries a strong seasonal pattern, with a winter dip and a summer peak. We therefore plot seasonally adjusted series in the main text and relegate the raw series to Appendix A. We use adjustment on log series in three steps. First, we estimate the trend as a centred thirteen-month moving average (a 2×12 average, overlapping such that the two end months get half weight). Second, for each calendar month, we compute its average deviation from this trend over January 2022 to December 2024; that is the seasonal factor for that month. Third, we subtract these factors from every month of the series. This is the same procedure used for the seasonally adjusted series on kiindeksen.no, where readers can also apply moving-average smoothing interactively.

Table 2: Five largest occupations by AI-exposure quintile, February 2026.

Code	Occupation	Eloundou score	Employment (Feb 2026)	Share of quintile
Quintile 1 (least exposed)				
5321	Health care assistants	0.113	109,215	22.2%
9112	Cleaners and helpers in offices, hotels and other establishments	0.028	65,582	13.3%
7411	Building and related electricians	0.128	30,088	6.1%
8160	Food and related products machine operators	0.093	25,376	5.2%
5153	Building caretakers	0.000	22,982	4.7%
Quintile 2				
5311	Child care workers	0.249	105,062	22.0%
5329	Personal care workers in health services not elsewhere classified	0.216	74,748	15.6%
7115	Carpenters and joiners	0.144	38,993	8.1%
2342	Early childhood educators	0.230	34,719	7.3%
5120	Cooks	0.193	21,479	4.5%
Quintile 3				
5223	Shop sales assistants	0.342	125,837	16.7%
2341	Primary school teachers	0.329	84,386	11.2%
2223	Nurses	0.343	65,945	8.7%
4321	Stock clerks	0.325	35,362	4.7%
2221	Nursing professionals	0.343	32,577	4.3%
Quintile 4				
1120	Managing directors and chief executives	0.494	38,459	7.4%
2310	University and higher education teachers	0.486	36,847	7.1%
1420	Retail and wholesale trade managers	0.481	34,117	6.6%
1219	Business services and administration managers not elsewhere classified	0.492	26,900	5.2%
2142	Civil engineers	0.482	26,840	5.2%
Quintile 5 (most exposed)				
2422	Policy administration professionals	0.566	92,327	17.4%
4110	General office clerks	0.595	55,605	10.5%
3322	Commercial sales representatives	0.572	43,488	8.2%
2511	Systems analysts	0.626	34,144	6.4%
2519	Software and applications developers and analysts not elsewhere classified	0.765	21,880	4.1%

Notes: Occupations are ranked by the Eloundou et al. (2024) exposure score. Employment is the February 2026 headcount across both sectors and decade age groups 21–60; share is the occupation's percentage of the quintile's total employment. Occupation titles use official English ISCO-08 labels for overlapping codes; STYRK-specific codes use register labels or direct translations.

2.2 Institutional Context

Norway is an informative high-AI adoption setting: a 2026 Microsoft report ranks Norway third in the world for population-level AI use (Microsoft AI Economy Institute, 2026), OECD data place it first among European countries for individual use of generative AI (Ostertag, 2026), and enterprise adoption rose from 11 percent of firms in 2021 to 30 percent in 2025 (Walther-Zhang and Rybalka, 2025). Furthermore, Kompetansebehovsutvalget (2026) reports that AI-related job postings nearly doubled between 2023 and 2024, concentrated in IT but spreading to other sectors; and Jordell et al. (2026) reports, from successive firm surveys, that the share of firms using AI rose from 24 percent in 2023 to 55 percent in 2025 (the latter wave covering 4,294 firms), concentrated in ICT, finance, and professional services. Flobakk-Sitter et al. (2024) interviews members of professional unions and finds AI use that is exploratory and concentrated in augmentation rather than automation.

Wage determination in Norway is relatively centralized: unions and employer organizations negotiate sector-level agreements that compress the wage distribution relative to more purely market-based systems such as the United States. Employment protection is strong.

The period we study partly overlaps with declining unemployment and monetary policy tightening: Norges Bank raised the policy rate from zero percent in September 2021 to 4.5 percent by January 2024 (Figure A1). This tightening affected labor demand broadly.

The size of the age groups are not constant over time. The early-career cohort shrank slightly between 2022-Q1 and 2025-Q1, while the two oldest age grups grew (Figure A2). This should be kept in mind when comparing the indexed series of different age groups.

2.3 AI Exposure Measures

The task framework that underlies much of the work that maps occupations to AI exposreu is set out in (Autor et al., 2003; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018, 2019). The measures in current use differ in whether they capture potential task exposure, revealed usage, or historical AI progress on the abilities a job requires.

Our main measure of occupational AI exposure is the Eloundou et al. (2024) GPT-4 exposure score. We also use the Handa et al. (2025) automation and augmentation shares, which capture revealed patterns of AI usage. Table 3 summarizes these measures.

A concern is that exposure indices that aggregate task-level scores linearly implicitly treat tasks as more separable than they are in reality. Drawing on the O-ring production function of (Kremer, 1993), Gans and Goldfarb (2025) argue that in many occupations, tasks are complements rather than independent. In those cases, automating some tasks frees the worker to focus on the remaining ones, raising their quality and potentially increasing labor income, depending on how automation reshapes worker time around them. Imas and Shukla (2026) argue that job dimensionality (the number of distinct tasks in a job) determines whether AI augments or displaces. Low-dimensionality jobs built around a small number of core tasks face higher displacement risk even if their average exposure score is low, while high-dimensionality jobs with many complementary tasks are more likely to be augmented. Exposure indices that average across tasks will overstate displacement risk for complex jobs and understate it for narrow ones. We abstract from these concerns in the present paper.

Eloundou et al. (2024), GPT-4 exposure. Eloundou et al. (2024) combine expert and GPT-4 assessments of each occupation's tasks to estimate the share of tasks for which access to a large language model (LLM) would reduce completion time by at least 50 percent. The occupation-level score, denoted β, is defined as $E_1 + 0.5 \times E_2$, where E_1 is the share of tasks directly exposed to an LLM and E_2 is the additional share exposed only when complementary software is included. The measure captures theoretical LLM capability as assessed in early 2023, not automation or displacement risk. We map 397 STYRK-08 codes, covering 97.5 percent of all four-digit occupations in our data.

Handa et al. (2025), Anthropic Economic Index. Handa et al. (2025) measure revealed AI usage patterns from a sample of Claude.ai conversations, with each conversation classified by O*NET task. The occupation-level score reflects the share of conversations associated with that occupation's tasks, decomposed into automation modes (directive task delegation with minimal human involvement) and augmentation modes (collaborative task iteration), which may carry opposite labor-market implications. We map 352 STYRK-08 codes (86.5 percent coverage). The lower coverage reflects the concentration of observed Claude usage: a small set of occupations accounts for most conversations, leaving many occupations with negligible observed usage. The conversations may include personal use, experimentation, and failed attempts. This measure of revealed Claude usage, by Claude users, may measures something quite different from what is relevant for workplace adoption.

Crosswalk Construction

Both measures originate in US SOC codes. The Eloundou et al. (2024) measure uses SOC 2018 codes, which we first map to SOC 2010 using the official BLS crosswalk (November 2017). The Handa et al. measure uses SOC 2010 codes directly. From SOC 2010, we apply the BLS SOC-to-ISCO crosswalk (August 2012, updated June 2015) to obtain ISCO-08 unit-group codes. We then match those four-digit ISCO-08 codes to the official STYRK-08 list by code. STYRK-08 is based on ISCO-08 and is code-compatible for overlapping four-digit unit groups, but it includes Norwegian adaptations, so this final step is a filtered code match rather than a claim that the two classifications are exactly the same.[4]

The BLS crosswalk contains partial matches: 38.8 percent of its rows are flagged as one-to-many or many-to-one mappings. When multiple SOC codes map to a single STYRK-08 code, we take the unweighted average of their exposure scores. For each STYRK-08 code, we note whether it is a partial-match and the number of SOC codes contributing to a single STYRK-08 score. Of the 397 STYRK-08 codes with an Eloundou et al. (2024) score, 57.7 percent have at least one partial-match contributor.

Data Availability

The exposure measures and crosswalks are public: the Eloundou et al. (2024) scores, the Handa et al. (2025) Anthropic Economic Index, the BLS SOC-to-ISCO crosswalk, and the STYRK-08 classification.[5] Norwegian labor market data are accessed through microdata.no; the aggregated tabulations underlying the analysis are available from the authors, and the indexed series through the companion dashboard (Hernæs and Kostøl, 2026). We also access population individual-level data on the Frisch Centre's secure server, which we use to validate the cell-level approach.

[4]Four STYRK-08 codes in our register list are absent from the BLS SOC–ISCO crosswalk. Two nursing-related Norwegian codes, 2223 (nurses) and 2224 (social educators), are manually assigned the exposure scores of 2221 (nursing professionals) and flagged in the mapping files. The unspecified occupation code 0000 receives no exposure score and is excluded from exposure-quintile analyses; in the parsed analysis aggregates for ages 21–60 it appears only in January–March 2021 and accounts for 35,828 worker-months, 0.023 percent of worker-months across the two analysis sectors. We also override two overlapping-code Norwegian adaptations after comparing SSB detailed occupation titles with BLS titles: 2267 (occupational therapists) receives SOC 29-1122 Occupational Therapists rather than BLS/ISCO 2267 optometrists/ophthalmic opticians, and 2269 (chiropractors and osteopaths) receives SOC 29-1011 Chiropractors rather than the full BLS/ISCO 2269 residual health-professional group. A handful remaining unmapped STYRK-08 occupation codes receive no exposure score and are excluded from exposure-quintile analyses, see percent coverage in Table 3.

[5]Eloundou et al. (2024) GPT-4 scores: https://github.com/openai/GPTs-are-GPTs. Handa et al. (2025) Anthropic Economic Index: https://github.com/anthropics/anthropic-economic-index. BLS SOC-to-ISCO crosswalk: https://www.bls.gov/soc/soccrosswalks.htm. STYRK-08 classification: https://www.

Table 3: AI Exposure Measures Mapped to Norwegian STYRK-08 Occupations

Measure	Type	Vintage	STYRK-08 coverage	Conceptual basis
Eloundou et al. (2024) β	Theoretical	2023	397 / 407 (97.5%)	Expert and GPT-4 assessment of task exposure to LLMs; $\beta = E_1 + 0.5 \times E_2$
Handa et al. (2025) overall	Revealed usage	2025	352 / 407 (86.5%)	Share of Claude conversations per O*NET task
Felten et al. (2021) AIOE	Ability-based	2018–2021	392 / 407 (96.3%)	AI application performance linked to occupational abilities via O*NET
Anthropic (2026) job exposure	Observed, time-weighted	2026	388 / 407 (95.3%)	Time-weighted Claude usage with automation penalty

Notes: All measures are mapped to STYRK-08 via a SOC 2010 → ISCO-08 crosswalk (BLS, 2012); the Eloundou et al. measure additionally uses the BLS SOC 2018 → SOC 2010 crosswalk (November 2017) as a first step. STYRK-08 is identical to ISCO-08 at the four-digit level (SSB Notater 17/2011). When multiple SOC codes map to a single STYRK-08 code, the STYRK-08 score is the unweighted mean of the contributing SOC scores. Coverage is expressed as the share of 407 STYRK-08 four-digit codes observed in our employment data.

3 Employment Gaps by AI Exposure Quintile

3.1 Aggregate Employment

We start by exploring aggregate employment trends across the exposure distribution. To do so, we rank every four-digit occupation by its Eloundou et al. (2024) GPT-4 score, assign it to a quintile from Q1 (least exposed) to Q5 (most exposed), and pool all private-sector workers aged 21–60, as described in detail in Section 2.1. The most-exposed quintile does not pull away from the least-exposed after the ChatGPT release (Figure 1): the five series largely move together through the sample, and the Q5–Q1 gap in the most recent month is small. The systematic ranking shows little separation from what one would expect if AI were reshaping employment across the whole labor market. The raw counterpart is Appendix Figure A3.

3.2 Occupation-specific Employment

Next, we explore the "canary" pattern by plotting employment growth across occupations and age groups. We focus on four occupations chosen for their AI relevance as case studies, also tracked on the companion dashboard: software developers and customer service agents, both highly exposed to AI and emphasized by Brynjolfsson et al.

`ssb.no/klass/klassifikasjoner/7`.

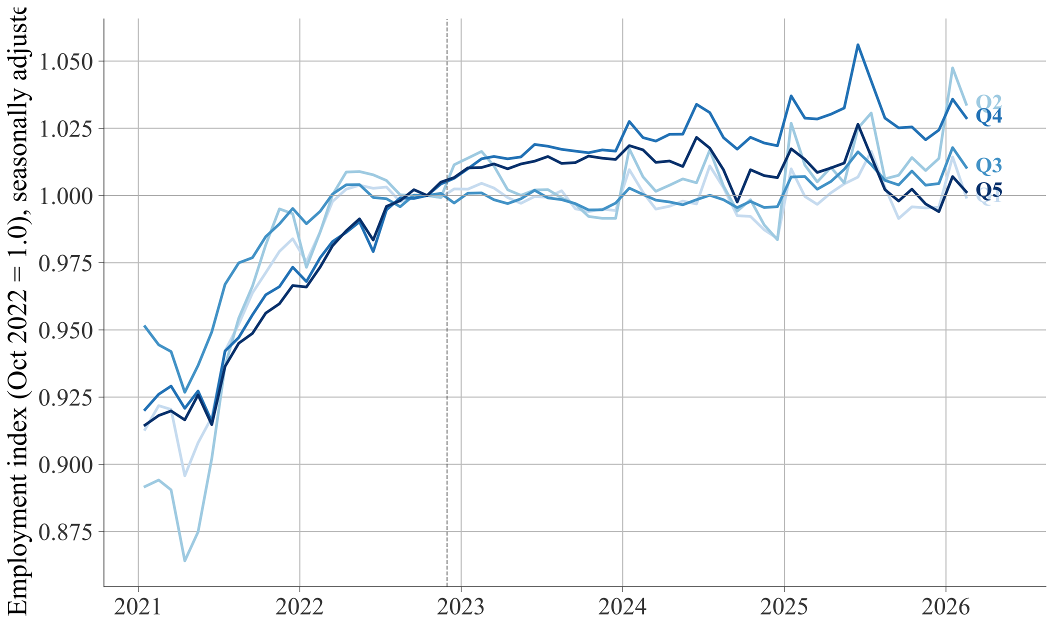

Figure 1: Employment by AI-exposure quintile, all ages 21–60, private sector, seasonally adjusted.

Notes: Private-sector headcount pooled over ages 21–60, seasonally adjusted by removing fixed calendar-month factors, estimated over 2021–2024 as the average log-deviation from a centred 2×12 moving-average trend, indexed to October 2022 = 1. Occupations are ranked by the Eloundou et al. (2024) exposure score. Q1 (lightest) = least exposed; Q5 (darkest) = most exposed. This is the paper analog of the kiindeksen.no headline "Sysselsetting etter KI-eksponering" figure. The raw (unadjusted) series is Appendix Figure A3.

(2025), and electricians and home health aides, two low-exposure occupations that serve as a benchmark.[6] The four differ sharply in measured exposure: software developers and customer service agents are in the top Eloundou quintile and also rank high on the Handa et al. (2025) usage and automation measures, whereas electricians and home health aides fall in the bottom quintiles on all three measures, so the contrast does not depend on which exposure measure one uses.

Figure 2 plots seasonally adjusted private-sector employment (headcount) for selected occupations by decade age group, indexed to October 2022. In software development, employment grows clearly before November 2022. Afterward, 31–40 and 51–60 continue to rise, while 41–50 flattens out and the 21–30 group declines rapidly. Customer service agents show a similar but milder pattern: the youngest group ends near the baseline, while older groups end higher in 2026 than at the end of 2022. The case-study patterns are similar to those reported in Brynjolfsson et al. (2025), where young workers in high-exposure jobs lose ground while low-exposure occupations show no such gap. The two low-exposure occupation case studies show no young-worker decline: electricians aged 21–30 end close to the baseline, and home health aides grow across every age group, the youngest most of all.

3.3 Age-specific Employment

To test whether the case-study evidence generalizes beyond these occupations, we rank all occupations by exposure and follow each quintile separately within each decade age group. We find no clear pattern that the most-exposed occupations systematically lose ground among the youngest workers. Each of the four panels in Figure 3 is one decade age group, with quintile lines from light blue (Q1, least exposed) to dark blue (Q5, most exposed) and a red line for the overall age-group trend.

In the 21–30 group, the Q5 series tracks Q1 after the ChatGPT release, so the broader ranking does not reproduce the decline seen in the selected occupations. Among the older groups, the Q5 series runs above Q1 at 31–40, ends a few points below at 41–50, and shows no clear separation at 51–60; these older movements are smaller than the pre-period swings discussed in Section 3.7. The raw panels are in Appendix Figure A4.

[6] STYRK-08 codes, code-compatible with overlapping ISCO-08 unit groups for these occupations: software developers 2512–2514 and 2519; customer service agents 4222; electricians 7411; home health aides 5322.

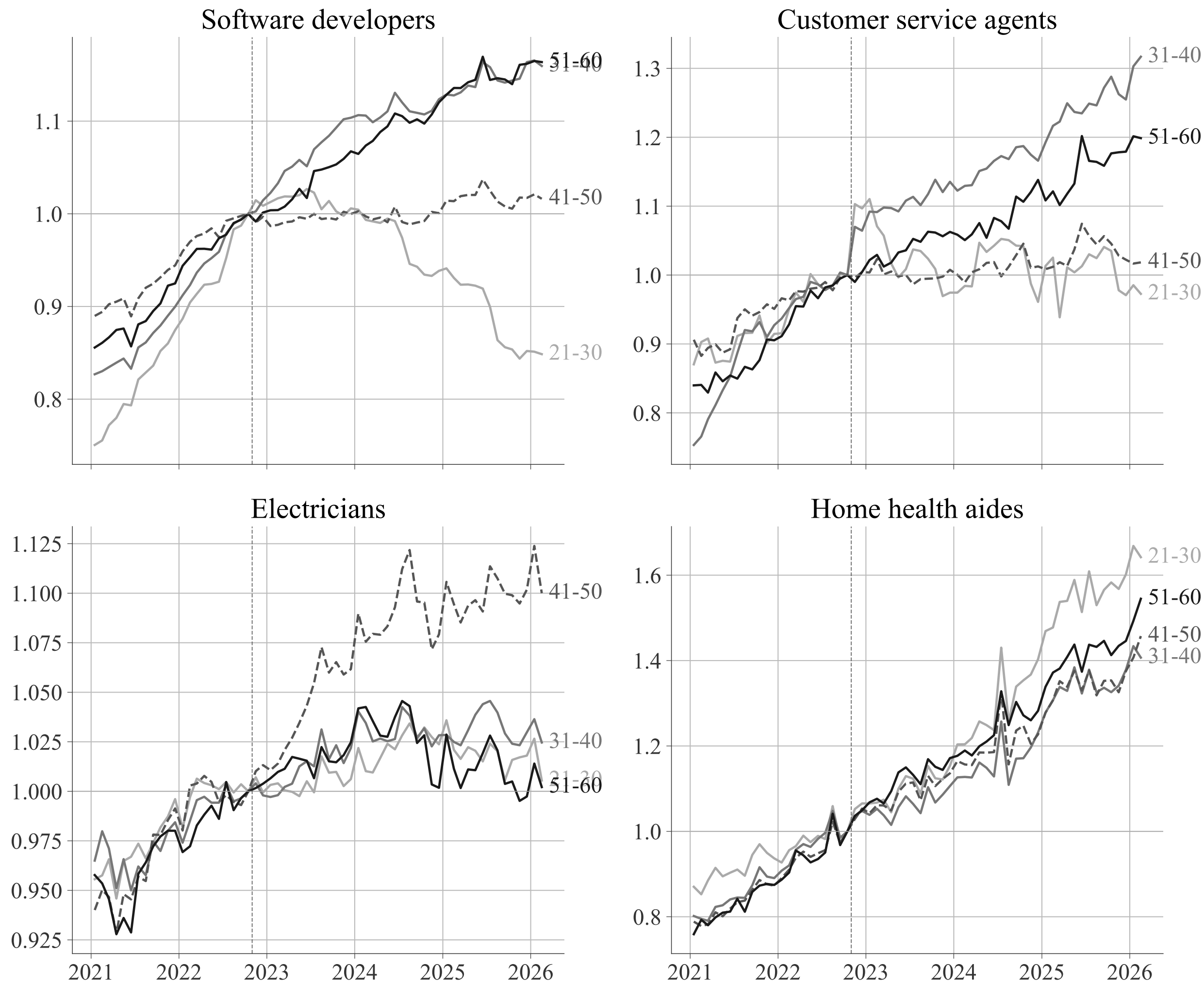

Figure 2: Employment in selected occupations, by decade age group, seasonally adjusted.
Notes: Private-sector headcount, seasonally adjusted by removing fixed calendar-month factors, estimated over 2021–2024 as the average log-deviation from a centred 2×12 moving-average trend, indexed to October 2022 = 1. Panels show the kiindeksen.no case-study occupations: software developers (STYRK-08 2512–2514, 2519) and customer service agents (4222), both high-exposure, and electricians (7411) and home health aides (5322), both low-exposure. The vertical dashed line marks the November 2022 ChatGPT release.

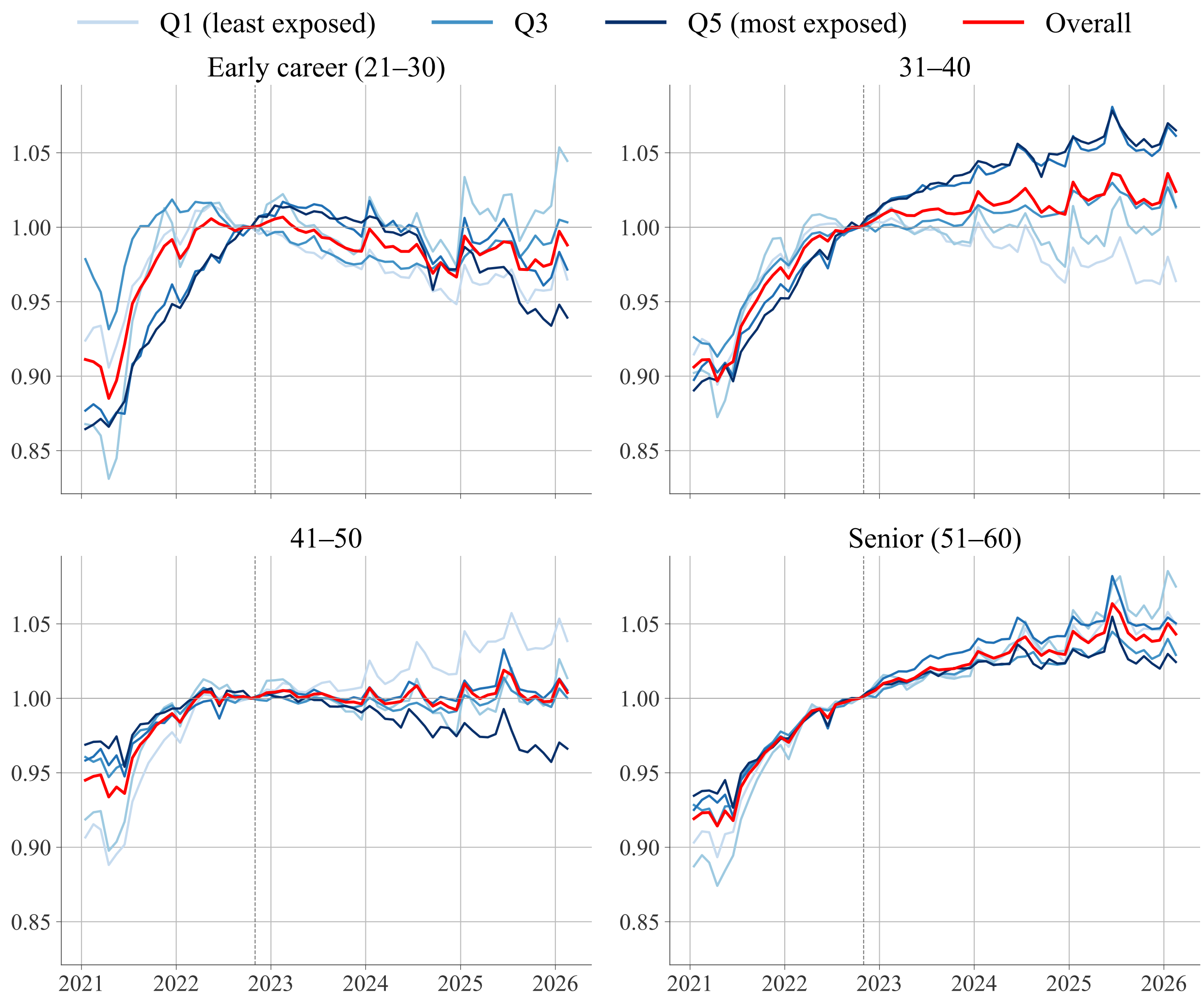

Figure 3: Employment by AI-exposure quintile and decade age group, private sector, seasonally adjusted.

Notes: Private-sector headcount, seasonally adjusted by removing fixed calendar-month factors, estimated over 2021–2024 as the average log-deviation from a centred 2×12 moving-average trend, indexed to October 2022 = 1. Occupations are ranked by the Eloundou et al. (2024) exposure score. Q1 (lightest) = least exposed; Q5 (darkest) = most exposed. Red line = overall age-group trend. Vertical dashed line marks the November 2022 ChatGPT release. The raw (unadjusted) per-capita series is Appendix Figure A4.

3.4 Automation versus Augmentation

To assess the potentially opposing forces of automation and augmentation, we split AI exposure into these two components using the Handa et al. (2025) decomposition of observed Claude.ai usage. The decomposition distinguishes directive task delegation (automation) from collaborative iteration (augmentation). We rank occupations separately by both measures, and plot seasonally adjusted employment by quintile within each age group.

Under this grouping, the youngest workers show a more negative gradient in automation exposure.[7] This is visible for the two youngest groups in Figure 4, where the most exposed occupations decline relative to the least exposed and the gap appears to widen. Figure 5 shows less pronounced gaps, and the least exposed occupations are sometimes on par with the most exposed occupations in terms of employment growth. From the second half of 2025, the most-exposed automation quintile begins to separate more visibly among the youngest workers. This provides suggestive evidence that a widening employment gap due to AI seems more consistent with automation than with augmentation. Appendix Table A1 reports the corresponding cell-level difference-in-differences estimates. The most-exposed automation quintile carries negative point estimates in all four age groups, none individually significant, whereas the augmentation gradient is positive and significant for the 31–40 group, consistent with the figures.

3.5 Secondary outcomes

A labor-demand shift could in principle show up on the price margin rather than the quantity margin. At the same time, the automation and augmentation forces of AI can cause strong selection of worker types across occupations, further complicating comparisons across exposure groups. We find no divergence by exposure quintile, but the wage plots are dominated by seasonal patterns (June holiday pay, December bonuses). Appendix Figure A7 shows the earnings series. Brynjolfsson et al. (2025) and Humlum and Vestergaard (2026) likewise find no wage divergence over a similar horizon in the US and Denmark. Norway's two-tier bargaining system (Bhuller et al., 2022), with sectoral wage floors and strong employment protection, makes the employment margin the more likely site of adjustment.[8]

[7] The raw automation and augmentation panels are in Appendix Figures A5 and A6.

[8] Similarly, new hires are likely to adjust more quickly, but the data are also more sparse. Appendix Figure A8 shows trends in new hires, and Appendix Figure A9 shows overtime hours.

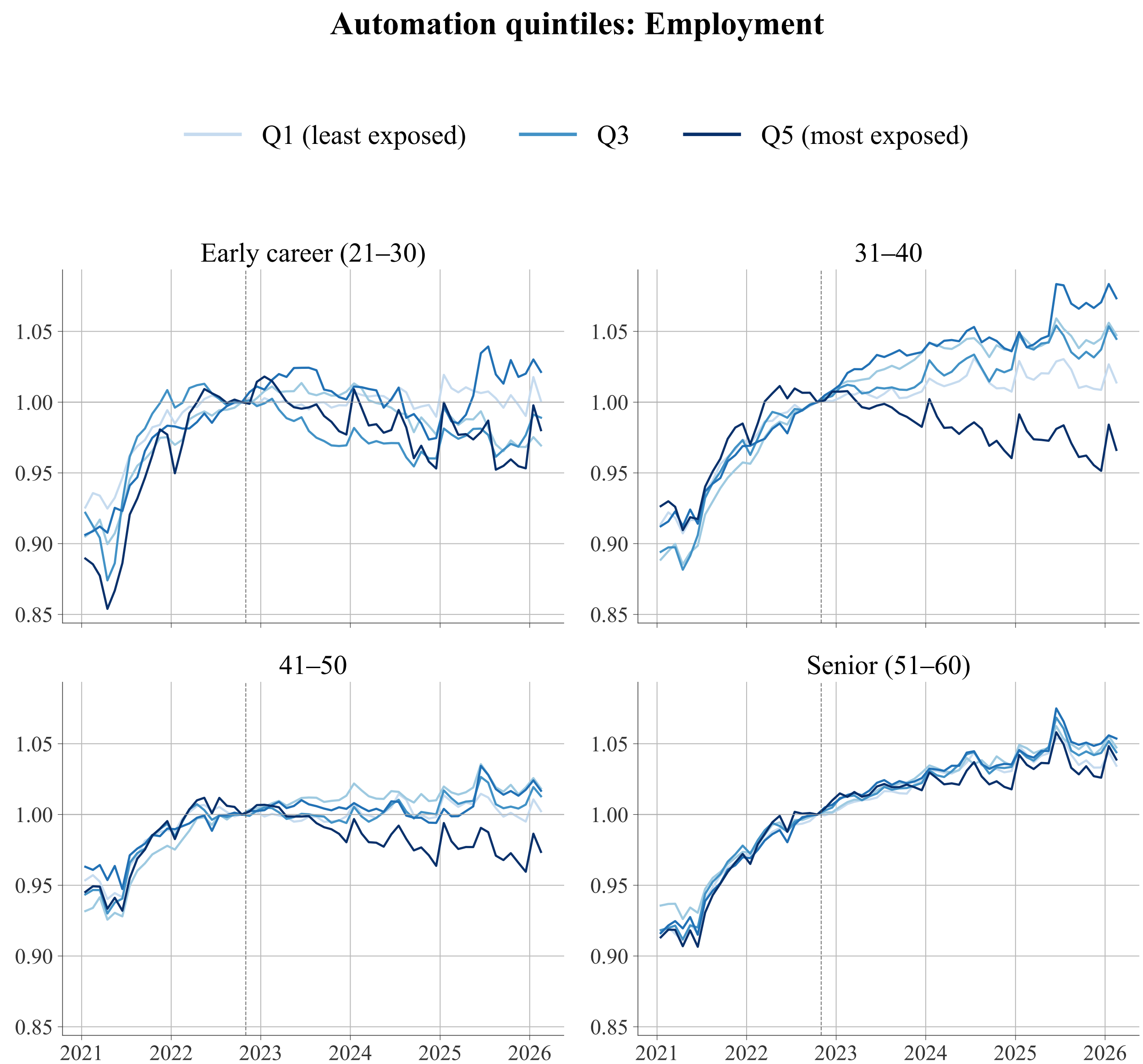

Figure 4: Employment by Handa et al. automation-exposure quintile and decade age group, private sector, seasonally adjusted.

Notes: Private-sector headcount, seasonally adjusted by removing fixed calendar-month factors, estimated over 2021–2024 as the average log-deviation from a centred 2×12 moving-average trend, indexed to October 2022 = 1. Occupations are ranked by the Handa et al. (2025) automation share. Q1 (lightest) = least exposed; Q5 (darkest) = most exposed. The raw series is Appendix Figure A5.

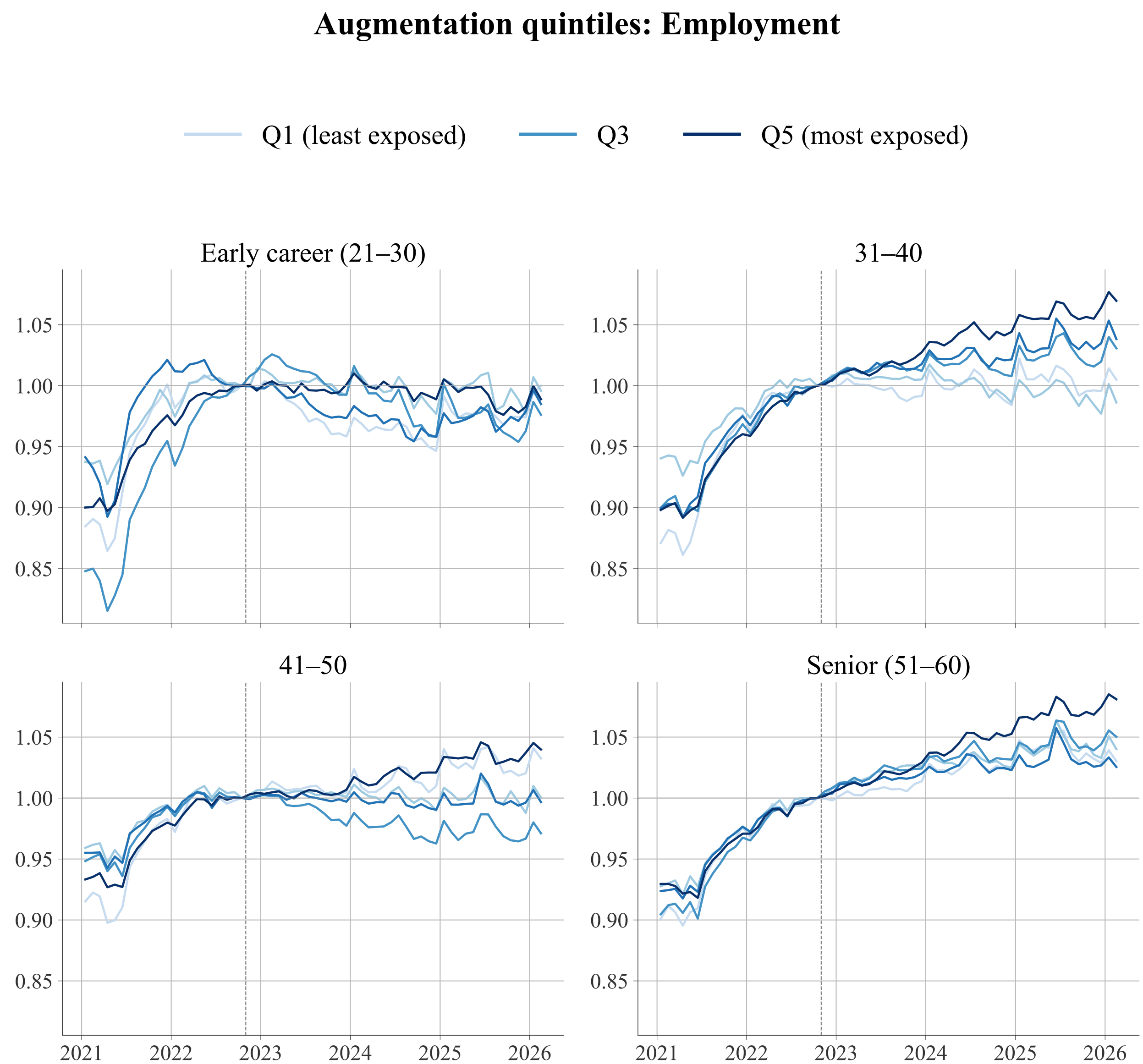

Figure 5: Employment by Handa et al. augmentation-exposure quintile and decade age group, private sector, seasonally adjusted.

Notes: Private-sector headcount, seasonally adjusted by removing fixed calendar-month factors, estimated over 2021–2024 as the average log-deviation from a centred 2×12 moving-average trend, indexed to October 2022 = 1. Occupations are ranked by the Handa et al. (2025) augmentation share. Q1 (lightest) = least exposed; Q5 (darkest) = most exposed. The raw series is Appendix Figure A6.

3.6 Regression Analysis

Because the pooled cross-section shows little widening, we now let the exposure gradient differ by decade age group. The youngest workers are the main margin of interest, the canary in the coal mine in the language of Brynjolfsson et al. (2025). We also adopt their baseline specification, a Poisson event study on the worker counts.[9]

The cell-level microdata are tabulated at the (occupation $\times$ age group $\times$ month) level. We estimate

$$\log E[\text{count}_{j,a,t}] = \alpha_j + \beta_t + \gamma_{q,k},$$

separately per decade age group a in the private sector, where j indexes occupations and $q(j)$ is the Eloundou GPT-4 quintile of occupation j. The occupation fixed effect absorbs the permanent employment level of each occupation; the month fixed effect absorbs the aggregate time path of the age cohort. Standard errors are clustered at occupation, with Q1 and $k = -1$ (October 2022) as the reference.

Figure 6 reports the resulting $\gamma_{q,k}$ for $q \in \{2, 3, 4, 5\}$ across the four decade age groups, in log points. The path matches the indexed series in Figure 3. At 41–50 the Q5 path turns negative after October 2022, reaches about -0.08 log points by mid-2025, and ends near -0.03 by early 2026. At 21–30 the Q5 path is noisy and ends near zero; at 31–40 it rises to about $+0.15$; at 51–60 it stays near zero.

Table 4 collapses the event study into a post-versus-pre difference-in-differences by age group, for employment and new hires. For the youngest workers the most-exposed quintiles are not statistically distinguishable from Q1, and new hires show no systematic gradient in any age group. Among the older groups the employment estimate is positive at 31–40 (Q5 about $+0.078$ log points, $p < 0.01$) and a small, insignificant negative at 41–50 (-0.015). The percentage-change-in-employment outcome computed within each age group gives the same signs. Because pre-trends differ across these groups (Section 3.7), we read these post-period summaries as descriptive: an insignificant estimate is an absence of a detectable gradient, not evidence that exposure has no effect.

3.7 Sensitivity to Pre-Trends

The event studies above show that the pre-ChatGPT coefficients are not zero. In the cell-level event study, the most-exposed quintile's pre-period path moves over a peak-to-trough range of 0.11 to 0.18 log points across the four age groups, as large as or larger

[9] The percentage-change-in-employment outcome computed within age groups gives the same qualitative picture and is available upon request.

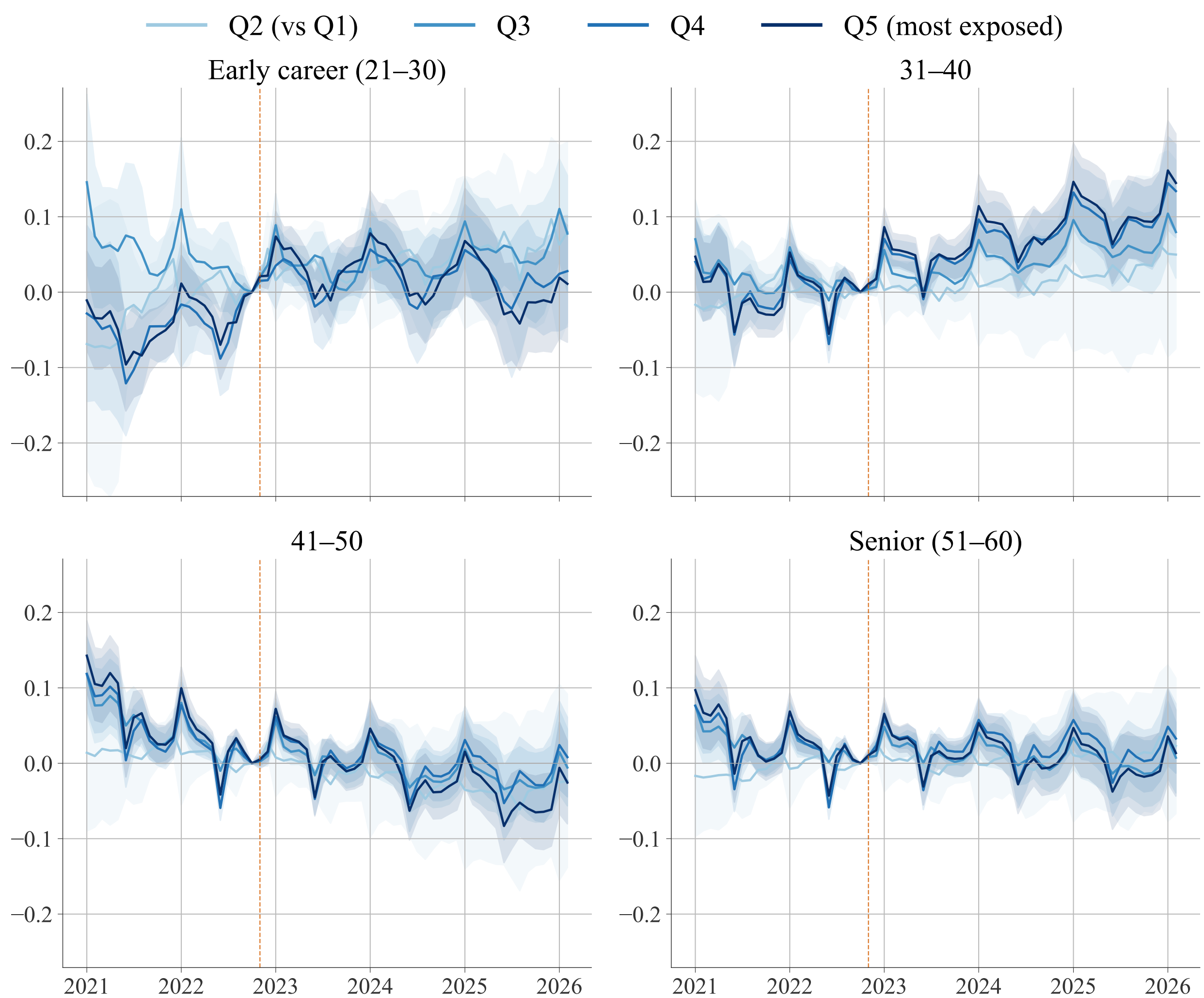

Figure 6: Poisson event-study coefficients by AI-exposure quintile and decade age group, private sector.

Notes: Coefficients $\gamma_{q,k}$ for $q \in \{2, \ldots, 5\}$ relative to $q = 1$, in log points. Cell-level microdata.no aggregates (occupation × age × month), private sector; fixed effects for occupation and month. Sample 2021m1–2026m2. Shaded bands: 95% confidence intervals based on standard errors clustered at occupation. Reference: October 2022. Dashed line marks the November 2022 ChatGPT release.

Table 4: Cell-level difference-in-differences by AI-exposure quintile and decade age group, private sector.

	Early career (21–30) (1)	31–40 (2)	41–50 (3)	Senior (51–60) (4)
Panel A. Employment (Poisson)				
Q2 $\times$ Post	0.0428	0.0181	-0.0206	0.0080
	(0.0341)	(0.0357)	(0.0339)	(0.0268)
Q3 $\times$ Post	0.0450**	0.0433***	-0.0052	0.0099
	(0.0204)	(0.0167)	(0.0153)	(0.0135)
Q4 $\times$ Post	0.0194	0.0708***	0.0004	0.0217
	(0.0203)	(0.0169)	(0.0155)	(0.0134)
Q5 $\times$ Post	0.0213	0.0782***	-0.0146	0.0104
	(0.0220)	(0.0185)	(0.0169)	(0.0165)
Panel B. New hires (Poisson)				
Q2 $\times$ Post	0.1247	0.2475**	0.1836	0.2422*
	(0.0810)	(0.1223)	(0.1247)	(0.1452)
Q3 $\times$ Post	0.1156	0.1772*	0.0990	0.0648
	(0.0739)	(0.1019)	(0.1100)	(0.1129)
Q4 $\times$ Post	0.0722	0.1299	0.0620	-0.0032
	(0.0770)	(0.1024)	(0.1075)	(0.1191)
Q5 $\times$ Post	-0.0424	0.0170	-0.0131	0.0196
	(0.0845)	(0.1054)	(0.1103)	(0.1120)
Occupations	393	391	393	392
Observations (count)	24,366	24,242	24,366	24,304

Notes: Each entry is the post-October-2022 change in the indicated quintile relative to Q1 (least exposed), by decade age group. Employment and new hires are Poisson. Occupation and month fixed effects; standard errors clustered by occupation. Sample 2021m1–2026m2. *, **, *** denote $p < 0.1, 0.05, 0.01$.

than the post-2022 movements, and joint tests reject parallel pre-trends in every age group in both the cell and firm-FE specifications.

Two non-AI channels in particular could make the exposure quintiles trend apart for reasons unrelated to AI. The first is a post-COVID technology correction: a normalization of the demand for digital services after an immediate post-pandemic high could reproduce the post-2022 decline in selected occupations with no AI involvement. The second is supply-side reallocation: workers entering the labor market after 2022 may be avoiding occupations they perceive as exposed to AI, generating the same young-worker pattern through worker choice rather than employer substitution.

The non-parallel pre-period motivates a sensitivity analysis using the honest difference-in-differences approach of Rambachan and Roth (2023). This method does not require us to decide whether the parallel-trends assumption is exactly true or false. Instead, it asks how large the post-ChatGPT violation of parallel trends would have to be to overturn the estimated exposure gradient. In practice, it uses the pre-treatment event-study coefficients to discipline the amount of post-treatment confounding that is allowed, and constructs confidence intervals that are valid under the chosen restriction.

We apply the procedure to the Q5-versus-Q1 event-study coefficients from the private-sector Poisson specifications. The main target is the average post-ChatGPT Q5-vs-Q1 employment difference for workers aged 21–30 over the full post period, November 2022 through February 2026, using the same cell-level event study, October 2022 reference, and post window as the difference-in-differences of Section 3.6. The monthly coefficients are aggregated to quarters, so the procedure tests the robustness of exactly that estimate.

Our preferred sensitivity parameter is the relative-magnitude bound $\bar{M}$. The benchmark value $\bar{M} = 1$ allows the post-ChatGPT violation of parallel trends to be as large as the largest violation observed in the pre-ChatGPT period. We also report results for $\bar{M} \in \{0, 0.5, 1, 1.5, 2\}$, where $\bar{M} = 0$ corresponds to exact parallel trends and $\bar{M} = 2$ allows post-period violations twice as large as the worst pre-period violation. We report the breakdown value of $\bar{M}$, the largest value for which the conclusion remains statistically significant.

The sensitivity analysis asks whether the post-2022 exposure gradient survives violations of parallel trends as large as those already visible before ChatGPT. Intervals that include zero for values of $\bar{M}$ near one indicate little robustness; one-sided intervals at $\bar{M} \geq 1$ would be stronger evidence.

Table 5 reports the HonestDiD confidence intervals for the main 21–30 sample. The conventional interval already includes zero, so the robust relative-magnitude intervals include zero at the benchmark $\bar{M} = 1$ and at every other value, and the breakdown value is

Table 5: HonestDiD sensitivity of the Q5-vs-Q1 employment effect to violations of parallel trends, ages 21–30, private sector.

Restriction	Robust 95% CI
Original ($\bar{M} = 0$, parallel trends)	[-0.022, +0.065]
$\bar{M} = 0.5$	[-0.221, +0.301]
$\bar{M} = 1.0$	[-0.475, +0.555]
$\bar{M} = 1.5$	[-0.729, +0.796]
$\bar{M} = 2.0$	[-0.983, +1.064]
Breakdown $\bar{M}$	0.00

Notes: Robust 95% confidence intervals for the average post-ChatGPT Q5-vs-Q1 employment difference (November 2022–February 2026), ages 21–30, private sector, under the relative-magnitude restriction of Rambachan and Roth (2023). Monthly event-study coefficients are aggregated to quarters; the target is the average over all post-period quarters, matching the difference-in-differences of Section 3.6. $\bar{M} = 0$ imposes exact parallel trends; $\bar{M} = 1$ allows post-period violations as large as the worst pre-period violation. "Breakdown" is the largest $\bar{M}$ for which the interval excludes zero. "Original" is the conventional 95% interval. Computed from the cell-level Poisson event study of Section 3.6.

zero. The 21–30 exposure gradient is not a fragile negative estimate; it is essentially absent under the paper's preferred design. For the youngest workers the systematic exposure-quintile result is therefore a relatively precise null: there is no post-ChatGPT employment gradient for the relative-magnitude restriction to overturn, rather than a negative effect whose robustness is in question. This is consistent with the descriptive series, in which the most-exposed quintile does not separate from the least-exposed.

3.8 Cross-Country Comparison

Table A2 summarizes the cross-country evidence, separating descriptive time series (Panel A) from formal econometric estimates (Panel B).

On the descriptive case studies, Norway looks like the US and Sweden with an early-career decline in AI-exposed occupations. The Norwegian per-capita decline of about 18 percent for young software developers is between the US (−20%, Brynjolfsson et al., 2025) and the Swedish raw figure (−44%, Lodefalk et al., 2026). On the systematic full-distribution evidence ranking all occupations by exposure, Norway looks like Denmark and Finland: the most-exposed quintile does not fall behind the least-exposed among young workers, and the narrow 22–25 replication diverges only late and on rejected pre-trends (Section 4.3).

This does not rule out an impact of AI: Regressions may absorb effects that operate outside direct firm-level adoption, such as competitive pressure from AI-adopting rivals, supply-side reallocation by workers anticipating disruption, and firm exit. But it does make the descriptive trends, including ours, hard to interpret on their own, because monetary tightening and the post-COVID correction may move the same occupations. Humlum and Vestergaard (2026), the only study with individual-level adoption data, finds that workplace AI-chatbot adoption does not drive the Danish early-career decline; Lodefalk et al. (2026) attribute much of the Swedish decline to the Riksbank rate cycle; and at the industry level Bick et al. (2026) find no clear link between AI adoption and employment in either Europe or the US. Norway, Sweden, Denmark, and Finland share similar institutions yet differ in their formal results, so institutional structure alone does not explain the heterogeneity.

A limited wage response is consistent with Norway's two-tier bargaining system (Bhuller et al., 2022) channelling any AI-related adjustment toward the quantity margin in the private sector. Downward-rigid wage floors limit short-run wage adjustment; the locally negotiated drift channel could deliver a wage response over a longer horizon.

4 Validation with individual-level administrative data

4.1 Individual-Level Estimates

The cell-level estimates absorb the average employment path of each occupation but do not separate reallocation *within* firms from changes in firm composition. Using the individual-level records, we estimate the within-firm composition design of Brynjolfsson et al. (2025),

$$\log E[\text{count}_{f,q,a,t}] = \alpha_{f,q} + \beta_{f,t} + \gamma_{q,k},$$

on the panel of firm f × quintile q × month t cells, separately per decade age group. Firm means a Norwegian *foretak*, not an establishment (*virksomhet*). Firm-by-quintile and firm-by-month fixed effects absorb the firm's persistent composition and any firm-level demand shock; identification rests on within-firm reallocation across exposure quintiles. Standard errors are clustered at the firm. The sample is private-sector firms with at least 20 workers in the 21–60 age window per month, January 2021 through February 2026.

Figure 7 reports the firm-FE $\gamma_{q,k}$. For the youngest workers, the Q5 path is noisy and ends slightly positive, so the within-firm comparison, like the cell-level one, does not show the most-exposed quintile among the young falling behind. The older groups also line up with the cell-level estimates: at 31–40 the Q5 path rises to about +0.12, at 41–50 it drifts negative through 2025 and recovers to near zero by early 2026, and at 51–60 it stays near zero. The collapsed within-firm estimates in Table 6 are consistent with this: the Q5 employment coefficient is not distinguishable from zero at 21–30, positive at 31–40

($+0.050$, $p < 0.01$), marginally negative at 41–50 (-0.021, $p < 0.1$), and near zero at 51–60. New hires show no systematic exposure gradient.

4.2 Reconciling the Cell and Individual-Level Estimates

The cell-level estimates use microdata.no aggregates; the firm-FE estimates use the individual records aggregated to the firm level. We attempt to reconcile the two approaches in the following steps. Table 7 reports the Q5-vs-Q1 post-October-2022 employment coefficient under four specifications, all on the private sector: (1) the microdata.no cell specification; (2) the same cell specification on the individual records; (3) the cell specification on firms with at least 20 workers; and (4) the firm-FE specification on that restricted sample. Step (1) to (2) changes only the data source, (2) to (3) adds the size restriction, and (3) to (4) changes the specification.

The estimate is stable along the columns. The data source contributes almost nothing: columns (1) and (2) differ by at most 0.003 log points in any age group. The size restriction moves the early-career coefficient from $+0.020$ to $+0.010$ and leaves the others within 0.01. The move from the cell to the firm-FE specification is the largest single step; it falls mainly on the 31–40 group, where the coefficient drops from $+0.084$ to $+0.050$, and on the 41–50 group, where the firm-FE estimate becomes marginally significant (-0.021, $p < 0.1$). Signs are unchanged throughout. Figure 8 plots the cell and firm-FE event-study paths for Q5 together, and the two track each other in every age group. Despite relying on different variation, the two paths tell much the same story: moving from occupation cells to within-firm comparisons does not materially change the Q5-vs-Q1 pattern.

4.3 Replication of the design of Brynjolfsson et al. (2025)

In the main analyses, we use decade age groups, 21–30 and so on. To ease comparison with the cross-country literature that uses a narrower 22–25 early-career definition, we replicate the Brynjolfsson et al. (2025) design using that definition. The sample is a balanced panel of full-time private-sector workers in firms, with workers placed in six age bins from 22–25 to 50–55 and occupations ranked by the Eloundou GPT-4 quintile; the construction and supporting figures are in Appendix B.

For workers aged 22–25 the post-October-2022 average Q5-vs-Q1 gap is small, about 3 log points, but it masks a clear time profile (Appendix Figure B4): the most- and least-exposed quintiles track each other through early 2025, and from spring 2025 the most-exposed quintile falls below, with the gap widening to about 35 log points by February

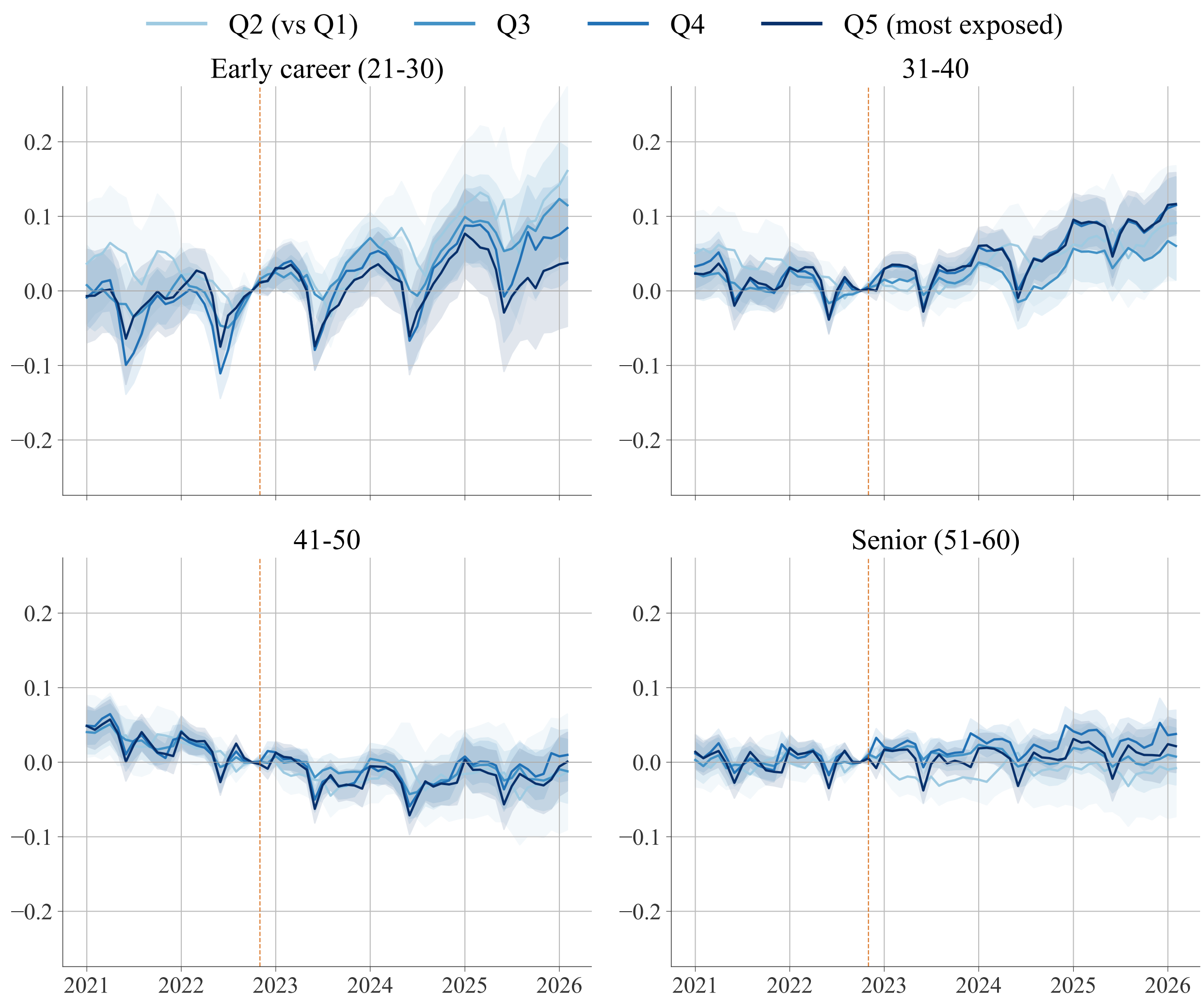

Figure 7: Firm-fixed-effects Poisson event-study coefficients by AI-exposure quintile and decade age group, private sector.

Notes: Coefficients $\gamma_{q,k}$ for $q \in \{2, \ldots, 5\}$ relative to $q = 1$, in log points. Estimated on the individual-level firm $\times$ quintile $\times$ month panel; fixed effects for firm $\times$ quintile and firm $\times$ month. Private-sector firms with at least 20 workers in the 21–60 age window per month. Sample 2021m1–2026m2. Shaded bands: 95% confidence intervals based on standard errors clustered at the firm. Reference: October 2022. Dashed line marks the November 2022 ChatGPT release.

Table 6: Within-firm difference-in-differences by AI-exposure quintile, private sector.

	Early career (21–30) (1)	31–40 (2)	41–50 (3)	Senior (51–60) (4)
Panel A. Employment (Poisson)				
Q2 × Post	0.0611**	0.0403**	-0.0190	-0.0125
	(0.0276)	(0.0205)	(0.0194)	(0.0169)
Q3 × Post	0.0482***	0.0253**	-0.0122	0.0089
	(0.0184)	(0.0125)	(0.0113)	(0.0107)
Q4 × Post	0.0286*	0.0510***	-0.0127	0.0247***
	(0.0161)	(0.0108)	(0.0095)	(0.0089)
Q5 × Post	0.0126	0.0503***	-0.0206*	0.0074
	(0.0210)	(0.0122)	(0.0108)	(0.0096)
Panel B. New hires (Poisson)				
Q2 × Post	0.0117	0.0386	-0.0099	0.1023
	(0.0991)	(0.0940)	(0.1032)	(0.1230)
Q3 × Post	0.0454	-0.0369	-0.0217	-0.0882
	(0.1011)	(0.0902)	(0.0913)	(0.1110)
Q4 × Post	0.0376	0.1252	-0.0215	-0.0518
	(0.1227)	(0.0942)	(0.1004)	(0.1235)
Q5 × Post	-0.0029	0.0314	-0.0549	-0.2331*
	(0.1146)	(0.1129)	(0.1230)	(0.1379)
Panel C. Log monthly earnings (OLS)				
Q2 × Post	-0.0141*	0.0003	-0.0011	0.0040
	(0.0085)	(0.0058)	(0.0056)	(0.0058)
Q3 × Post	-0.0039	0.0074	0.0065	0.0044
	(0.0072)	(0.0048)	(0.0045)	(0.0045)
Q4 × Post	-0.0060	0.0098**	0.0186***	0.0199***
	(0.0072)	(0.0049)	(0.0044)	(0.0046)
Q5 × Post	0.0020	0.0161***	0.0180***	0.0130***
	(0.0081)	(0.0053)	(0.0047)	(0.0050)
Firms	21,842	21,893	21,769	21,246
Observations	2,223,363	2,420,004	2,439,205	2,313,546

Notes: Each entry is the post-October-2022 change in the indicated quintile relative to Q1 (least exposed), by decade age group. Estimated on the individual-level firm × quintile × month panel; firm-by-quintile and firm-by-month fixed effects. Employment and new hires are Poisson; log monthly earnings is OLS. Private-sector firms with at least 20 workers in the 21–60 age window per month. Sample 2021m1–2026m2. Standard errors clustered at the firm. *, **, *** denote $p < 0.1, 0.05, 0.01$.

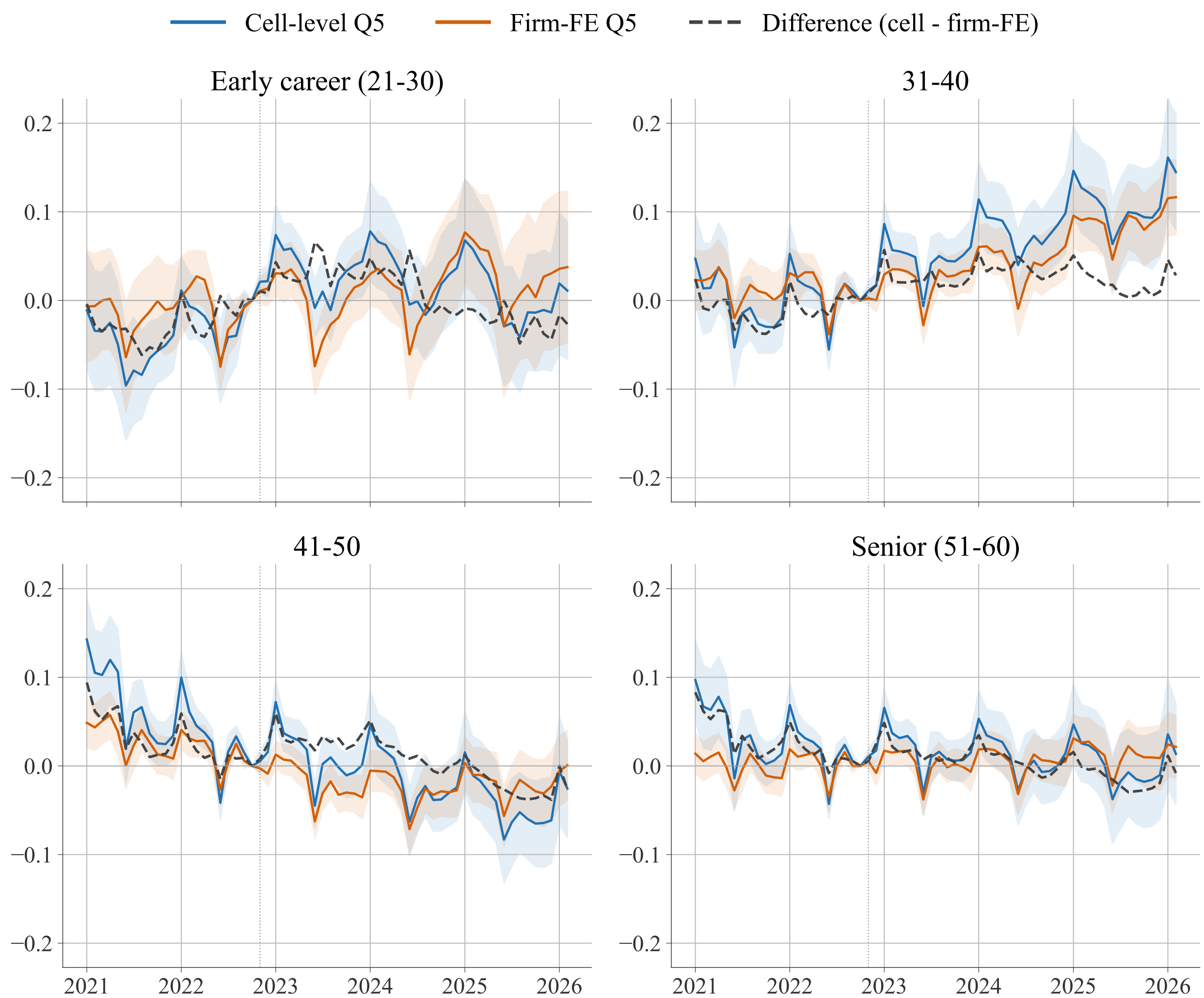

Figure 8: Cell-level and firm-FE event-study coefficients for the most-exposed quintile, by decade age group, private sector.

Notes: Q5-vs-Q1 Poisson event-study coefficients, in log points, relative to October 2022. Blue: cell-level microdata.no spec (Figure 6). Orange: individual-level firm-FE spec (Figure 7). Gray: cell minus firm-FE. Shaded bands: 95% confidence intervals. Sample 2021m1–2026m2.

Table 7: Cell-vs-individual reconciliation: Q5-vs-Q1 employment effect across nested specifications, private sector.

	microdata.no	Individual records		
	cell	cell, all	cell, $\geq$20	firm FE
	(1)	(2)	(3)	(4)
Early career	+0.0213	+0.0202	+0.0101	+0.0126
(21–30)	(0.0220)	(0.0214)	(0.0240)	(0.0210)
31–40	+0.0782***	+0.0753***	+0.0843***	+0.0503***
	(0.0185)	(0.0181)	(0.0197)	(0.0122)
41–50	-0.0146	-0.0159	-0.0156	-0.0206*
	(0.0169)	(0.0168)	(0.0185)	(0.0108)
Senior	+0.0104	+0.0081	+0.0095	+0.0074
(51–60)	(0.0165)	(0.0160)	(0.0193)	(0.0096)

Notes: Each entry is the post-October-2022 change in employment for the most-exposed quintile (Q5) relative to the least-exposed (Q1), Poisson, by decade age group. Column (1) uses microdata.no cell aggregates (occupation $\times$ age $\times$ month, occupation and month fixed effects). Columns (2)–(4) use the individual records: (2) the same cell spec on all private firms, (3) the cell spec on firms with at least 20 workers in the 21–60 window, (4) the firm-FE spec (firm $\times$ quintile and firm $\times$ month fixed effects) on the same sample as (3). Standard errors in parentheses, clustered at occupation in (1)–(3) and at the firm in (4). Sample 2021m1–2026m2. *, **, *** denote $p < 0.1$, 0.05, 0.01.

2026. The recent gap exceeds the 15 log points Brynjolfsson et al. (2025) report for the United States.

5 Tracking the dynamics with the public dashboard

5.1 Quintile Analysis

To what extent is AI shaping the distribution of employment? To answer this question, we develop an approach that performs a cross-sectional analysis of the whole exposure distribution and updates the answer continuously as new data arrive. As previously described in Section 2.1, we divide occupations into quintiles and measure each occupation's percentage change in employment from its pre-ChatGPT baseline. Following the unequal exposure to aggregate shocks specification in Yagan (2019), we define the percentage change in employment as

$$\Delta_j = \frac{\text{emp}_{j,\text{last 3}} - \text{emp}_{j,\text{Oct 2022}}}{\text{emp}_{j,\text{Oct 2022}}},$$

Table 8: Employment change by AI-exposure quintile: all ages 21–60, private sector.

	Q1	Q2	Q3	Q4	Q5
Average change (%)	+0.30	+3.48	+1.25	+3.10	+0.08
Difference vs. Q1 (%)	—	+3.19	+0.95	+2.80	-0.21
		(5.40)	(2.71)	(2.16)	(2.38)
Occupations			374		

Notes: Percentage change in employment $\Delta_j = (\text{emp}_{j,\text{last }3} - \text{emp}_{j,\text{Oct }2022})/\text{emp}_{j,\text{Oct }2022}$ for each occupation's seasonally adjusted private-sector headcount, pooled over ages 21–60, where $\text{emp}_{j,\text{last }3}$ is the mean over December 2025 to February 2026. The top row is the employment-weighted mean change by exposure quintile (occupations ranked by the Eloundou et al. (2024) score); the bottom row is the double difference relative to Q1 (the base quintile, hence no entry), with heteroskedasticity-robust standard errors in parentheses. Occupations are weighted by October 2022 employment, reproducing the headcount aggregation of the companion index. *, **, *** denote significance at the 10, 5, and 1 percent levels.

where $\text{emp}_{j,\text{last }3}$ is occupation j's seasonally adjusted private-sector headcount averaged over the most recent three months of data (December 2025 to February 2026), and the denominator is its October 2022 level. This is the three-month headline specification, which smooths out some of the monthly fluctuations and allows the reader to track the Q5−Q1 difference from the companion dashboard *kiindeksen.no* (Hernæs and Kostøl, 2026). To do so, we regress Δ_j on exposure-quintile dummies, and report heteroskedasticity-robust standard errors across occupations.

Table 8 reports the result. The top row is the employment-weighted mean change in each quintile; the bottom row is the double difference relative to Q1, the least-exposed quintile, which serves as the base. The most-exposed quintile has not grown differently from the least-exposed since ChatGPT: the Q5−Q1 double difference is small and not statistically significant. We return to the time profile of this result in Section 5.2, where we omit the most recent month one at a time and re-estimate the gap at each expanding data vintage to show how it has changed as new data arrive and how stable it is across vintages.

5.2 The dashboard *kiindeksen.no*

The public dashboard at kiindeksen.no/en publishes the monthly series used in the paper by age group and AI-exposure quintile (Hernæs and Kostøl, 2026). It updates as administrative data arrive monthly and lets readers change the indexing, seasonal adjustment, and smoothing. The paper documents the definitions, sample restrictions, and regression checks behind the dashboard. The purpose of the dashboard is to monitor developments with as little lag as the data publication allows.

The dashboard's headline number, the "KI-indeks," is the relative employment growth of the most- versus least-exposed quintile over the most recent three months relative to October 2022, pooled over private-sector workers aged 21 to 60 and seasonally adjusted; it is a descriptive growth gap, not a regression coefficient. Because the seasonal factors are estimated once over 2021 to 2024 and held fixed, the only input that changes as data accrue is which three months form the most recent window. The published value in the most recent vintage, which contains data up to and including February 2026, is a relative growth of about -0.2 percentage points. Re-estimating it on expanding windows, one month at a time from data through January 2025 to February 2026, the headline drifts from about $+1.7$ to about -0.2 percentage points (Appendix Figure A10). An occupation cluster bootstrap puts the standard error at roughly two percentage points throughout, so the index is never statistically distinguishable from zero in any vintage, and the full drift over 2025 is comparable to a single vintage's bootstrap standard error. For a live indicator this sets what to watch for. In every vintage so far the index is consistent with zero, so the most-exposed quintile shows no detectable separation from the least-exposed. The month-to-month movements, including the recent dip below zero, stay inside the bootstrap band and look like noise; a genuine change would show up only as a sustained move beyond it.

6 Conclusion

This paper is about whether generative AI has begun to displace young workers in the occupations most exposed to it. Young workers are the natural place to look, because hiring and entry adjust faster than the stock of incumbent workers, so a shift in labor demand should show up among them first, the "canary in the coal mine" in the language of Brynjolfsson et al. (2025). Whether it does is not obvious from theory. In task-based models, AI automates tasks that workers used to perform, but it also raises the productivity of the tasks that remain in human hands, and when those tasks are complements rather than substitutes, automating some of them can raise a worker's output and income rather than lower it. The net employment effect depends on the balance between displacement, productivity gains, and the creation of new tasks, none of which is pinned down in advance. The effect is also a moving target, because the capability frontier has kept advancing. Making progress requires data broad enough to cover the whole distribution of occupations and current enough to track a fast-moving technology, and the monthly Norwegian population registers, lagged by only three months, let us make some progress on both.

We find no evidence of an aggregate job crisis: private-sector employment has been growing, and the employment rate stable. Since October 2022, the month before ChatGPT's release, employment in the most AI exposed occupations has grown by 0.1 percent against 0.3 percent in the least exposed occupations, a gap that is small and not statistically significant. Differential pre-trends, potentially related to the post-pandemic recovery, make the results even more uncertain. In selected high-exposure occupations, such as software development and customer service, the picture is different: employment among the youngest workers fell after ChatGPT, both relative to young workers in less exposed occupations and relative to older workers in the same occupations. Low-exposure occupations such as electricians and home health aides showed no such gap. However, this canary pattern does not generalize to the rest of highly exposed occupations in the full distribution of occupations. Grouping all occupations into exposure quintiles, the most exposed quintile did not fall behind the least exposed for workers aged 21 to 30.

These patterns place Norway alongside its neighbors. On the case-study evidence, Norway resembles the United States and Sweden, where young workers in exposed occupations also lost ground. On the economy-wide level, the Norwegian evidence resembles that of Denmark and Finland, where AI exposure does not widen employment gaps. However, because none of these settings can strictly separate the impact of AI from the post-COVID correction, monetary tightening, and supply-side reallocation, we interpret the cross-country differences with caution. We may have differently confounded environments rather than evidence that AI has shifted employment by different amounts across countries.

Whether a systematic effect emerges is a question for future research, and the answer will keep changing as long as the technology and adoption continue to evolve. We therefore built a public monthly dashboard, kiindeksen.no, that updates the full-distribution comparison as each new month of administrative data arrives. The dashboard may help researchers, policymakers and other interested parties monitor the development of AI in the labor market in Norway. However, it is not a substitute for better measures of what the technology can do as its capabilities advance, and better measures of how workers actually use it, since the same occupation can be automated or augmented depending on the skills workers bring to it.

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Appendix A: Additional Figures and Tables

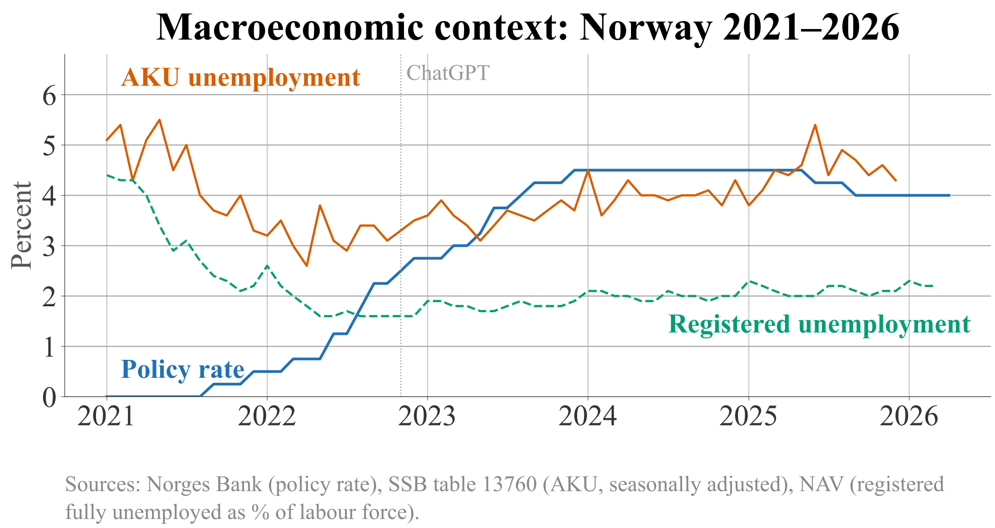

Figure A1: Macroeconomic context: Norges Bank policy rate and registered unemployment rate, 2021–2026.

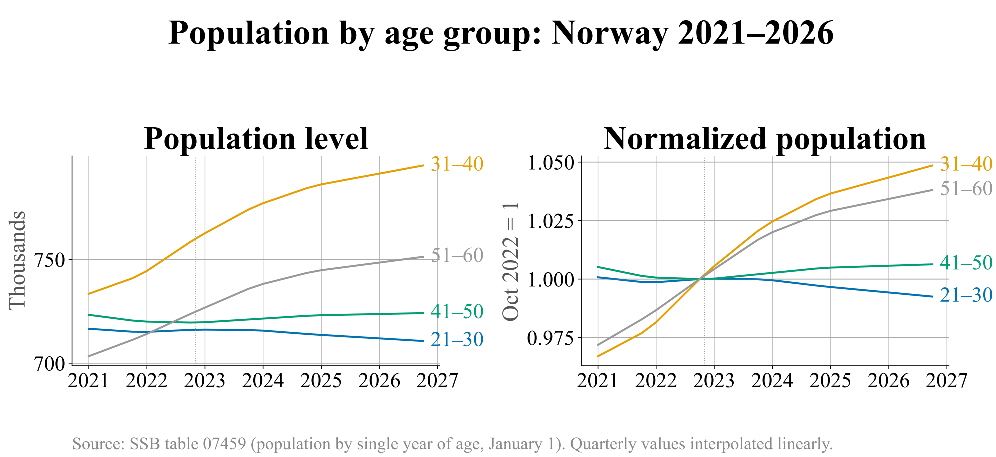

Figure A2: Resident population by decade age group, 2021–2026.

Table A1: Cell-level difference-in-differences by Handa et al. automation- and augmentation-exposure quintile and decade age group, private sector.

	Early career (21–30) (1)	31–40 (2)	41–50 (3)	Senior (51–60) (4)
Panel A. Automation exposure (Employment, Poisson)				
Q2 × Post	-0.0111	0.0253	0.0161	0.0083
	(0.0201)	(0.0192)	(0.0192)	(0.0144)
Q3 × Post	-0.0091	0.0143	0.0036	0.0048
	(0.0188)	(0.0195)	(0.0202)	(0.0136)
Q4 × Post	0.0028	0.0346*	0.0102	0.0088
	(0.0291)	(0.0208)	(0.0194)	(0.0109)
Q5 × Post	-0.0126	-0.0274	-0.0149	-0.0012
	(0.0348)	(0.0290)	(0.0292)	(0.0208)
Panel B. Augmentation exposure (Employment, Poisson)				
Q2 × Post	0.0339	0.0149	0.0022	0.0166
	(0.0297)	(0.0217)	(0.0203)	(0.0172)
Q3 × Post	0.0025	0.0254	-0.0276	0.0129
	(0.0371)	(0.0364)	(0.0269)	(0.0185)
Q4 × Post	0.0216	0.0355	-0.0042	0.0088
	(0.0229)	(0.0221)	(0.0188)	(0.0138)
Q5 × Post	0.0168	0.0469**	0.0132	0.0277
	(0.0245)	(0.0228)	(0.0189)	(0.0171)
Occupations	349	347	350	348
Observations (count)	21,638	21,514	21,700	21,576

Notes: Handa-measure counterpart of Table 4, the regression analog of Figures 4 and 5. Each entry is the post-October-2022 change in employment of the indicated quintile relative to Q1 (least exposed), by decade age group, estimated by Poisson with occupation and month fixed effects and standard errors clustered by occupation. Panel A ranks occupations by the Handa et al. (2025) automation share, Panel B by the augmentation share. Sample 2021m1–2026m2. *, **, *** denote $p < 0.1, 0.05, 0.01$.

Table A2: Cross-Country Comparison of Early Labor Market Patterns under Generative AI

Country	Study	Method	Direction (22–25)	Notes
Panel A: Descriptive time series				
US	Brynjolfsson et al. (2025)	Descriptive	Decline	SW developers 22–25: −20%; top-2 quintiles: −6%
Sweden	Lodefalk et al. (2026)	Descriptive	Decline	≈ −44% raw in top quartile (Fig. A23)
Denmark	Humlum & Vestergaard (2026)	Descriptive	Decline	Aggregate early-career decline mirrors US (App. D.2)
Finland	Kauhanen & Rouvinen (2026)	Descriptive	Null	Trends reflect demographics, not AI
UK	Teeselink (2025)	Descriptive	Decline	High-wage, junior positions
Norway	This paper	Descriptive	Decline	Software developers 21–30: −18% (Fig. 1), top quintile decline
Panel B: Formal estimation				
US	Brynjolfsson et al. (2025)	Poisson event study, firm FE	Decline	−15 log pts, most vs. least exposed quintile
Sweden	Lodefalk et al. (2026)	DiD, employer FE	Decline	−5.5% within-employer by 2025H1; posting decline driven by rate hikes, not AI
Denmark	Humlum & Vestergaard (2026)	DiD, worker/workplace FE	Null	Aggregate decline not driven by firm AI adoption; rules out > 2% earnings effect
UK	Teeselink (2025)	DiD	Decline	Junior positions at high-wage firms
Norway	This paper	Poisson event study, firm FE	Mixed / late decline	22–25: near zero on average, Q5 falls below Q1 from spring 2025 to ≈ −35 log pts by early 2026; 21–30 ≈ 0 (App. B)

Notes: Studies sorted by year within each panel. "Direction" refers to the qualitative sign of the relative employment change for workers aged 22–25 in the most AI-exposed occupations after November 2022. Panel A reports descriptive patterns (raw or per-capita trends); Panel B reports results from formal econometric methods with controls and fixed effects. The descriptive-formal gap is substantial in all studies that employ both: Lodefalk et al. find −44% raw vs. −5.5% in the employer-FE event study; Humlum & Vestergaard find an aggregate decline descriptively but a precise null when using firm-level adoption as treatment. Norway shows a descriptive young-worker decline in selected occupations and a 22–25 formal estimate that is near zero on average but widens to a sizable gap at the end of the sample (App. B replicates the Brynjolfsson et al. design on Norwegian data). Magnitudes across rows use different units and baselines and are not directly comparable.

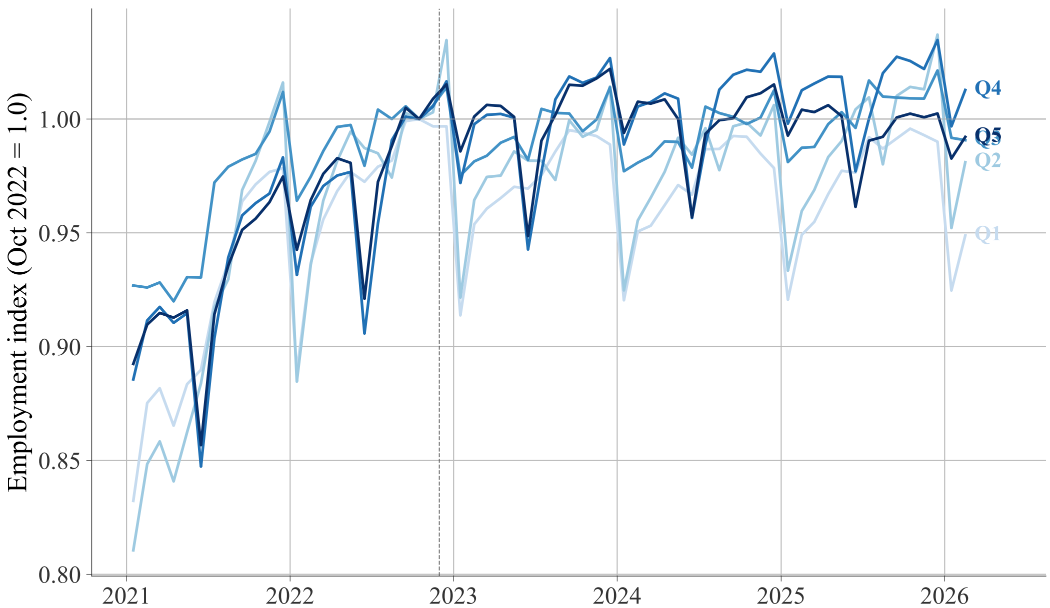

Figure A3: Employment by AI-exposure quintile, all ages 21–60, private sector, raw (unadjusted).

Notes: Raw (not seasonally adjusted) twin of Figure 1; private-sector headcount pooled over ages 21–60, indexed to October 2022 = 1. Occupations are ranked by the Eloundou et al. (2024) score. The same series, with user-adjustable smoothing, is on the companion dashboard (Hernæs and Kostøl, 2026).

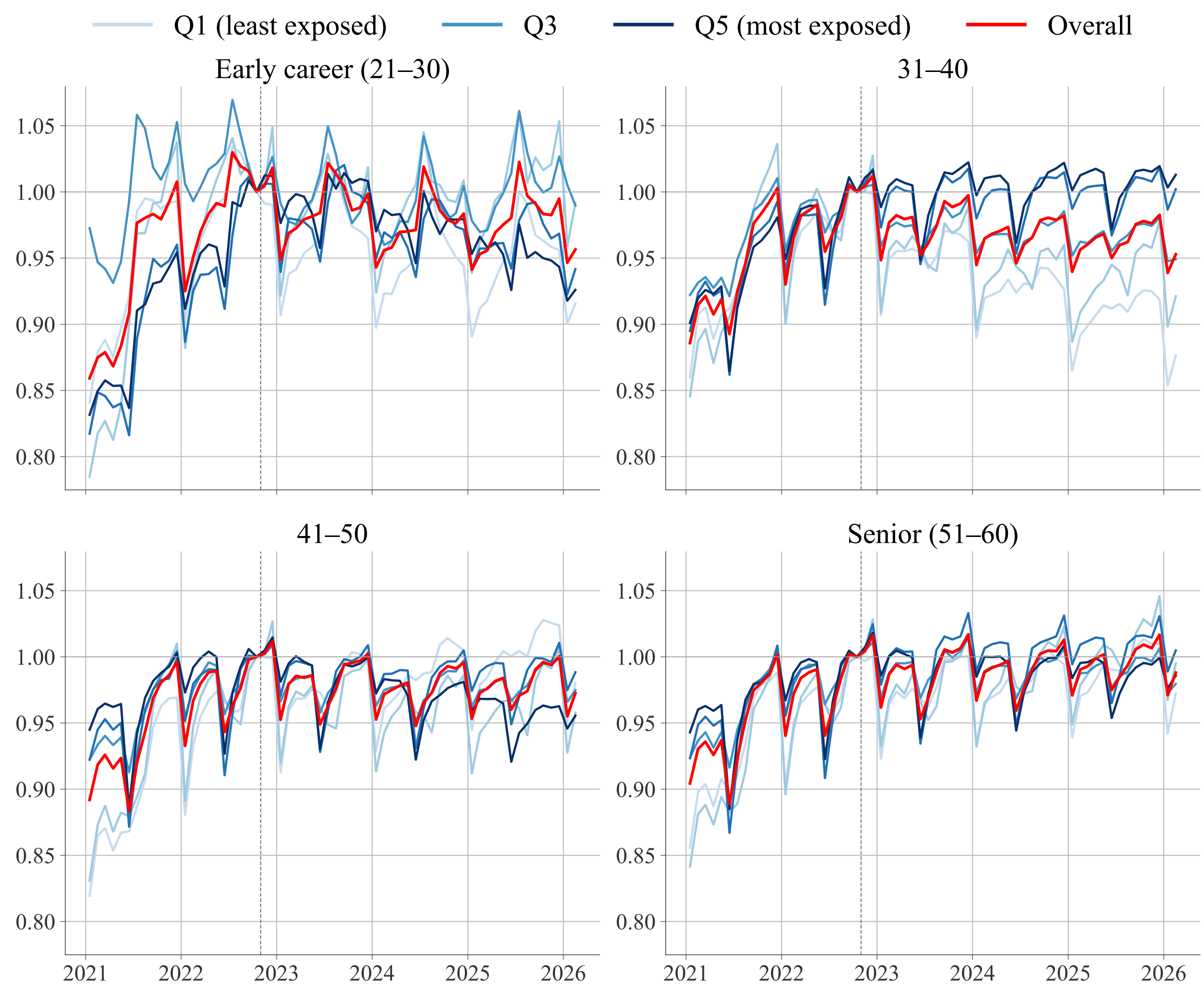

Figure A4: Employment by AI-exposure quintile and decade age group, private sector, raw (unadjusted).

Notes: Raw (not seasonally adjusted) twin of Figure 3; private-sector employment per capita, indexed to October 2022 = 1. Occupations are ranked by the Eloundou et al. (2024) score. Q1 (lightest) = least exposed; Q5 (darkest) = most exposed. The same series, with user-adjustable smoothing, is on the companion dashboard (Hernæs and Kostøl, 2026).

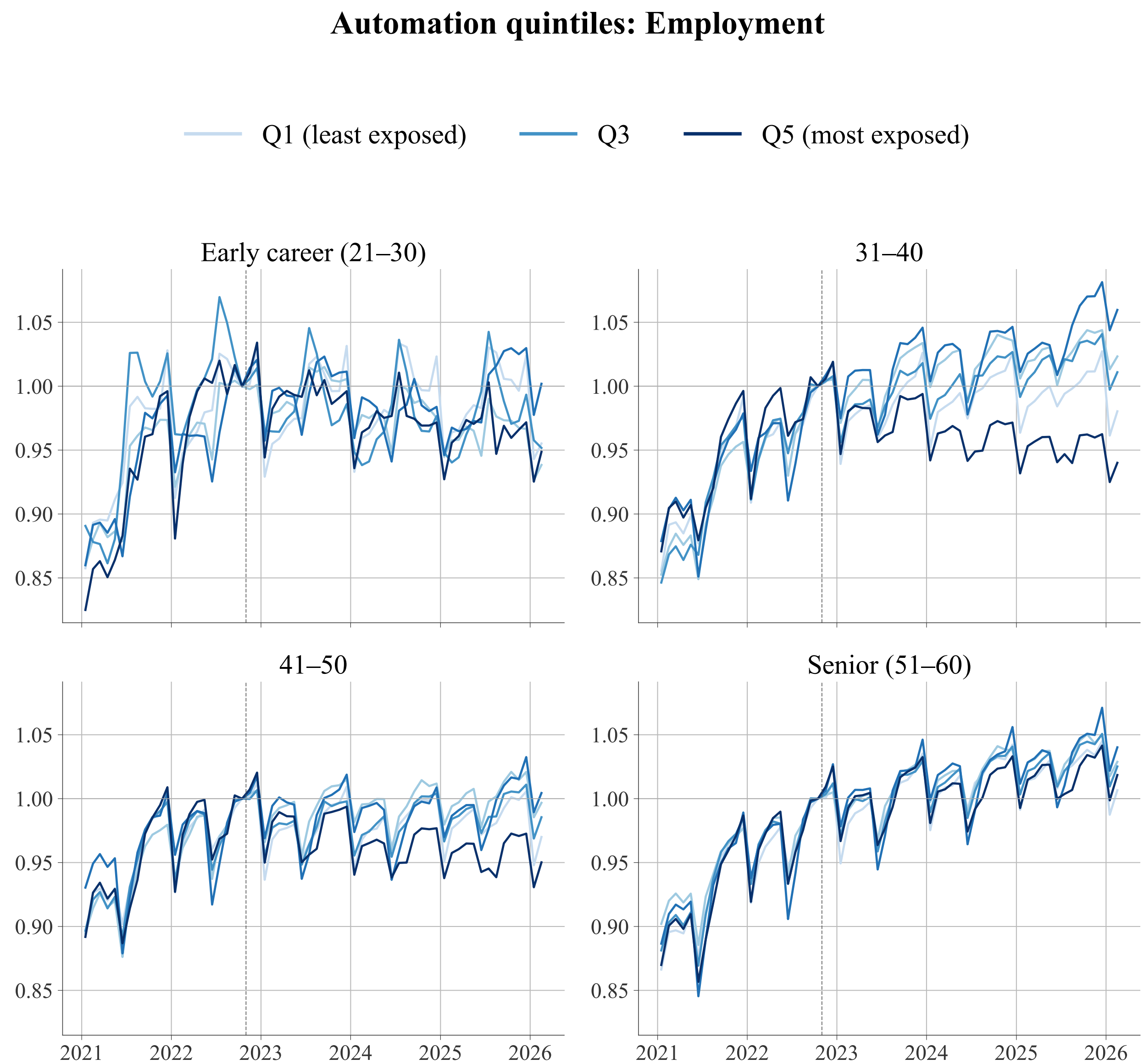

Figure A5: Employment by Handa et al. automation-exposure quintile and decade age group, private sector.
Notes: Private-sector employment indexed to October 2022 = 1. Occupations are ranked by the Handa et al. (2025) automation share.

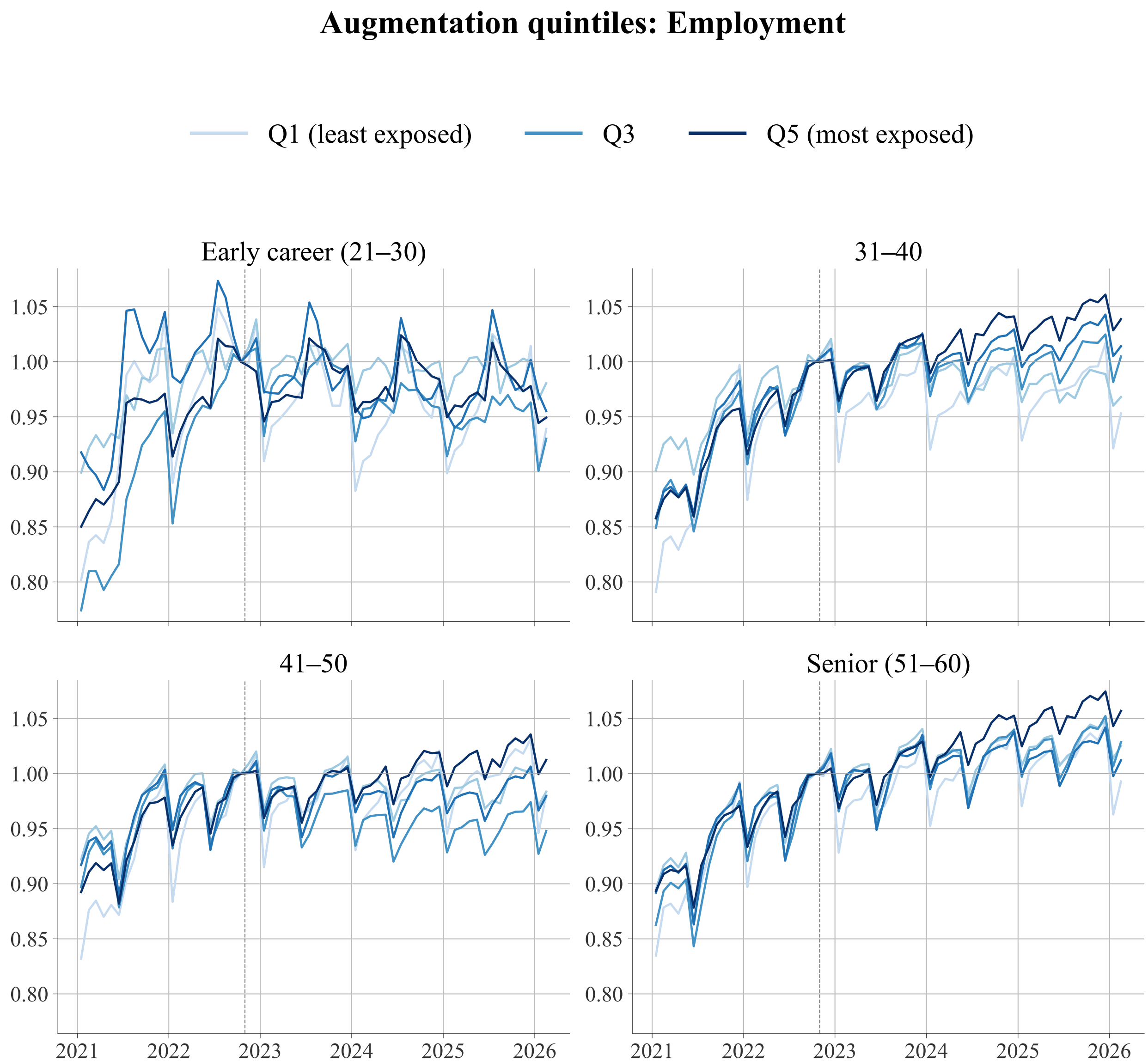

Figure A6: Employment by Handa et al. augmentation-exposure quintile and decade age group, private sector.

Notes: Private-sector employment indexed to October 2022 = 1. Occupations are ranked by the Handa et al. (2025) augmentation share.

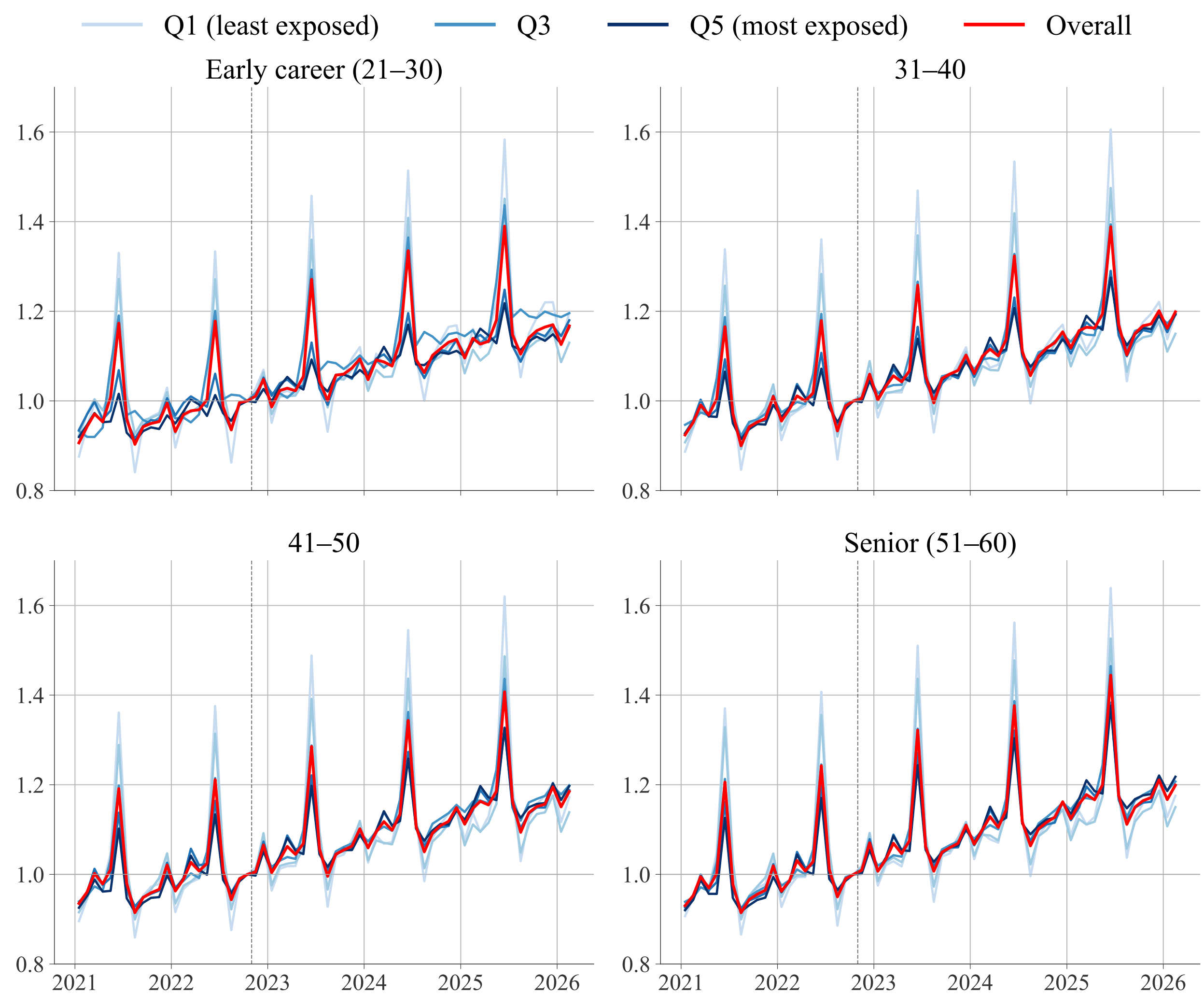

Figure A7: Monthly cash earnings by AI-exposure quintile and decade age group, private sector.

Notes: Mean monthly cash earnings, indexed to October 2022 = 1. Occupations are ranked by the Eloundou et al. (2024) exposure score. Strong seasonal patterns (December bonuses, June holiday pay) are visible in all panels.

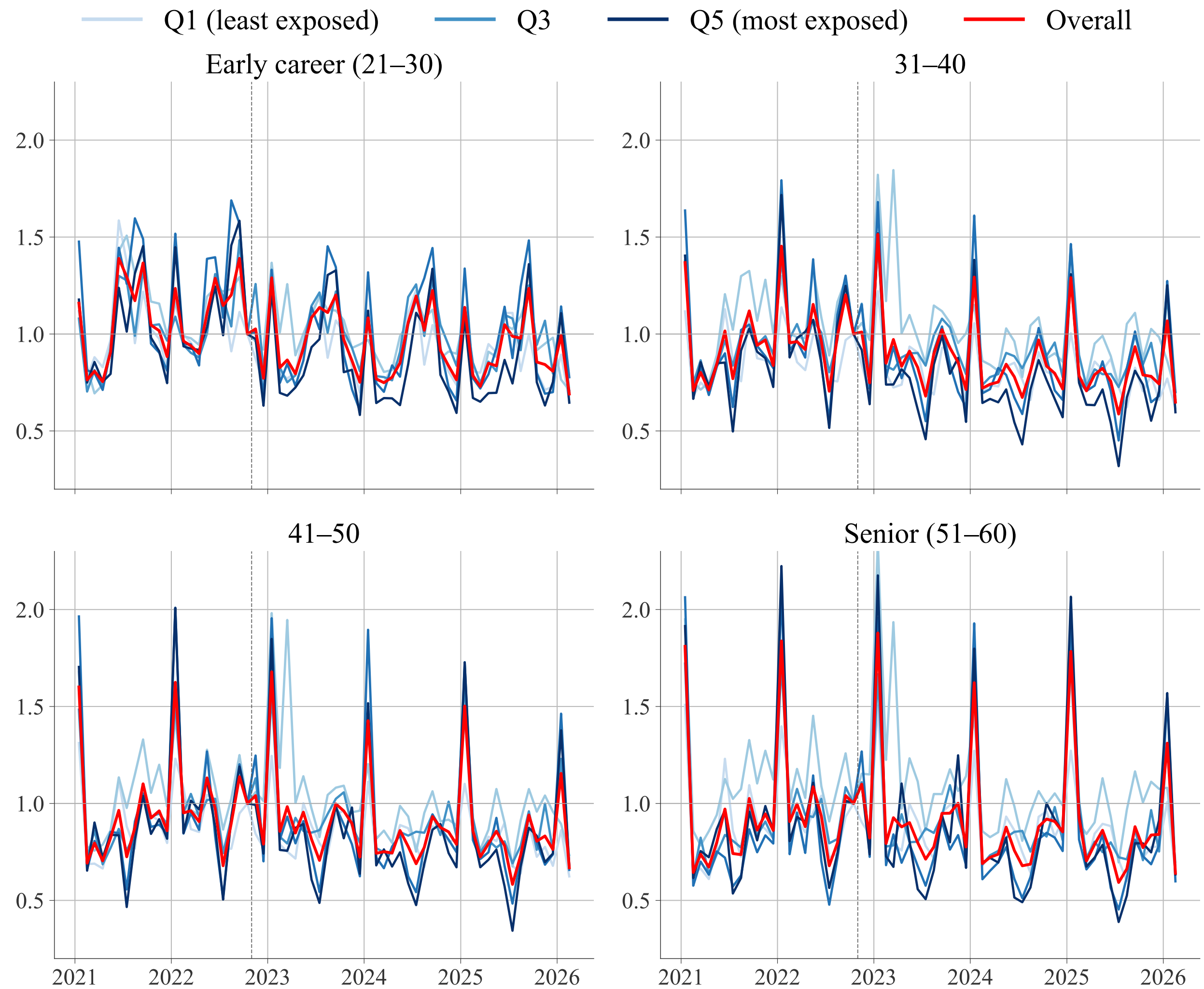

Figure A8: New-hire share by AI-exposure quintile and decade age group, private sector.
Notes: Mean new-hire share, indexed to October 2022 = 1. Occupations are ranked by the Eloundou et al. (2024) exposure score.

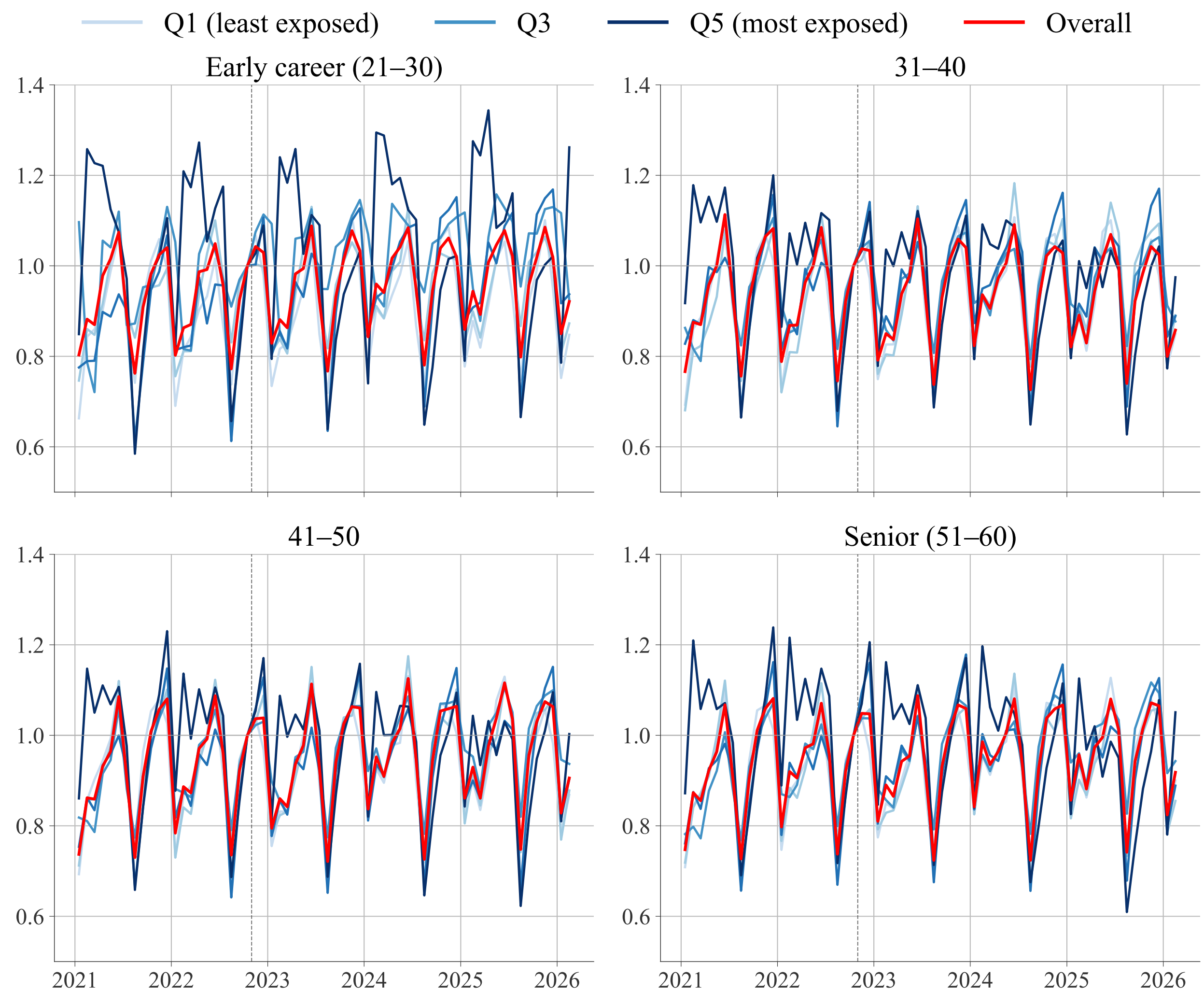

Figure A9: Overtime hours by AI-exposure quintile and decade age group, private sector.
Notes: Mean overtime hours, indexed to October 2022 = 1. Occupations are ranked by the Eloundou et al. (2024) exposure score.

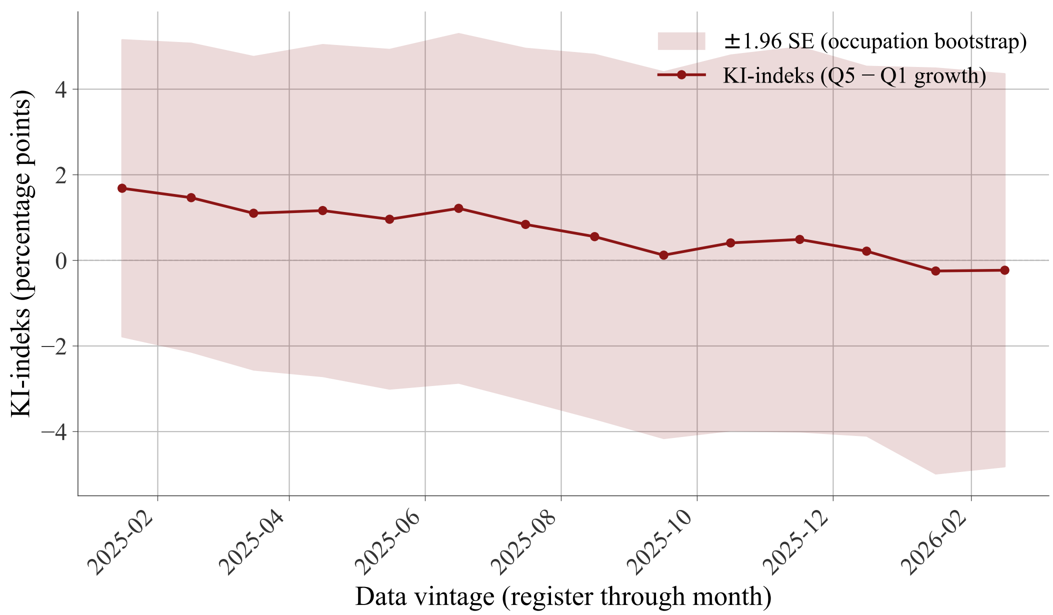

Figure A10: Real-time reliability of the dashboard headline ("KI-indeks"), re-estimated on expanding data vintages.

Notes: The dashboard headline is the relative employment growth of the most- versus least-exposed quintile over the most recent three months relative to October 2022, pooled over private-sector workers aged 21 to 60 and seasonally adjusted (seasonal factors frozen on 2021–2024). Each point re-estimates it from the occupation panel on an expanding window, from data through January 2025 to February 2026. The shaded band is ±1.96 occupation cluster-bootstrap standard errors (1,000 replications); the dashboard itself reports no uncertainty. The band spans zero in every vintage.

Appendix B: Brynjolfsson et al. (2025) Replication

We replicate the design of Brynjolfsson et al. (2025) on Norwegian register data, using the exact early-career definition used in the cross-country literature. Workers are placed in six age bins (22–25, 26–30, 31–34, 35–40, 41–49, 50–55) that match their age-group definitions, employment is indexed to October 2022, and occupations are ranked by the Eloundou GPT-4 quintile. The event study (Figure B4) uses the balanced-panel construction of their paper: full-time private-sector workers in firms with at least 10 workers in each age group every month and at least 100 worker-months per firm-quintile-age cell, a sample smaller and more concentrated in larger firms than the main analysis. The descriptive figures (Figures B1, B2, B3 and B5) instead use all full-time private-sector workers in these age bins, without the firm-balancing restriction; being narrower than the population series in the main text, their raw series move more.

Figure B4 reports the Poisson event study. For workers aged 22–25 the post-October-2022 average gap is small, about 3 log points, but it masks a clear time profile: the most-exposed and least-exposed quintiles track each other through early 2025, and from spring 2025 the most-exposed quintile falls below, with the gap widening to about 35 log points by February 2026. This widening rests on the final ten months of data, the confidence intervals are wide, and the joint pre-trend test rejects parallel trends, so it is an emerging pattern rather than an identified effect. The recent gap exceeds the 15 log points Brynjolfsson et al. (2025) report for the United States, but the US gap opened earlier and over a far larger sample. The descriptive series behind the replication appear in Figures B1, B2, B3 and B5: selected occupations, the Eloundou exposure quintiles, the Handa usage split, and cash earnings.

For the 22–25 event study, we run the same honest difference-in-differences sensitivity analysis as for the main 21–30 sample (Section 3.7), using the Q5-vs-Q1 firm-FE coefficients. The calculation uses the full clustered variance-covariance matrix exported from the secure server. Even under exact parallel trends ($\bar{M} = 0$), the conventional interval includes zero (Table B1), and the breakdown value is zero: the late-opening 22–25 gap remains too imprecise to distinguish from zero in the firm-FE design.

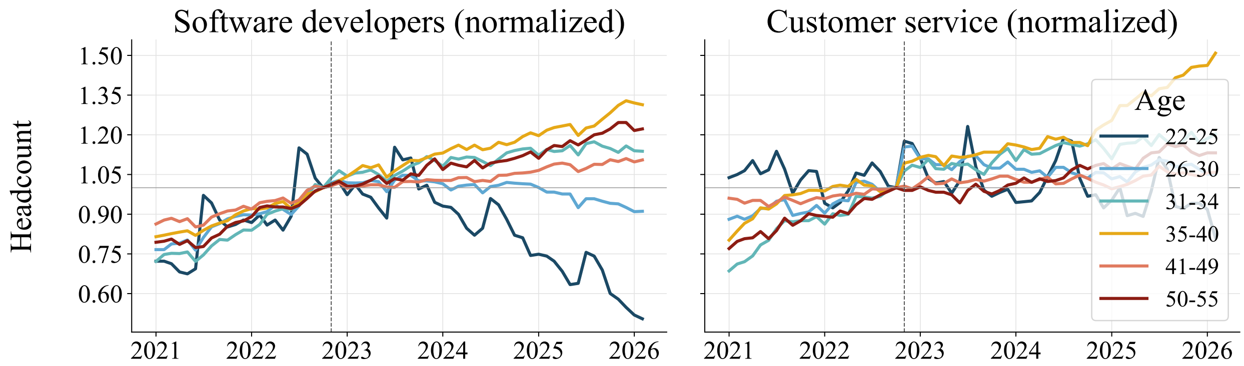

Figure B1: Employment in selected occupations by age group, Brynjolfsson et al. (2025) replication.
Notes: Employment indexed to October 2022 = 1, by age group, for software developers (ISCO-08 2512) and customer service (4222). Full-time private-sector workers (descriptive sample, without the event study's firm-balancing restriction).

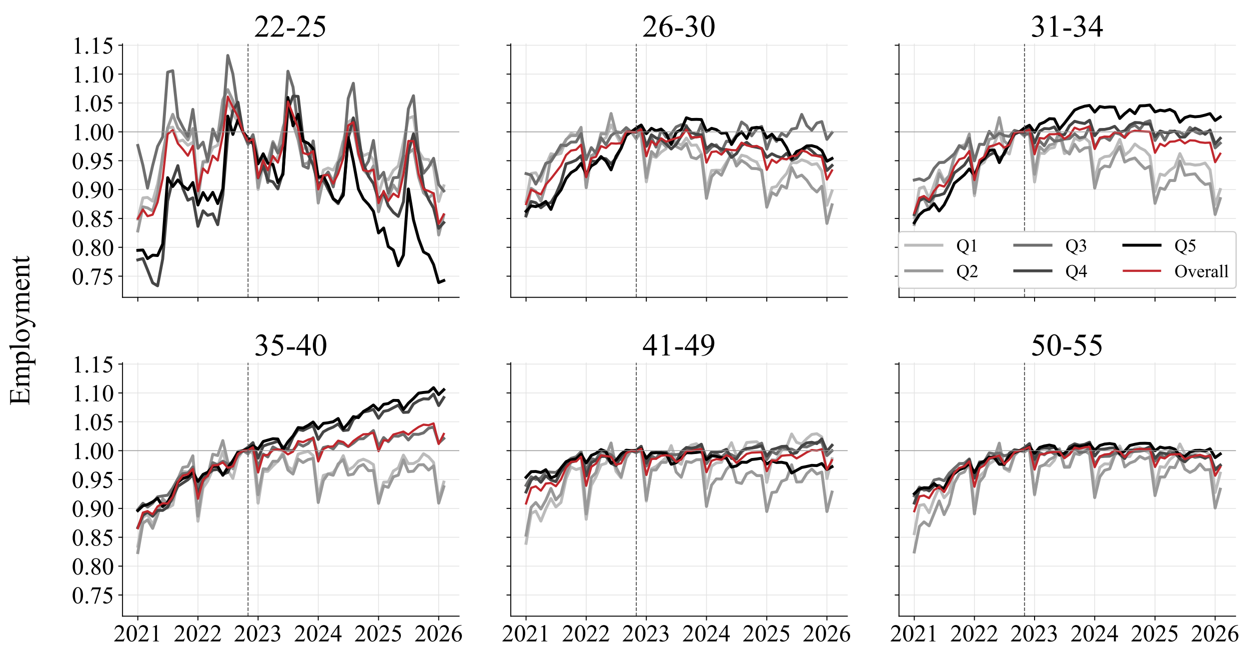

Figure B2: Employment by Eloundou exposure quintile and age group, Brynjolfsson et al. (2025) replication.
Notes: Employment indexed to October 2022 = 1, by Eloundou GPT-4 quintile within each age group, with a pooled overall line. Full-time private-sector workers (descriptive sample, without the event study's firm-balancing restriction).

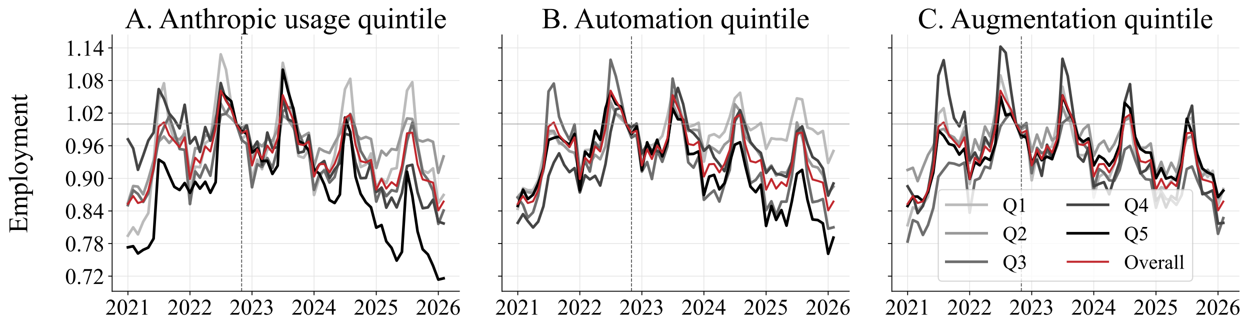

Figure B3: Employment by Handa usage, automation, and augmentation quintile, ages 22–25.
Notes: Employment indexed to October 2022 = 1 for workers aged 22–25, by Handa et al. (2025) usage, automation, and augmentation quintile, with a pooled overall line.

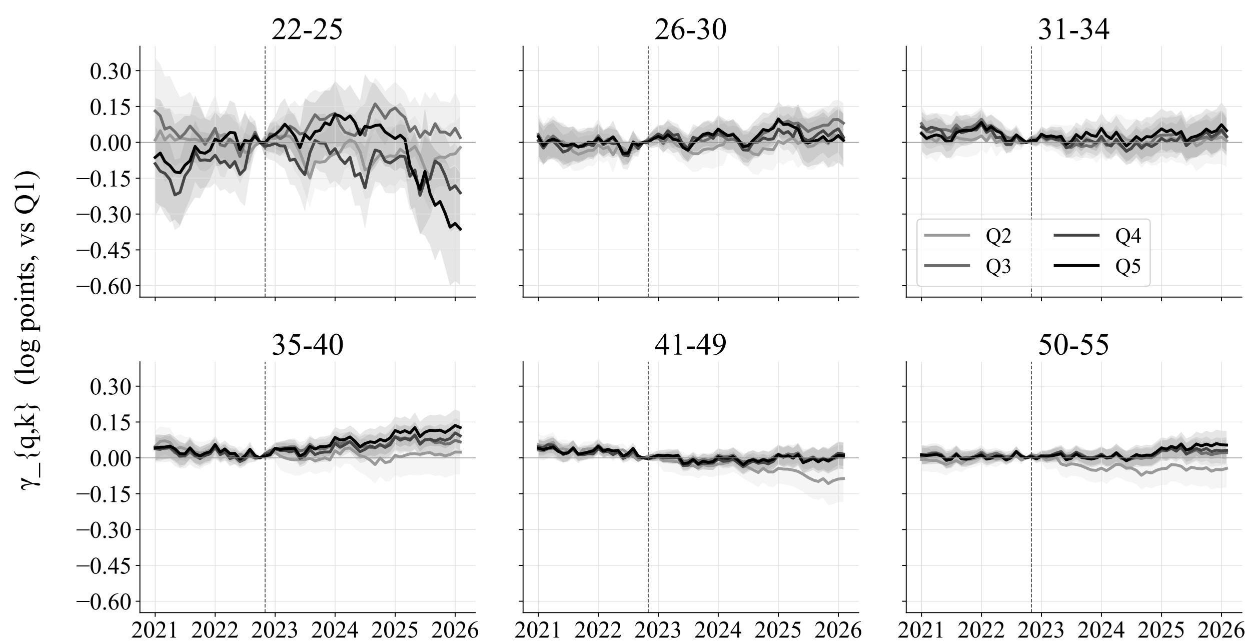

Figure B4: Poisson event-study coefficients, most versus least exposed quintile, by age group.
Notes: Q5-vs-Q1 Poisson event-study coefficients, in log points, by six age bins from 22–25 to 50–55, relative to October 2022. Firm fixed effects; standard errors clustered at the firm. Shaded bands: 95% confidence intervals. Sample 2021m1–2026m2. Dashed line marks the November 2022 ChatGPT release.

Table B1: HonestDiD sensitivity of the Q5-vs-Q1 employment effect, ages 22–25 (Brynjolfsson et al. (2025) sample).

Restriction	Robust 95% CI
Original ($\bar{M} = 0$, parallel trends)	[-0.150, +0.079]
$\bar{M} = 0.5$	[-0.686, +0.506]
$\bar{M} = 1.0$	[-1.257, +1.086]
$\bar{M} = 1.5$	[-1.817, +1.647]
$\bar{M} = 2.0$	[-2.408, +2.228]
Breakdown $\bar{M}$	0.00

Notes: Robust 95% confidence intervals for the average post-ChatGPT Q5-vs-Q1 employment difference, ages 22–25, under the relative-magnitude restriction of Rambachan and Roth (2023). Computed from the individual-level firm-FE event-study coefficients and their full clustered variance-covariance matrix; months are aggregated to quarters and the target is the average post-ChatGPT effect. $\bar{M} = 0$ is exact parallel trends; "Breakdown" is the largest $\bar{M}$ for which the interval excludes zero.

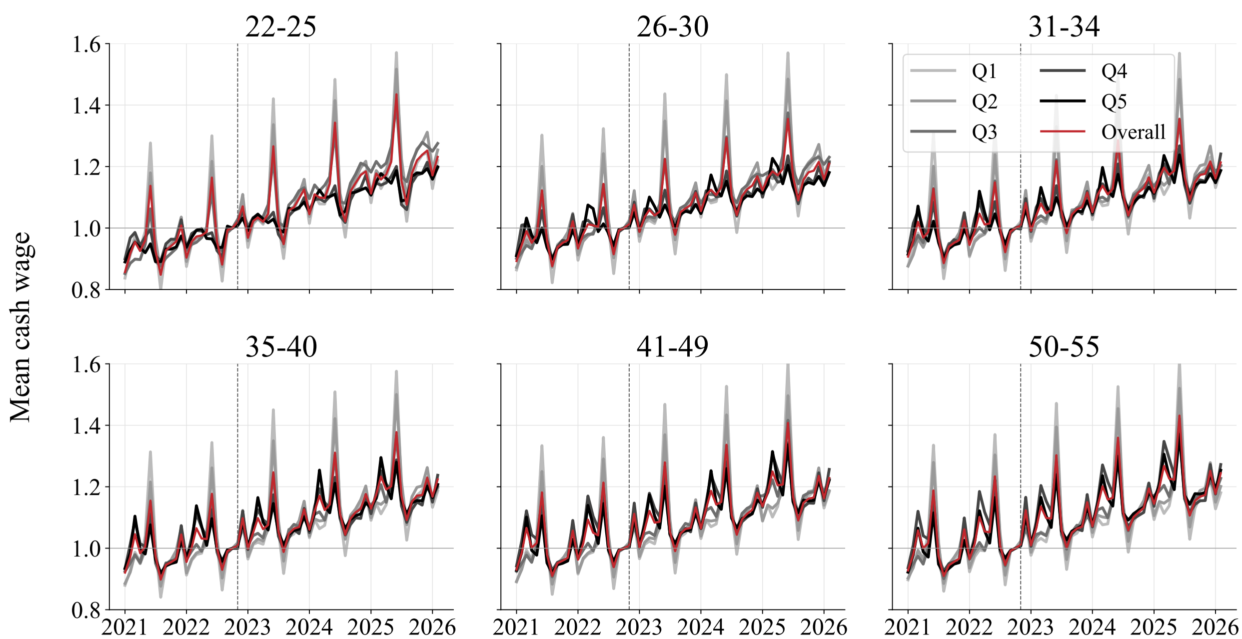

Figure B5: Mean cash earnings by Eloundou exposure quintile and age group, Brynjolfsson et al. (2025) replication.

Notes: Mean monthly cash earnings indexed to October 2022 = 1, by Eloundou GPT-4 quintile within each age group, with a pooled overall line. Full-time private-sector workers (descriptive sample, without the event study's firm-balancing restriction).