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BRIDGING SKILL GAPS FOR THE FUTURE: NEW JOB CREATION IN THE AI AGE

Florence Jaumotte, Jaden Kim, David Koll, Elmer Z. Li, Longji Li, Giovanni Melina, Alina Song, and ***Marina M. Tavares***

RES and MCD, IMF

The views expressed in this presentation are those of the authors and do not necessarily represent the views of the IMF, its Executive Board, or IMF management.

Key messages

40%

of workers are in jobs exposed to AI; about half could benefit from complementarity

1 in 10

job postings in advanced economies require at least one new skill

≈8%

wage return to new AI-developer skills in the United States and United Kingdom

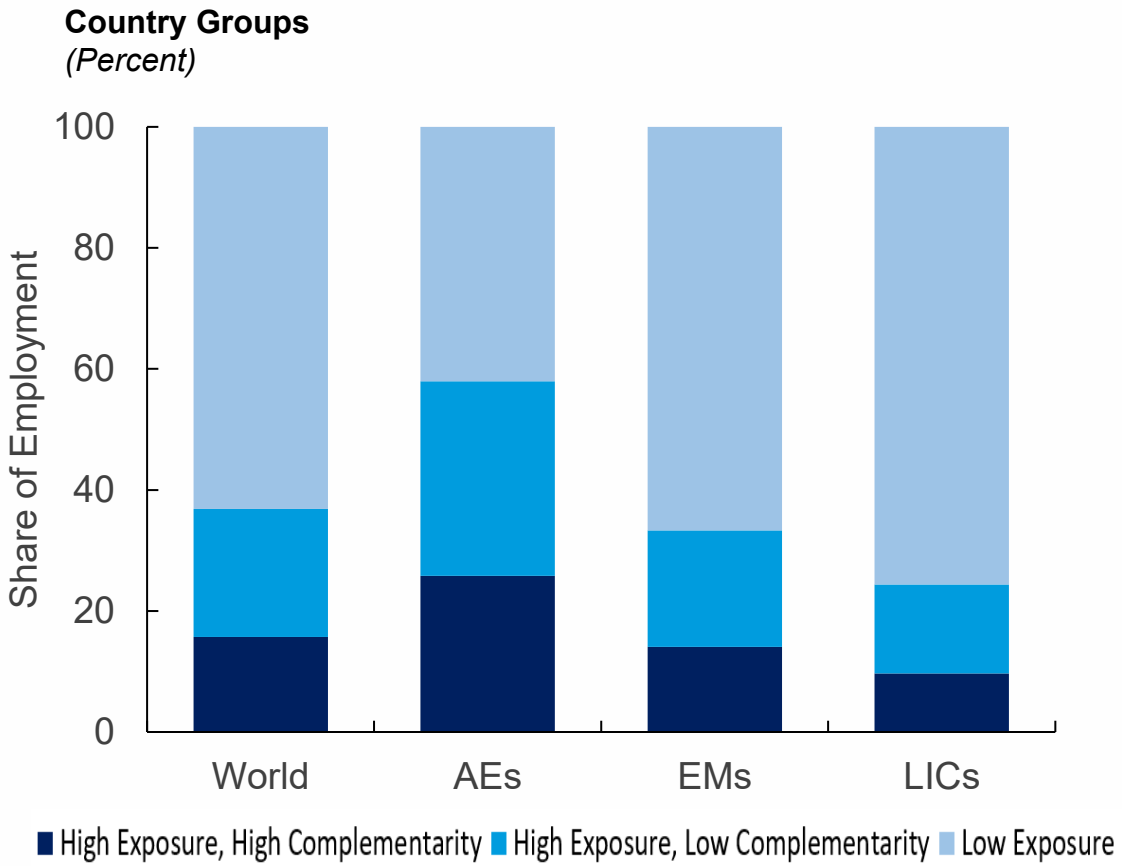
−6.3%

local employment in high-exposure, low-complementarity jobs per 1 pp rise in AI-skill demand (US)

Bottom line New skills raise wages and jobs, but AI also displaces some workers. The policy challenge is to accelerate skill adaptation while limiting the distributional costs of AI adoption.

AI exposure is meaningful

Employment Shares by AI Exposure and Complementarity



40%

of workers are in jobs exposed to AI

- Half high complementarity, half low complementarity
- Exposure is higher in AEs which dominate in cognitive-intensive roles

Sources: American Community Survey; Gran Encuesta Integrada de Hogares; India Periodic Labour Force Survey; International Labour Organization; Labour Market Dynamics in South Africa; Pesquisa Nacional por Amostra de Domicílios Contínua; UK Labour Force Survey; and IMF staff calculations.

Online job postings show which skills employers want, by occupation and country

- Leverage vacancy data from Lightcast: Brazil, Denmark, Germany, United Kingdom, the United States, and South Africa
- The data contain detailed information on:
  1. Job title
  2. Skills required
  3. Geographical location
  4. Company name
  5. Wages
- Combine Lightcast data with census data, firm data (Compustat), workers' profile data

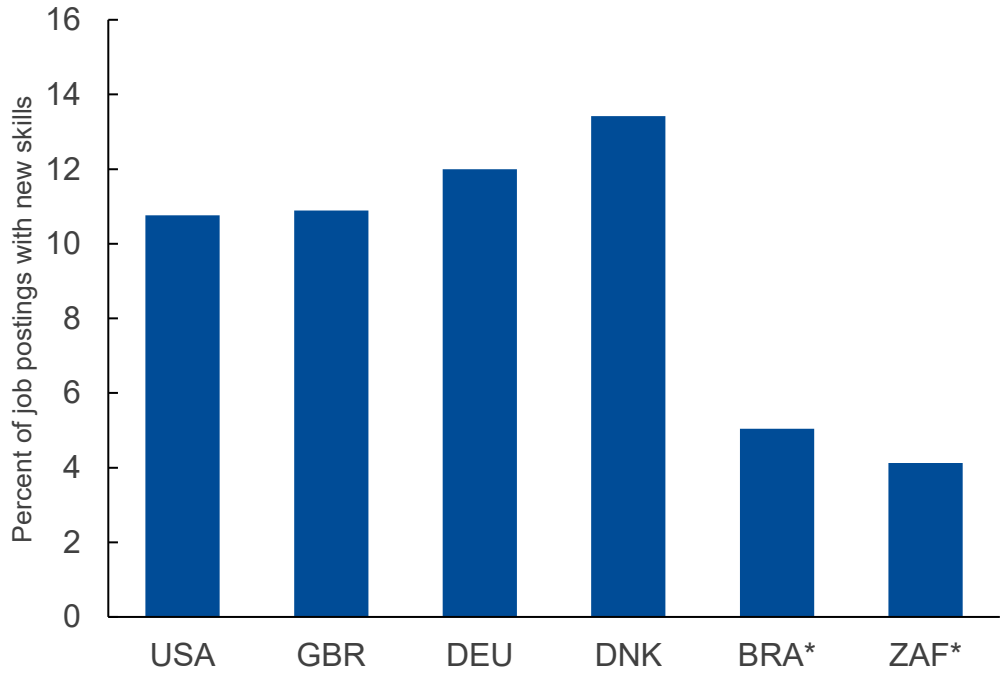
Examples of Occupations, Job Titles, and Skills Derived from Job Postings Data

ISCO-08 Occupation (4-digit)	Example job titles	Top skills in postings (6)
2512 Software Developers	Software Engineer; Data Engineer	Software Engineering; Software Development; Python*; SQL*; Amazon Web Services (AWS)*; Agile Methodology
3251 Dental Assistants & Therapists	Dental Hygienist; Dental Assistant	Dental Hygiene; Dentistry; Preventive Care; Medical History Documentation; Periodontology; Velscope*
3314 Statistical, Mathematical & Related Associate Professionals	Data Analyst; BI Analyst	Data Analysis; SQL*; Python*; Tableau*; Power BI*; Data Visualization
5230 Cashiers & Ticket Clerks	Cashier; Front-of-House Cashier	Customer Service; Point of Sale; Cash Register; Communication; Sales; Greeting Customers

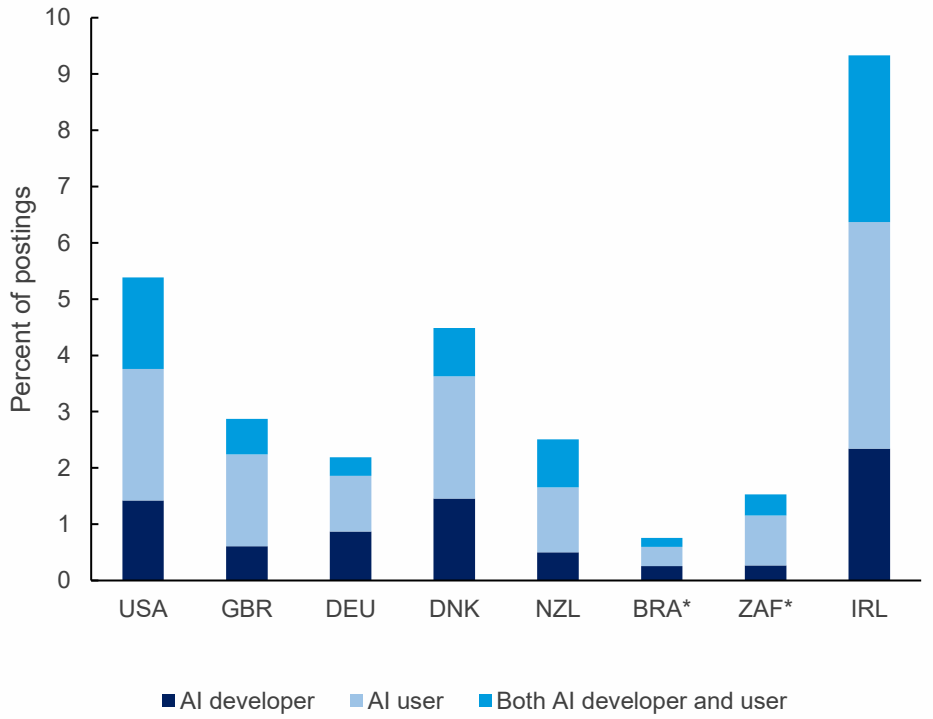
Demand for new skills is already macro-relevant, with AI new skills growing

New Skills' Distribution

1. Share of New Skills by Country
(Percent)



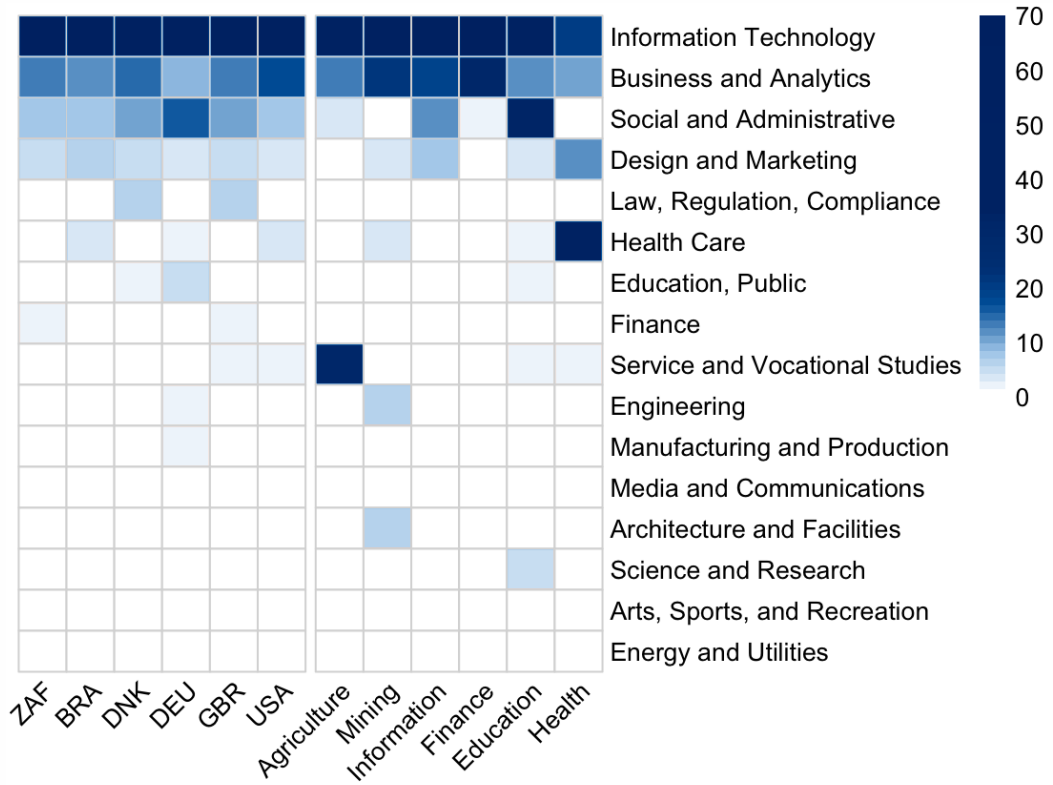
2. The Share of AI-Related New Skills in 2025
(Percent of total job posting)



Sources: Lightcast, and IMF staff calculations.

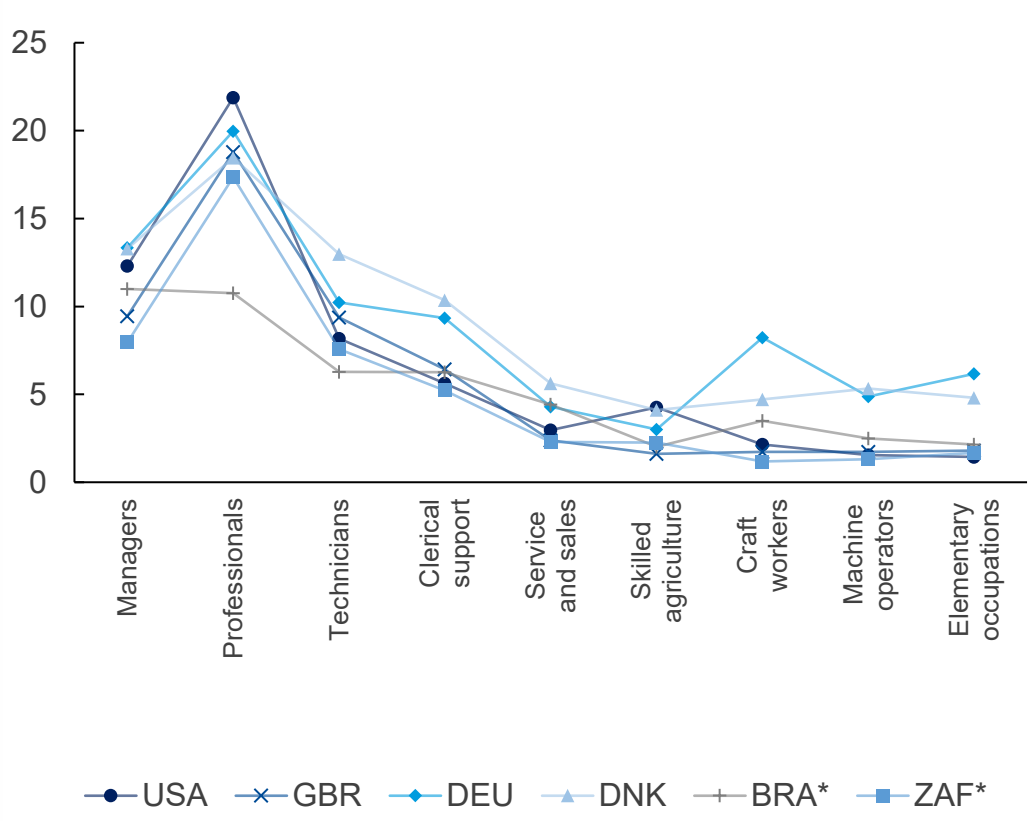
It affects all sectors and a wider range of jobs

1. Distribution of New Skills Across Fields



2. Share of New Skills by Occupation

(Percent)

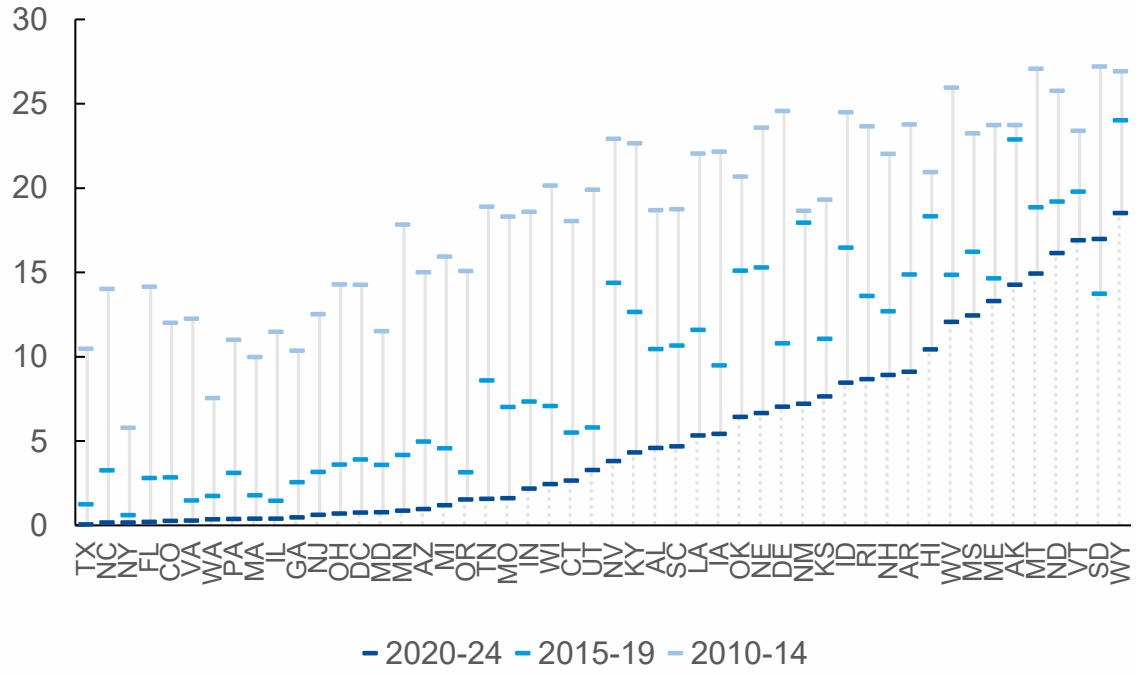


Sources: Lightcast, and IMF staff calculations.

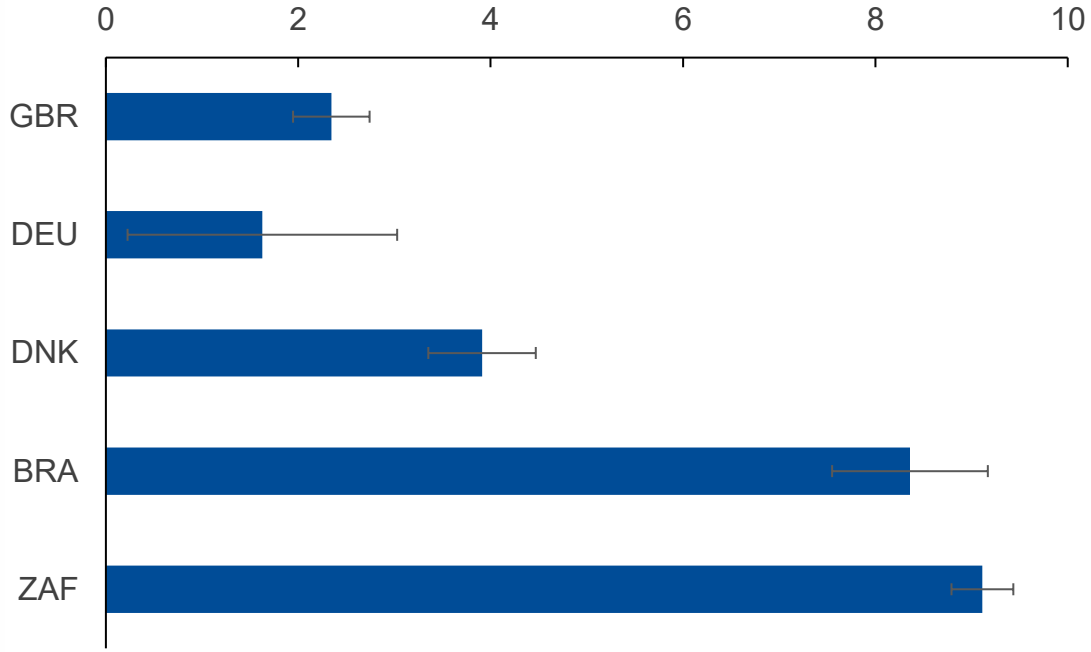
New skills are spreading faster, now crossing borders within months

Skill Diffusion within the United States

1. Skill Appearance Time Lag Relative to CA
(In months)



2. Skill Appearance Time Lag Relative to the United States
(Months)



- **The implication: workers and education systems have less time to adapt.**

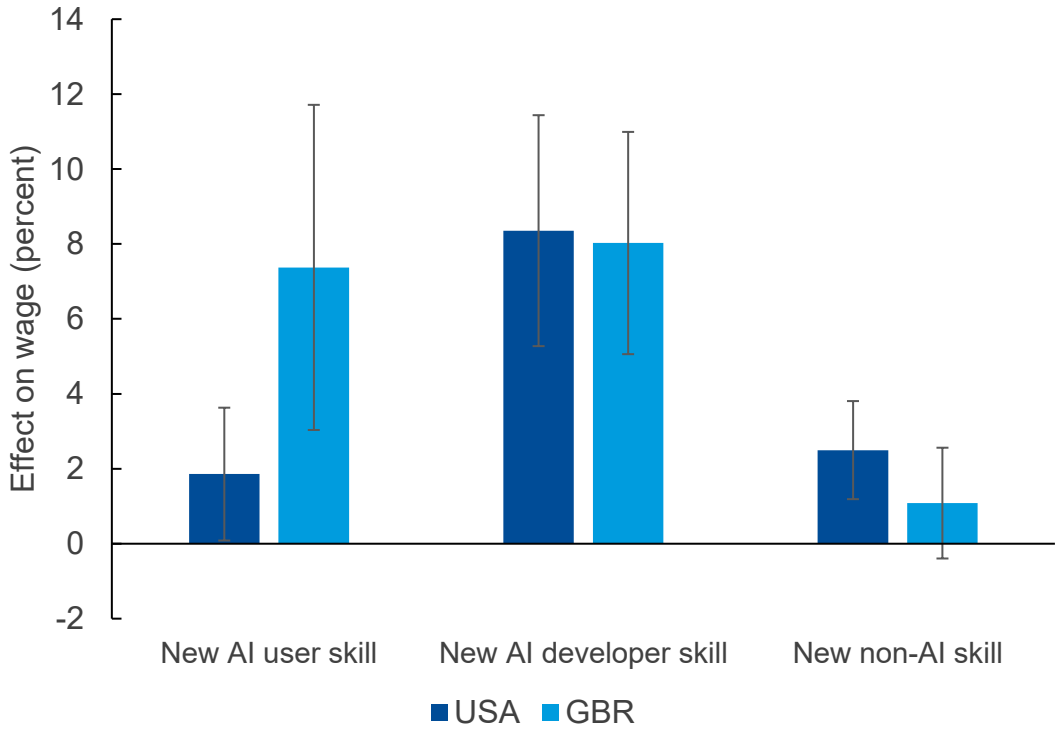
Sources: Lightcast, American Community Survey (ACS), Current Population Survey (CPS, via UnionStats), Wharton Residential Land Use Regulatory Index, Opportunity Lab, PIACC, Reinmuth and Rockall (2023), and IMF staff calculations.

New skills pay—and AI skills can pay particularly well

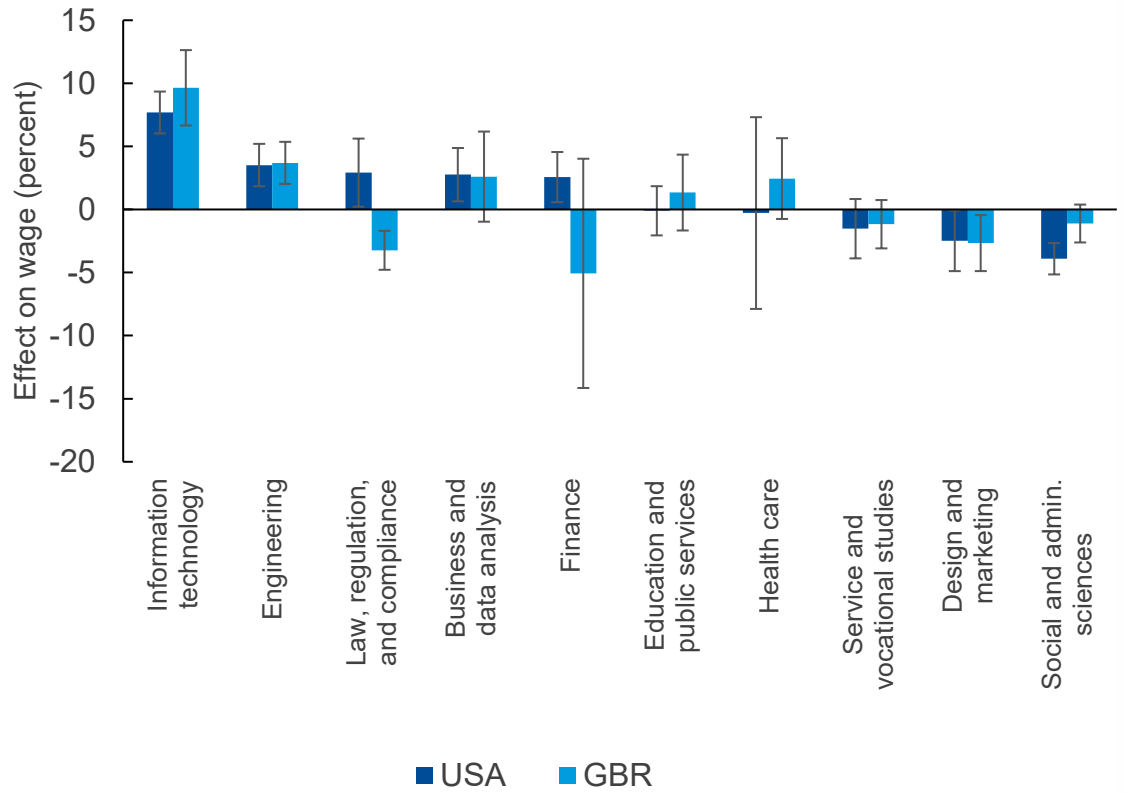
The Return of New and AI Skills

≈8% wage return to new AI-developer skills

1. Wage Return to AI Skills



2. Wage Return by Skill Type



Sources: Lightcast, and IMF staff calculations.

01

Economy-Wide Wage and Employment Impacts of New Skills

Empirical strategy: local labor market effects of new skills

Long-difference IV design, U.S. commuting zones, 2013–23

$$\Delta \ln Y_{c,d} = \delta \cdot \Delta \text{NewSkills}_{c}^{IV} + X_c'\gamma + \mu_d + \lambda_s + \varepsilon_{c,d}$$

Outcomes (Y)

- Log real hourly wages or employment
- Estimated overall and by occupation group
- High-skill, white-collar, blue-collar, and low-skill occupations

Exposure and identification

- Change in the local share of postings requiring new skills
- Shift-share weights use 2000 occupation employment shares
- Instrument: early adoption by occupation in California and the United Kingdom (2013)

Controls and inference

- Initial education, immigration, manufacturing, unemployment, demographics, and low-wage employment
- Demographic-group and state fixed effects
- Standard errors clustered by commuting zone

Policy heterogeneity

$$\Delta \ln Y = \delta_1 \Delta \text{NewSkills}^{IV} + \delta_2 (\Delta \text{NewSkills}^{IV} \times \text{High policy exposure}) + \delta_3 \text{High policy exposure} + \text{controls} + \text{fixed effects}$$

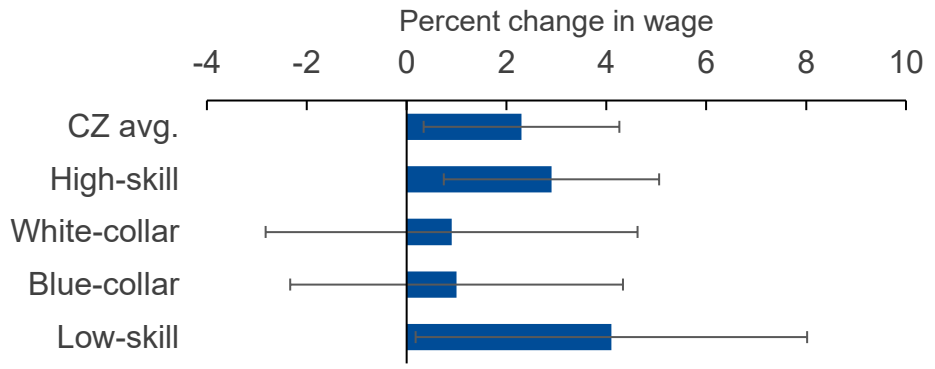
Interpretation: δ is the effect of a 1 percentage point increase in new-skill postings; δ_2 shows how the effect differs with pre-existing policy or institutional exposure.

Source: Lightcast, ACS, CPS/UnionStats, Opportunity Lab, PIACC, Wharton Index; IMF staff calculations. Controls and design follow Acemoglu and Restrepo (2020).

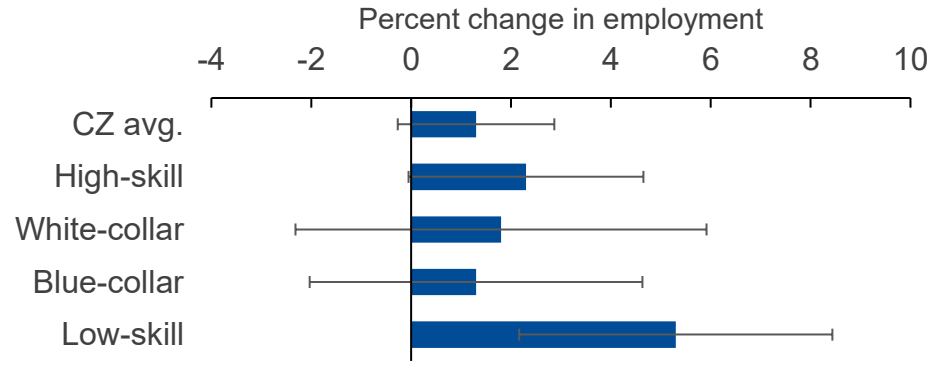
New skills are associated with higher wages and employment level at the local labor market in the United States

New Skills Impact on U.S. Local Labor Markets

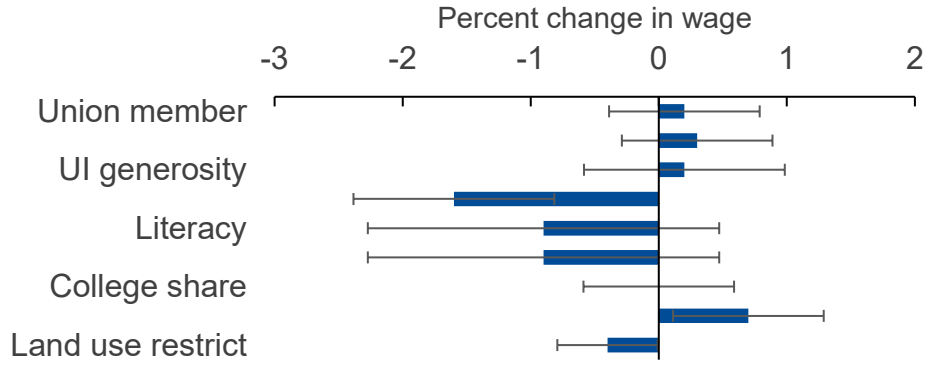
1. Wage Effects



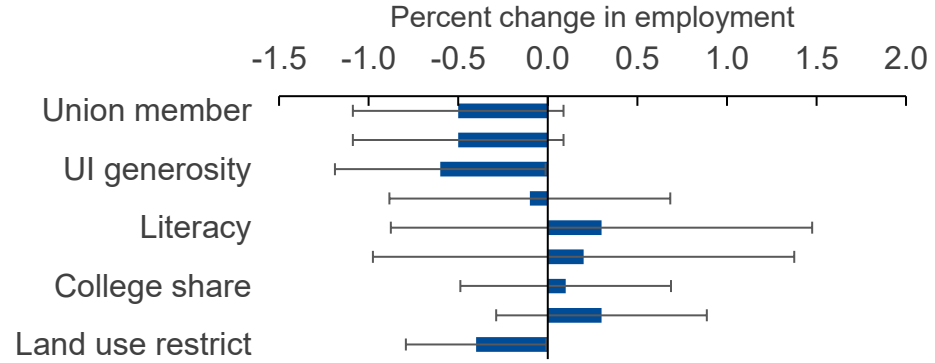
2. Employment Effects



3. Policy Effects on Wages



4. Policy Effects on Employment



Sources: Lightcast, American Community Survey (ACS), Current Population Survey (CPS, via UnionStats), Wharton Residential Land Use Regulatory Index, Opportunity Lab, PIACC, Reinmuth and Rockall (2023), and IMF staff calculations.

02

Economy-Wide Wage and Employment Impacts of AI Skills

Empirical strategy: dynamic effects of AI-skill diffusion

Event-study difference-in-differences with staggered, recurrent, and non-binary treatment

$$Y_{c,s,t} = \Sigma_{\ell} \beta_{\ell} \cdot \Delta\text{AI-skill exposure}_{c,s,t-\ell} + \text{state FE} + \text{year FE} + \varepsilon$$

Event time relative to AI-skill entry



Estimator

- De Chaisemartin and D'Haultfoeuille (2023, 2024)
- Valid group-time comparisons avoid two-way fixed-effect contamination

Unit and data

- Commuting zone × year, estimated separately by occupation group
- ACS employment outcomes + Lightcast AI-skill postings, 2013–23

Treatment and comparison

- Treatment intensity changes as AI-skill demand enters or expands
- Compared with not-yet-treated or never-treated locations at each event time

Reading the coefficients

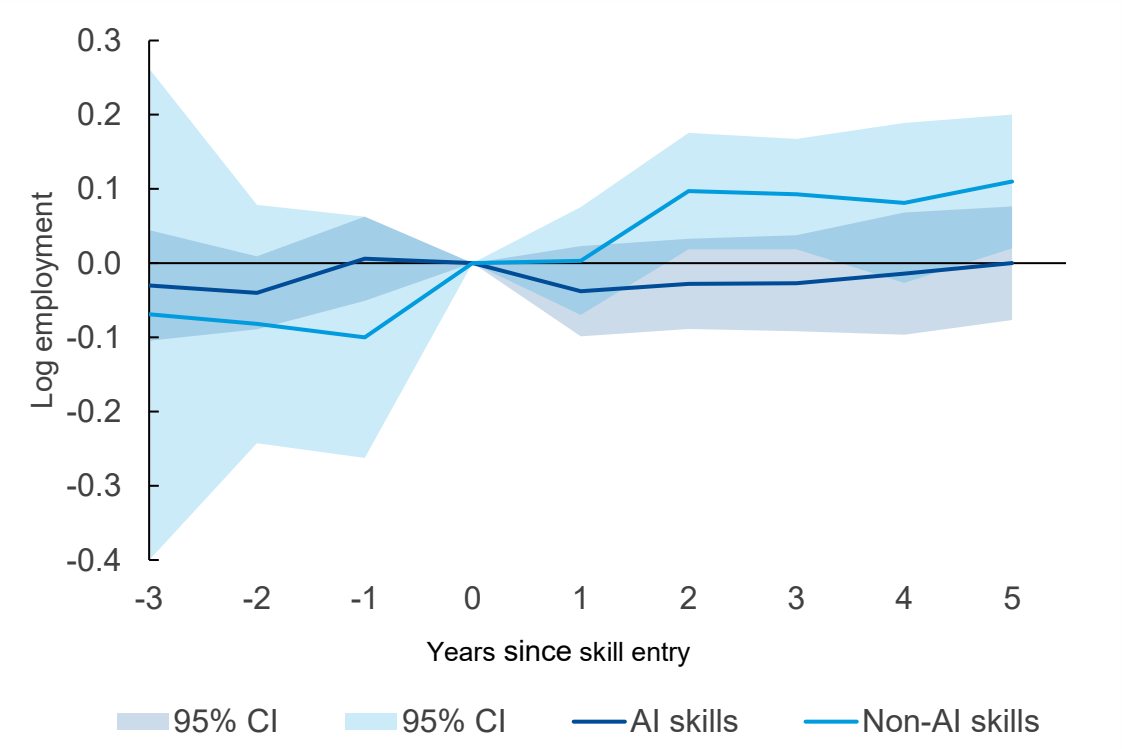
- $\beta\ell$ traces the response ℓ years around entry; year 0 is normalized
- Leads test pre-trends; lags show persistence; bands are 95% confidence intervals

Interpretation: for high-exposure, low-complementarity occupations, the year-5 estimate compares employment paths in regions with greater versus lower AI-skill demand. The design supports a dynamic association under parallel-trend assumptions.

Source: Lightcast, American Community Survey; IMF staff calculations. Occupation groups follow Pizzinelli and others (2023).

The demand for new skills boosts employment but AI is different

1. Impact of Demand for New Skills on Overall Employment (US local labor markets)



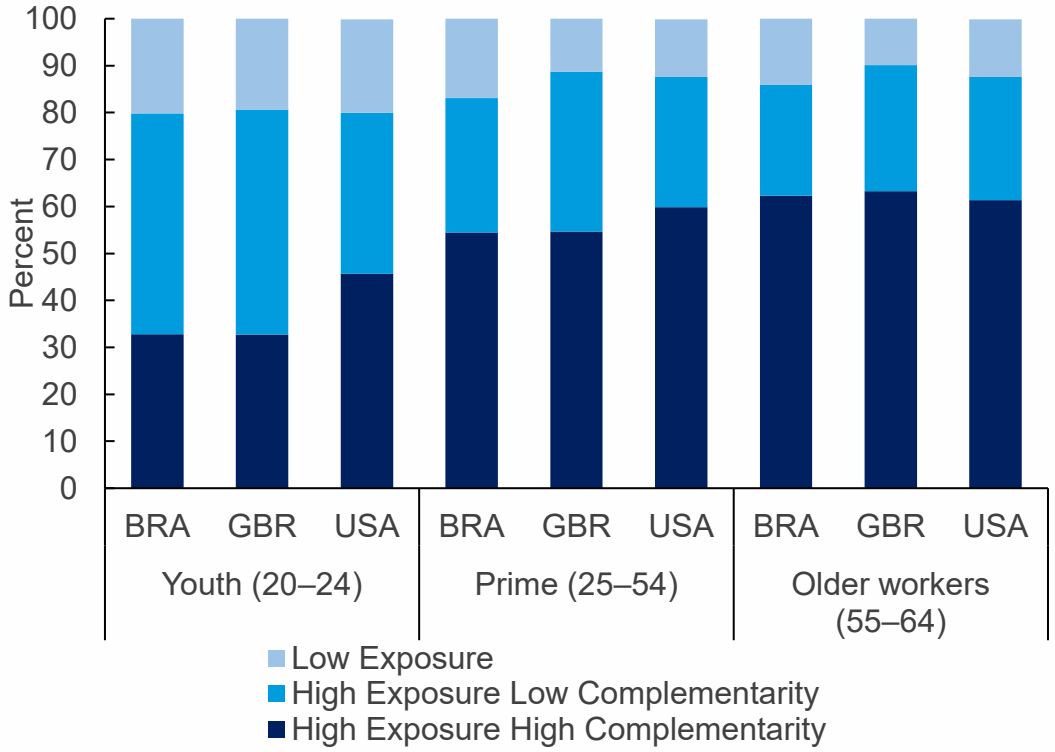
2. Impact of Demand for AI-related Skills on Occupations with High Exposure and Low Complementarity to AI (US local labor markets)



Sources: Lightcast, American Community Survey (ACS), and IMF staff calculations.

Younger workers are likely to be affected first

1. College Educated Workers: Employment Shares by AI Exposure and Complementarity



2. Employee headcount among software developers, by age
(Indexed to 100 at Oct. 2022)



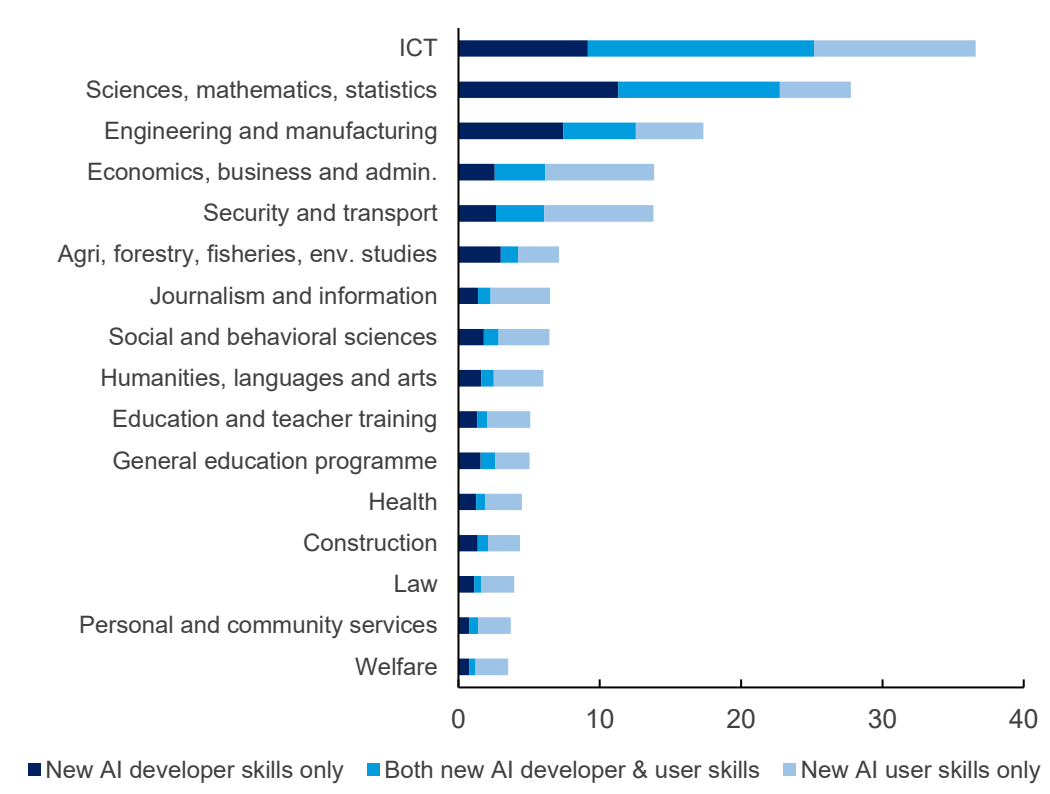
Sources: Cazzaniga and others 2024; Pizzinelli and others 2023; Brynjolfsson, Chandar and Chen; and IMF staff calculations.
Note: Panel 1 plots the estimated share of employment by age group for each exposure category for college-educated workers. Country labels use International Organization for Standardization (ISO) country codes.

03

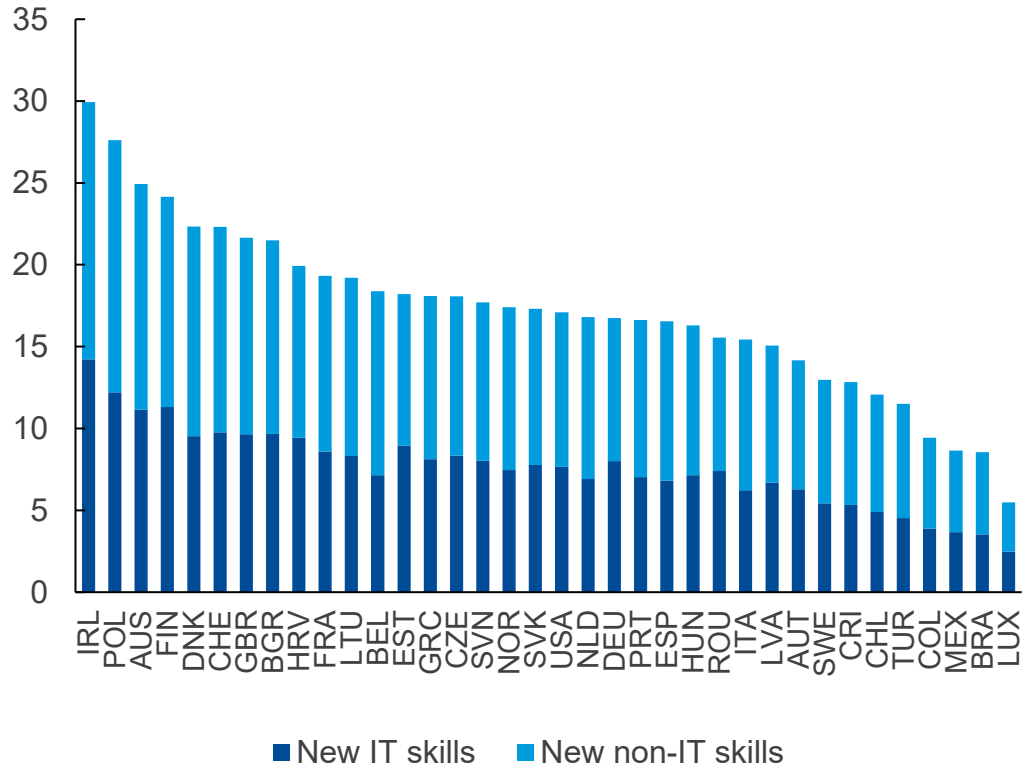
The Demand and Supply of Skills

New-skill supply is concentrated among ICT and science graduates and varies widely across countries

1. Share of AI New Skills by Field of Study in the United States
(Percent)



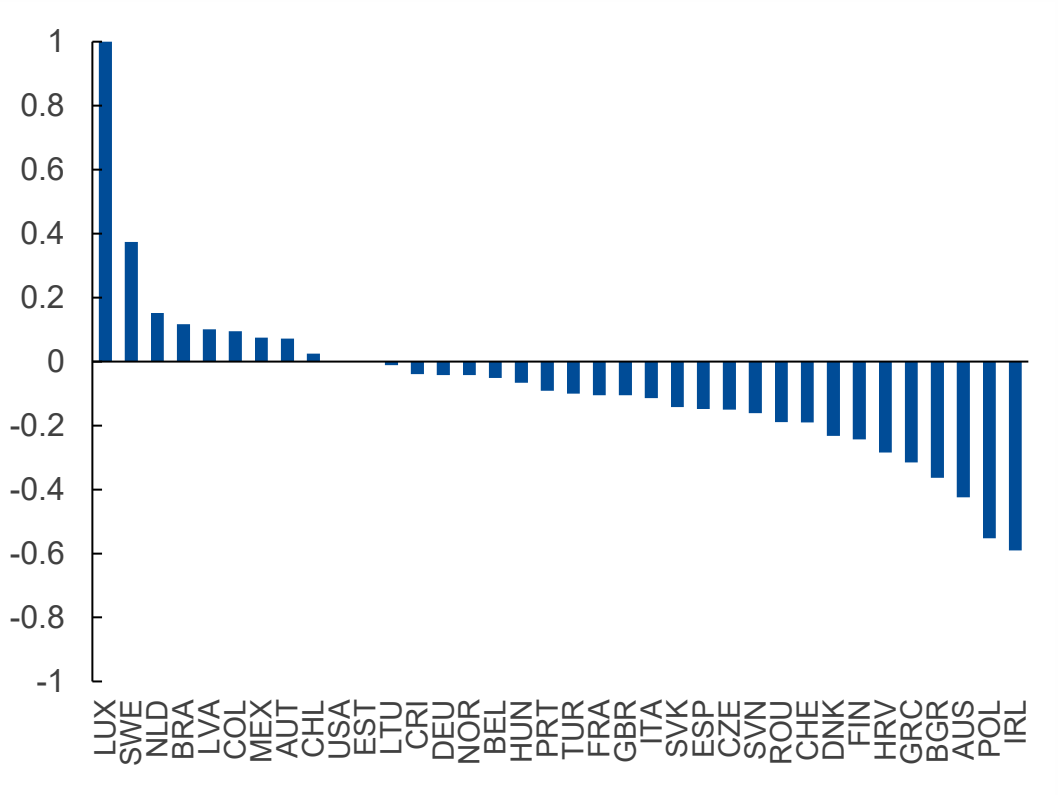
2. Supply: Share of Graduates with New Skills
(Percent of population age 20-24)



Sources: Lightcast; International Labour Organization; Organisation for Economic Co-operation and Development; and IMF staff calculations.

A new Skill Imbalance Index captures the relative weight of new skill demand versus supply relative to the United States, suggesting policy priorities

1. Skill Imbalance Index (projected demand minus domestic supply of new skills, relative to US today)
(Index: -1 to 1)



Sources: Lightcast; International Labour Organization; Organisation for Economic Co-operation and Development; and IMF staff calculations.

	Low supply of new skills	High supply of new skills
High demand	**DEMAND > SUPPLY** **Close the skills gap** • Expand lifelong training opportunities • Integrate IT skills into all fields of study • Strengthen STEM education	**BOTH HIGH** **Sustain the balance** • Keep skill supply and firm demand moving with the frontier
Low demand	**BOTH LOW** **Work on both margins** • Pair skill-building with measures that spur firm demand	**SUPPLY > DEMAND** **Boost demand for new skills** • Innovation incentives for firms • Easier business creation • Better access to finance

Conclusions and policy implications

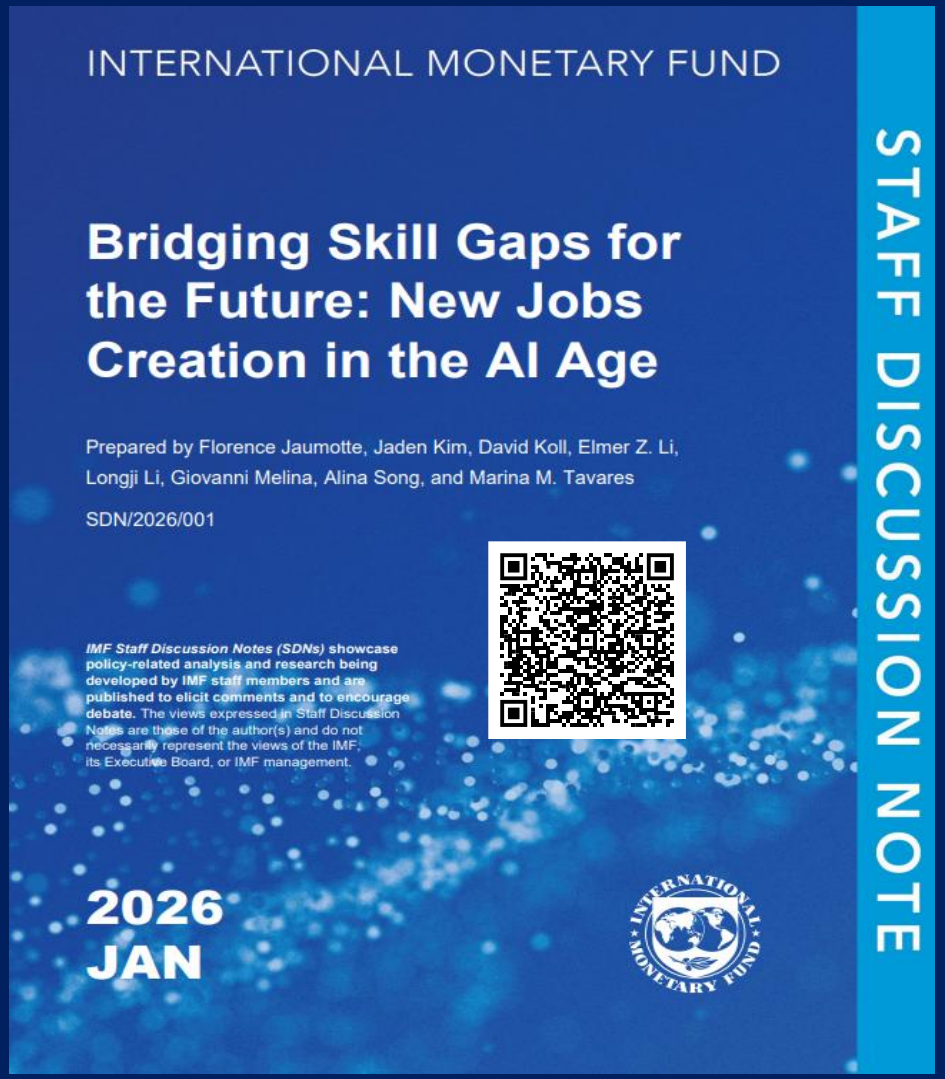
1. **New skills are becoming a meaningful part of labor demand.** In AEs, about **1 in 10 job postings** requires at least one new skill; the share is lower in emerging markets.

2. **New skills diffuse from frontier economies and are associated with better labor market outcomes.** They spread mainly from AEs, especially the U.S., and are linked to **higher posted wages**; in U.S. local labor markets they are also associated with **higher wages and employment**.

3. **AI-related skills create both opportunity and risk.** While they raise returns for some workers, they are also associated with **lower employment in high-exposure, low-complementarity (HELC) occupations**.

4. **Policy priorities depend on whether supply is keeping up with demand.** Countries facing skill shortages need stronger training, STEM, and broader IT integration; where supply is stronger than demand, priorities shift toward innovation, business dynamism, and finance.

5. **For policymakers, the key challenge is to accelerate skill adaptation while limiting the distributional costs of AI adoption.**


INTERNATIONAL MONETARY FUND
Bridging Skill Gaps for the Future: New Jobs Creation in the AI Age
Prepared by Florence Jaumotte, Jaden Kim, David Koll, Elmer Z. Li, Longji Li, Giovanni Melina, Alina Song, and Marina M. Tavares
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2026
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THANK YOU!

Generative AI and Firm Hiring Demand

Evidence from Advanced and Developing Economies

Faezeh Khosravi

Georgia State University

Labor Markets and Structural Transformation in Times of Change:
AI and Demographic Shifts

Washington, DC, 2026

Joint work with Elaine M. Liu and Alex Bell

Motivation

Generative AI can be used for many kinds of work.

- **Substitution:** Some tasks can be done with less human labor.
- **Expansion:** If broader use of AI makes a firm more productive, it may expand and recruit more.

The balance may depend on how widely firms can use AI in their work.

How is recruiting demand evolving in the age of generative AI?

1. Which occupations are more exposed firms recruiting for?
2. How much has their posting volume changed?
3. Is workforce education associated with those changes?

We use job postings from firms' websites in 200 economies. We compare changes around ChatGPT's release for firms with different levels of prior AI exposure.

Contribution

- **Cross-country evidence on firms' recruiting**
- **Occupational mix and total posting volume**
- **AI as a general-purpose technology:** Scope for productivity gains to support labor demand

Related literature

Data

- **LinkUp:** Job postings from employers' career websites, accessed through Dewey Data.
- **Coverage:** 115.9 million postings, 43,000 firm–country pairs, 200 economies.
- **Unit of analysis:** Firm–country–quarter, 2021Q2–2026Q1.
- **Timing:** ChatGPT was released in 2022Q4. The post period starts in 2023Q1.

Full summary statistics

Global Coverage and Sample Composition

	Advanced	Developing
Recruiting characteristics		
Postings per firm–country–quarter	167.6	42.7
Quarters with any posting	78.3%	70.3%
Share of high-substitution postings	31.8%	38.0%
Average AI exposure of postings	4.66	4.74
Sample coverage		
Firm–country pairs	31,702	11,298
Distinct firms	16,307	2,052
Economies	40	160
Firms operating in multiple countries	30.0%	93.9%

Posting statistics are measured at the firm–country–quarter level.

Full summary statistics

Measuring Firm Exposure to AI

$$\text{Exposure}_{fc} = \sum_{o} s_{ofc}^{2018\text{–}19} \times \text{C-AIOE}_{o}$$

- s_{ofc}: occupation o's share of firm f's 2018–2019 postings in country c.
- C-AIOE_{o}: occupational AI exposure adjusted for complementarity with workers (Pizzinelli et al., 2023).
- We standardize the firm–country exposure index.

Empirical Specification

$$Y_{fct} = \beta(\text{Exposure}_{fc} \times \text{Post}_t) + \alpha_{fc} + \gamma_{ct} + \delta_{it} + \varepsilon_{fct}$$

- **Volume:** Whether a firm posts any vacancies and its total number of postings.
- **Composition:** Share of postings in occupations with the highest AI substitution exposure (top 25%), and average occupational AI substitution score across postings.
- β compares post-period changes per one standard deviation of baseline exposure.
- Firm–country, country–quarter, and industry–quarter fixed effects. Standard errors clustered by firm and country.

AI Exposure and Firm Recruiting

	Any posting	Total postings	Share high-sub.	Avg. AI exposure
Advanced economies				
Exposure × post	−0.007*	−0.022**	−0.012***	−0.012***
	(0.004)	(0.011)	(0.002)	(0.002)
Pre-period outcome mean	0.853	212.247	0.332	4.676
Observations	634,020	633,954	496,444	496,444
Developing economies				
Exposure × post	−0.009**	−0.242***	−0.011***	−0.011***
	(0.004)	(0.070)	(0.003)	(0.003)
p (Adv = Dev)	0.707	**0.001**	0.705	0.905
Pre-period outcome mean	0.756	48.964	0.384	4.749
Observations	225,580	225,015	158,167	158,167

Standard errors in parentheses, clustered by firm and country. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

(1) Any posting: extensive margin

Full regression table | Posting counts over time

AI Exposure and Firm Recruiting

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(2) Total postings: PPML count outcome

Full regression table Posting counts over time

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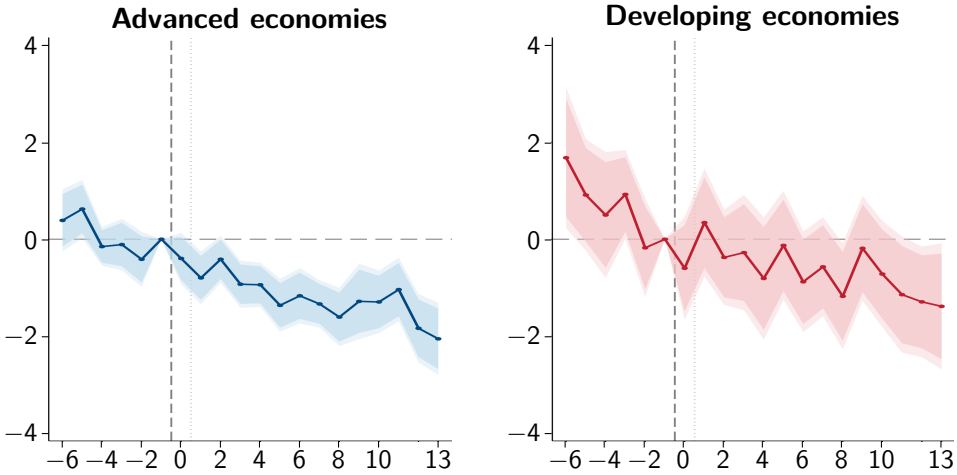
(3)–(4) Composition: high-substitution share and mean AI Substitution exposure

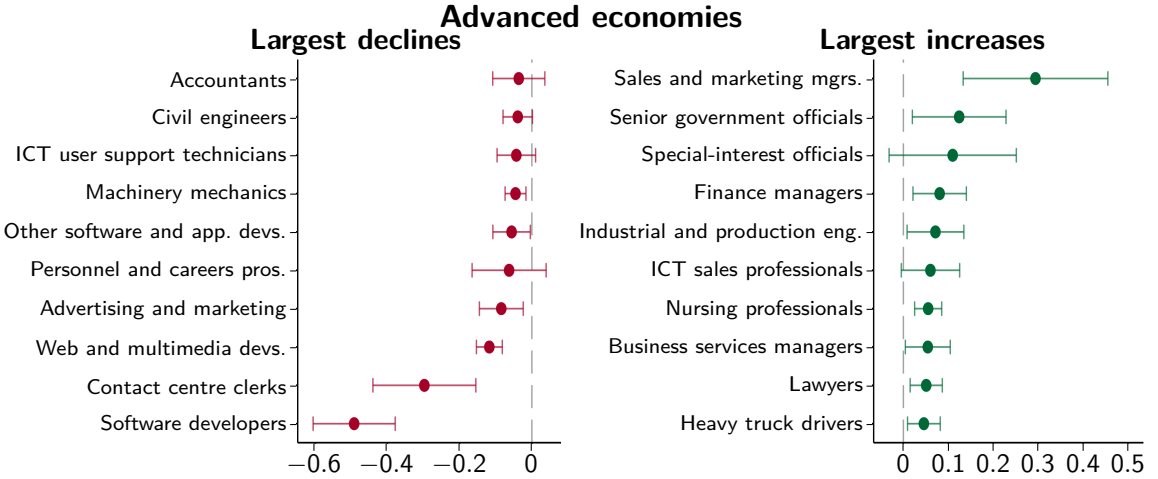
Full regression table Posting counts over time

High-Substitution Posting Share over Time



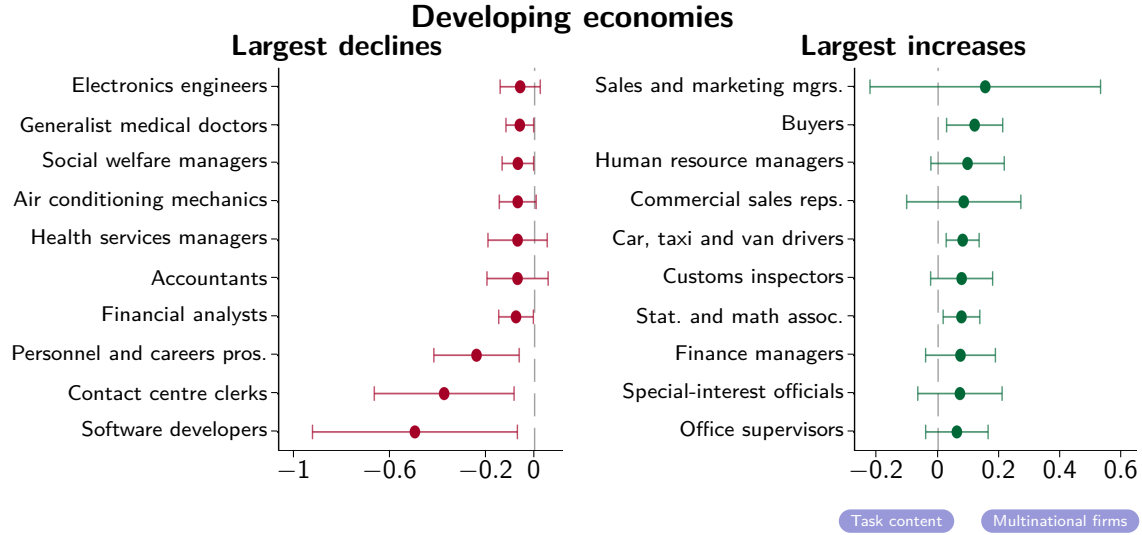
Cross-group difference | Total postings

Changes in Posting Share by Occupation

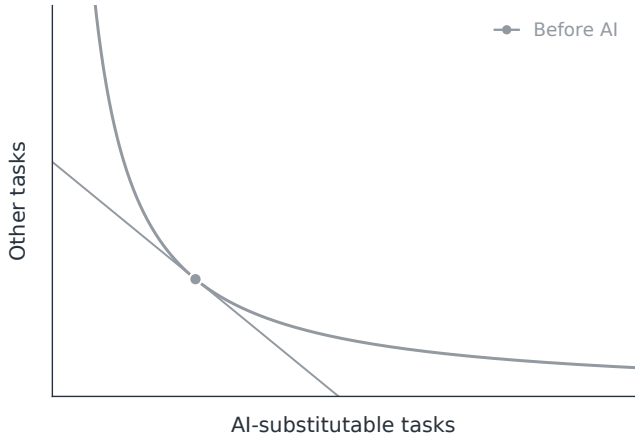


Task content | Multinational firms

Changes in Posting Share by Occupation



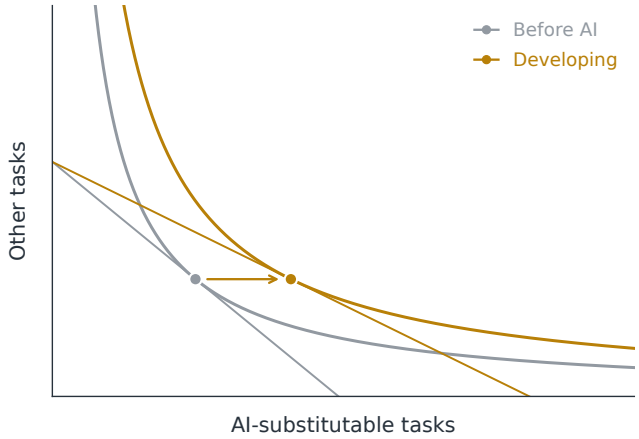
Conceptual Framework: Task Substitution



- Firms combine different tasks at a given level of spending.

Task displacement: Acemoglu and Restrepo (2019).

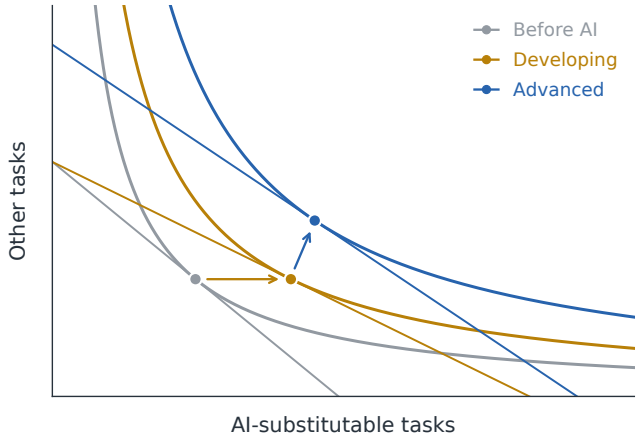
Conceptual Framework: Task Substitution



- Firms combine different tasks at a given level of spending.
- AI lowers the cost of tasks it can perform.

Task displacement: Acemoglu and Restrepo (2019).

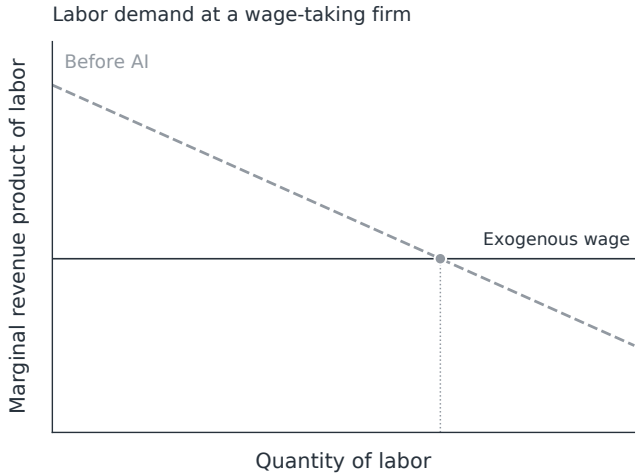
Conceptual Framework: Task Substitution



- Firms combine different tasks at a given level of spending.
- AI lowers the cost of tasks it can perform.
- Adaptation can expand capacity for other tasks too.

Task displacement: Acemoglu and Restrepo (2019).

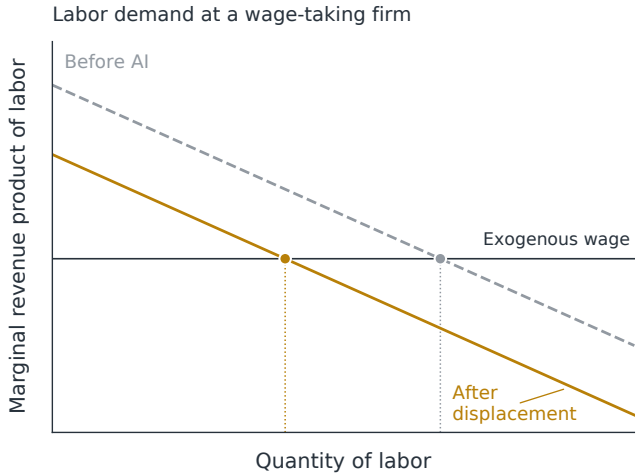
Conceptual Framework: Integration and Scale



- At the going wage, the firm hires to the point where the next worker's revenue equals the wage.

Adaptation: Nelson and Phelps (1966); Bartel and Lichtenberg (1987).
Reorganization: Bresnahan, Brynjolfsson, and Hitt (2002).

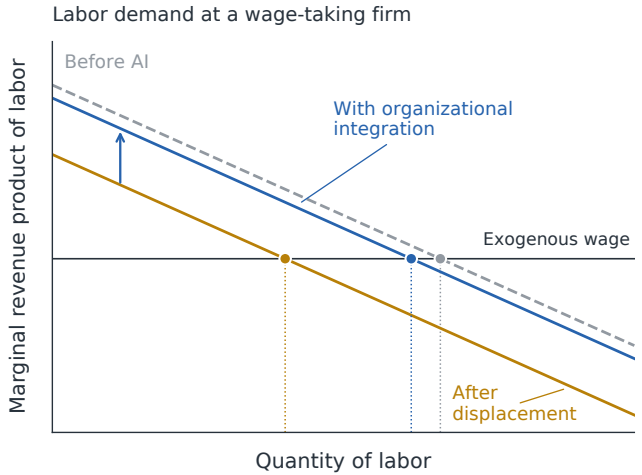
Conceptual Framework: Integration and Scale



- At the going wage, the firm hires to the point where the next worker's revenue equals the wage.
- Substitution can reduce desired labor.

Adaptation: Nelson and Phelps (1966); Bartel and Lichtenberg (1987).
Reorganization: Bresnahan, Brynjolfsson, and Hitt (2002).

Conceptual Framework: Integration and Scale



- At the going wage, the firm hires to the point where the next worker's revenue equals the wage.
- Substitution can reduce desired labor.
- **General-purpose AI:** Broader use can help firms expand. Education may help workers adapt.

Adaptation: Nelson and Phelps (1966); Bartel and Lichtenberg (1987).
Reorganization: Bresnahan, Brynjolfsson, and Hitt (2002).

Workforce Education and Posting Volume

Posting counts (PPML)	No schooling interaction	With schooling interaction
AI-exposure gradient: Developing minus advanced	-0.220^{***} (0.068)	-0.573^{***} (0.162)
× Schooling (standardized)	—	$+0.472^{***}$ (0.147)

Schooling is mean years of education among adults aged 25 and older in each country in 2019.

The developing-minus-advanced difference in posting-count responses to baseline AI exposure is less negative where average schooling is higher.

Full table

Conclusion

- More exposed firms shifted their posting mix away from occupations where AI could substitute for labor.
- The exposure-related decline in posting counts was smaller in advanced economies.
- The estimated volume gap was less negative where the labor force is more educated.

The smaller posting decline in advanced economies is consistent with greater expansionary gains from AI as a general-purpose technology.

Task Content of Posted Occupations

	Communi-cation	Responsi-bility	Physical conditions	Criticality	Skills	Non-routine
Advanced economies						
Exposure × post	0.017***	0.028***	0.016**	0.033***	0.018***	0.021***
	(0.002)	(0.002)	(0.008)	(0.004)	(0.004)	(0.002)
Pre-period mean	0.479	-0.275	-0.516	-0.010	0.606	0.270
Developing economies						
Exposure × post	0.015**	0.051**	**0.010**	0.033***	**0.008**	0.025***
	(0.008)	(0.022)	(0.010)	(0.011)	(0.009)	(0.008)
Pre-period mean	0.595	-0.371	-0.690	-0.033	0.794	0.339
p (equality)	0.897	0.306	0.654	0.981	0.319	0.636

No clear change in physical conditions or skills in developing economies.

◂ Back to occupations

Continue to framework

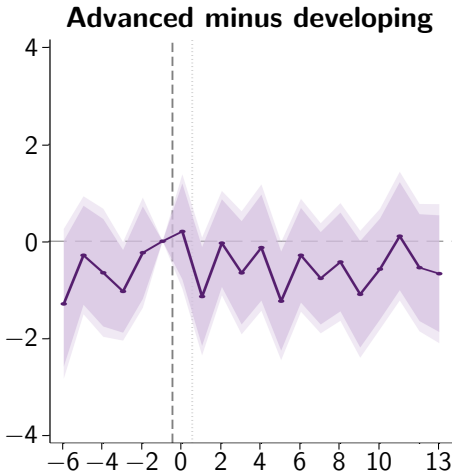
Multinational Firms

- Restrict to 4,958 firms posting in more than one country in 2018–2019

	Volume		*Composition*	
	(1) Any posting	(2) Total postings	(3) High-sub. share	(4) Avg. AI mix
Exposure × post	-0.005	-0.059***	-0.010***	-0.009***
	(0.004)	(0.016)	(0.002)	(0.002)
Exposure × post × developing	-0.004	-0.133***	-0.001	-0.002
	(0.005)	(0.051)	(0.003)	(0.003)
Firm-country FE	Yes	Yes	Yes	Yes
Country-quarter FE	Yes	Yes	Yes	Yes
Development group-NAICS-quarter FE	Yes	Yes	Yes	Yes
Multinational firms	4,958	4,958	4,958	4,958
Firm-country pairs	31,457	31,457	31,457	31,457
p (Developing total effect)	0.037	0.000	0.000	0.000
Pre-period outcome mean	0.797	135.228	0.364	4.738
Observations	628,700	628,039	460,274	460,274

Back

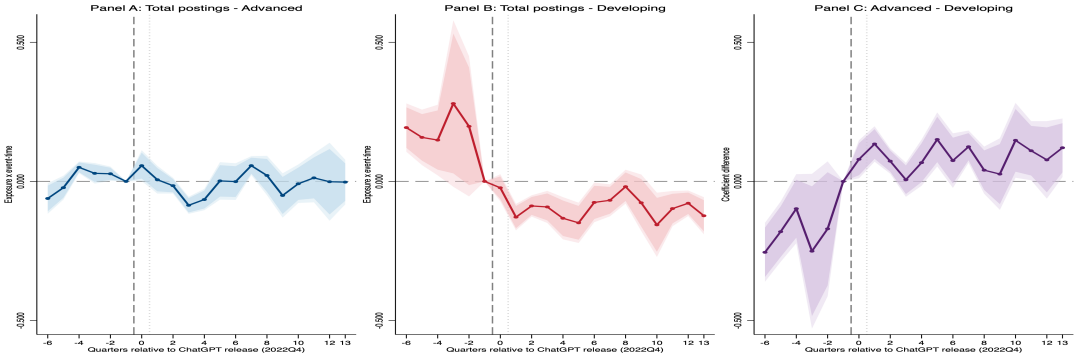
Event Study: Difference in Posting Mix



Quarter relative to ChatGPT's release (2022Q4). Reference: 2022Q3.

Back to event study

Event Study: Total Postings (PPML)

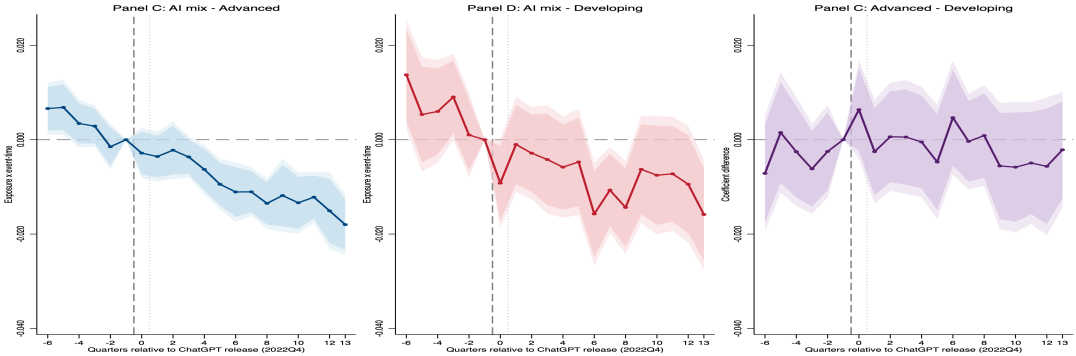


Reference: 2022Q3. The cross-group gap moves before the release.

Back to event study

Average substitution score

Event Study: Average Substitution Score



Posting-weighted occupation score. Reference: 2022Q3.

Back to event study

Full Summary Statistics

	Advanced	Developing
Job postings (quarterly)	167.631	42.650
	(1527.965)	(502.937)
Any posting	0.783	0.703
	(0.412)	(0.457)
Share of high-substitution postings	0.318	0.380
	(0.282)	(0.320)
Average AI exposure of postings	4.660	4.744
	(0.289)	(0.291)
Share of high-skill postings	0.758	0.864
	(0.283)	(0.231)
AI exposure (2018–2019, raw)	4.679	4.729
	(0.260)	(0.265)
AI exposure (standardized)	-0.032	0.139
	(0.884)	(0.900)
Firm-country pair belongs to a multi-country firm	0.640	0.989
	(0.480)	(0.105)
Sample composition		
Total postings	106,284,643	9,637,257
Firm-country pairs	31,702	11,298
Firms	16,307	2,052
Countries	40	160
Multi-country firms	4,890	1,926
Single-country firms	11,417	126
Share multi-country firms (%)	30.0	93.9
Share single-country firms (%)	70.0	6.1
Firm-country-quarter observations	634,040	225,960

◂ Back to sample composition

Baseline Estimates: Full Table

Advanced economies

	(1) Any posting	(2) Total postings	(3) Share high-sub.	(4) Avg. AI exposure
Exposure × post	-0.007*	-0.022**	-0.012***	-0.012***
	(0.004)	(0.011)	(0.002)	(0.002)
Firm-country FE	Yes	Yes	Yes	Yes
Country-quarter FE	Yes	Yes	Yes	Yes
NAICS-quarter FE	Yes	Yes	Yes	Yes
Pre-period outcome mean	0.853	212.247	0.332	4.676
Observations	634,020	633,954	496,444	496,444

Developing economies

	(1) Any posting	(2) Total postings	(3) Share high-sub.	(4) Avg. AI exposure
Exposure × post	-0.009**	-0.242***	-0.011***	-0.011***
	(0.004)	(0.070)	(0.003)	(0.003)
Firm-country FE	Yes	Yes	Yes	Yes
Country-quarter FE	Yes	Yes	Yes	Yes
NAICS-quarter FE	Yes	Yes	Yes	Yes
p (Adv = Dev)	0.707	0.001	0.705	0.905
Pre-period outcome mean	0.756	48.964	0.384	4.749
Observations	225,580	225,015	158,167	158,167

◂ Back to baseline results

Schooling Interactions: Full Table

	Any posting		Total postings		High-sub. share		Avg. AI exposure	
	No mod.	With mod.	No mod.	With mod.	No mod.	With mod.	No mod.	With mod.
Developing − Advanced differential	-0.002	-0.012	-0.220***	-0.573***	0.002	0.008	0.001	0.004
	(0.005)	(0.011)	(0.068)	(0.162)	(0.003)	(0.007)	(0.003)	(0.007)
× Education (std.)		0.015*		0.472***		-0.003		-0.002
		(0.009)		(0.147)		(0.006)		(0.006)
Pre-period outcome mean	0.828	0.828	170.654	170.654	0.344	0.344	4.693	4.693
Observations	852,940	852,940	852,428	852,428	650,247	650,247	650,247	650,247

Schooling is standardized country mean years of education, adults 25+, in 2019.

◂ Back to schooling

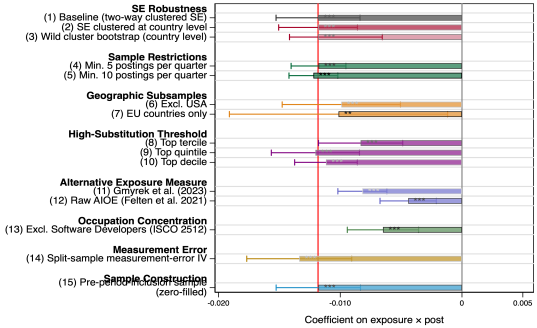
Persistence of the Composition Changes

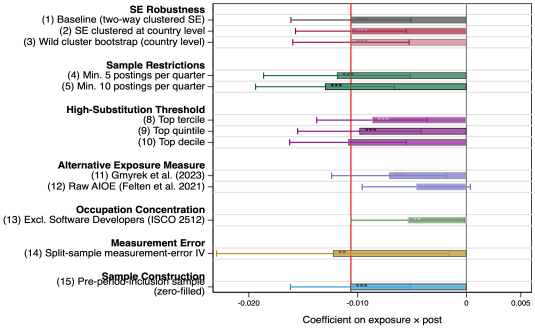
	(1) Advanced Economies	(2) Advanced Economies	(3) Developing Economies	(4) Developing Economies
	High-sub. share	AI mix	High-sub. share	AI mix
Exposure × post (2023)	-0.008***	-0.006***	-0.007**	-0.007**
	(-5.70)	(-3.20)	(-2.19)	(-2.30)
Exposure × post (2024)	-0.014***	-0.013***	-0.011***	-0.015***
	(-7.90)	(-6.74)	(-3.54)	(-5.55)
Exposure × post (2025+)	-0.015***	-0.016***	-0.014***	-0.013***
	(-5.41)	(-6.14)	(-4.47)	(-3.92)
Firm-country FE	Yes	Yes	Yes	Yes
Country-quarter FE	Yes	Yes	Yes	Yes
NAICS-quarter FE	Yes	Yes	Yes	Yes
Pre-period outcome mean	0.332	4.676	0.384	4.749
Observations	496,444	496,444	158,167	158,167

◂ Back to event study

Robustness

Robustness of the High-Substitution Share





◂ Back to persistence

Related Literature

- **AI and labor demand:** Acemoglu, Autor et al. (2022); Babina et al. (2025); Y. Liu, Wang and Yu (2025); Klein Teeselink (2025); Brynjolfsson, Chandar and Chen (2025).
- **Occupational exposure:** Felten, Raj and Seamans (2021); Pizzinelli et al. (2023); Eloundou et al. (2024); Gmyrek, Berg and Bescond (2023).
- **Technology, education, and organization:** Nelson and Phelps (1966); Bartel and Lichtenberg (1987); Bresnahan, Brynjolfsson and Hitt (2002); Acemoglu and Restrepo (2019).

Back to contribution

Aging Population and Technology Adoption

accepted at Review of Economic Studies

Daniele Angelini

University of Vienna

Labor markets and structural transformation in times of change: AI and demographic shifts (IMF - OECD - PIIE - World Bank)

17 November, 2026

Aging ⇒ input supply ⇒ technology

Population aging leads to:

a) increase in relative **labor scarcity**;

- shrinking working-age population
- lower interest rates

⇒ **higher** adoption of new tech. (labor-saving/capital-intensive)

b) change in the **age/skill composition** of workers;

⇒ **lower** adoption of new tech. (skill-intensive)

c) increase in **retirement** age

- effects on labor and capital supply, and age composition

⇒ **lower** adoption of new tech.

Research questions

1. How does aging affect the adoption of new technology?
2. Through which channels does aging affect technology?
3. What are the macroeconomic implications of aging in Europe?
4. What policies can be implemented?

In this paper

1. **Theoretical framework**
   - Task-based production: new(labor-saving, skill-intensive)/vintage tech.
   - R&D: new-technology blueprints
   - OLG: endogenous skill acquisition and saving decisions
   - Government: labor tax, pension benefits, retirement age

2. **Empirical evidence**
   a. hump-shaped ($\cap$) relation btw age and ICT, intangible, robot
   b. Employment analysis: young, college-educated have a CA in new tech
   c. Wage analysis: 1) aging increases age premium for college graduates
      2) skill-updating increases wages through IT tasks and innovation

3. **Policy analysis** (Europe, 1990-2040)
   - tax & pension benefits cuts $>>$ increase retirement age

Model

Production

CD task aggregator

$$Y_t = exp\left\{\int_0^1 \ln y_t(i)\ di\right\}$$

$$y_t(i) = \underbrace{A_t \cdot \mu_n(i) \cdot \ell_{n,t}(i)^{\alpha} k_{n,t}(i)^{1-\alpha}}_{y_{n,t}(i)} + \underbrace{\mu_v(i) \cdot \ell_{v,t}(i)^{\beta} k_{v,t}(i)^{1-\beta}}_{y_{v,t}(i)}$$

- $\frac{d\frac{\mu_n(i)}{\mu_v(i)}}{di} < 0 \quad \Rightarrow \quad y_t(i) = \begin{cases} y_{n,t}(i) & \text{if } i \in [0, I_t) \\ y_{v,t}(i) & \text{if } i \in [I_t, 1] \end{cases}$
- R&D: $A_t = A_{t-1} + \underbrace{\bar{\delta}_t\ (\ \eta,\quad \lambda\ )}_{\text{spillover, congestion}} \cdot\ \ell_{R\&D,t}$

Assumptions

1. New-tech. is labor-saving ($\alpha < \beta$)
2. New tech. tasks and the R&D sector employ skilled workers

Since I_t(Inputs(Demography)): **aging** $\Rightarrow$ **inputs** $\Rightarrow$ **technology**

Demographics and input supply

2-period OLG

1. **young**: acquire skills, work (1 unit of time), consume, and save
2. **old**: acquire skills, work $\phi_t \in [0, 1]$ (set by the **government** to balance the BC), and consume their wage, savings, and pensions

Endogenous capital accumulation

$$\text{demographics} \Rightarrow \text{aggregate savings} \Rightarrow \text{capital stock}$$

Endogenous skill acquisition

- agents are **heterogeneous in ability** to acquire skills, $a \sim F$
- skill **depreciation**: tech. evolves (R&D), old need to re-train
- skill **persistence**: skill acquisition cost depends on previous skills

Since young and old have different 1) working horizon 2) savings 3) costs:

$$\textbf{demographics} \Rightarrow \textbf{supply of skilled/unskilled workers}$$

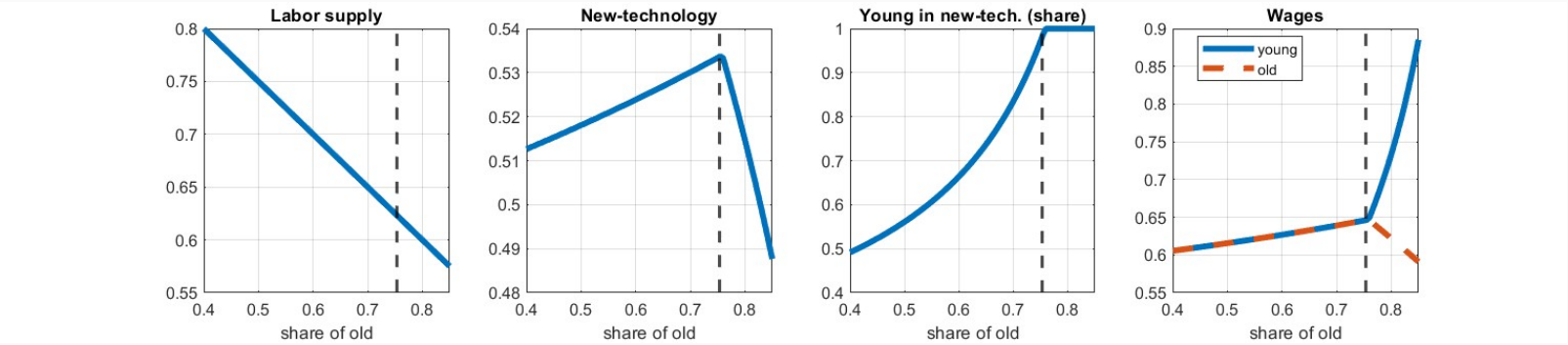
Model analysis

Mechanism

Simplifying assumptions:

1. Exogenous capital supply (no OLG)
2. Exogenous retirement age (no government)
3. Exogenous new-technology TFP (no R&D)
4. Exogenous skills: young can use either tech., old only vintage-tech.

$$Y = \begin{cases} \tilde{B}(I) \cdot \left(\frac{N^y + \bar{\phi} N^o}{\alpha I + \beta(1-I)}\right)^{\alpha I + \beta(1-I)} \cdot \left(\frac{\bar{K}}{1-\alpha I - \beta(1-I)}\right)^{1-\alpha I - \beta(1-I)} & \text{if } N^o < \hat{N}^o \\ \tilde{B}(I) \cdot \left(\frac{N^y}{\alpha I}\right)^{\alpha I} \cdot \left(\frac{\bar{\phi} N^o}{\beta(1-I)}\right)^{\beta(1-I)} \cdot \left(\frac{\bar{K}}{1-\alpha I - \beta(1-I)}\right)^{1-\alpha I - \beta(1-I)} & \text{if } N^o > \hat{N}^o, \end{cases}$$



Prop: if $N^o < \hat{N}^o$, $\frac{dI}{dN^o} > 0$, Labor Scarcity; if $N^o > \hat{N}^o$, $\frac{dI}{dN^o} < 0$, Age Comp.

Empirics

Data

a. Hump-shaped hypothesis
   - EU KLEMS Capital (ICT, 1995-2021), INTANProd (Intangibles, 1995-2021), IFR (Robots, 1993-2023)
   - UN-WPP (Age, Fertility)
   - European countries, Japan, and the United States

b. Employment analysis
   - EU KLEMS Labour (2008-2021, European countries, Japan)
   - BIBB/BAuA Employment Survey (Germany, 2006, 2012, 2018)

c. Wage analysis
   - same data used for the Employment analysis

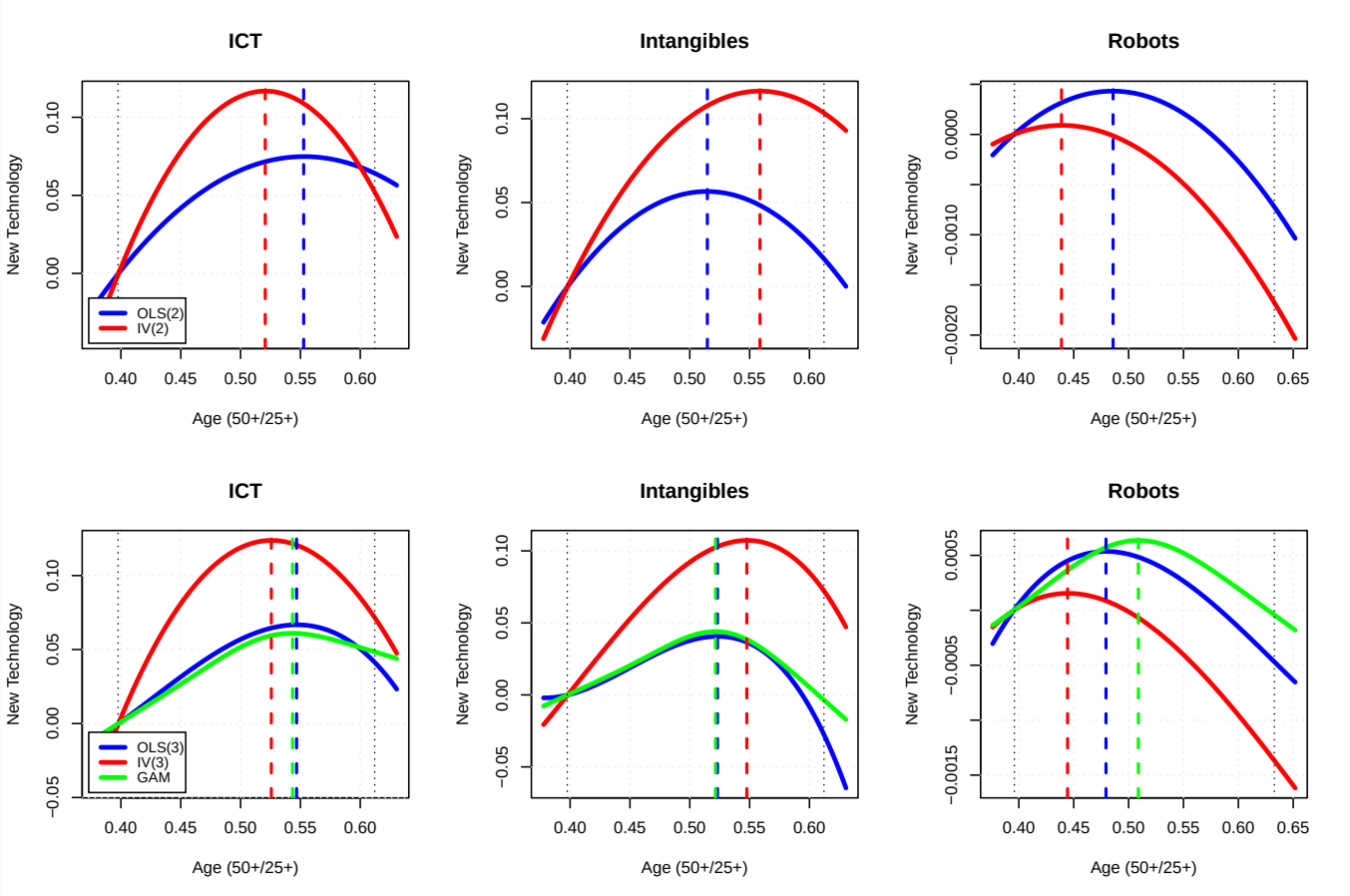
Is the relationship between age and new tech. hump-shaped?

$$NewTech_{c,t} = \beta_0 + \beta_1 Age_{c,t} + \beta_2 Age^2_{c,t} + \Gamma X_{c,t} + \gamma_c + \gamma_t + \varepsilon_{c,t}$$

Panel B	$ICT_{c,t}$		$Intangibles_{c,t}$		$Robots_{c,t}$	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
$Age_{c,t}$	3.469*	8.092***	4.289***	5.012**	0.052**	0.042***
	(1.937)	(3.107)	(1.236)	(2.360)	(0.024)	(0.006)
$Age^2_{c,t}$	−3.143	−7.773**	−4.154***	−4.466*	−0.054**	−0.048***
	(1.945)	(3.296)	(1.205)	(2.279)	(0.024)	(0.007)
Controls (c, t)	✓	✓	✓	✓	✓	✓
Fixed effects (c, t)	✓	✓	✓	✓	✓	✓
Craggâ€“Donald	-	34.42	-	34.41	-	171.05
Peak	0.552	0.521	0.516	0.561	0.485	0.439
Observations	557	557	530	530	540	540
R^2	0.811	0.790	0.928	0.926	0.677	0.669

Heteroskedasticity- and autocorrelation-robust standard errors

Hump-shape and robustness



- the hump remains when using 3rd degree poly and GAM
- the hump is robust to an **industry-level** analysis

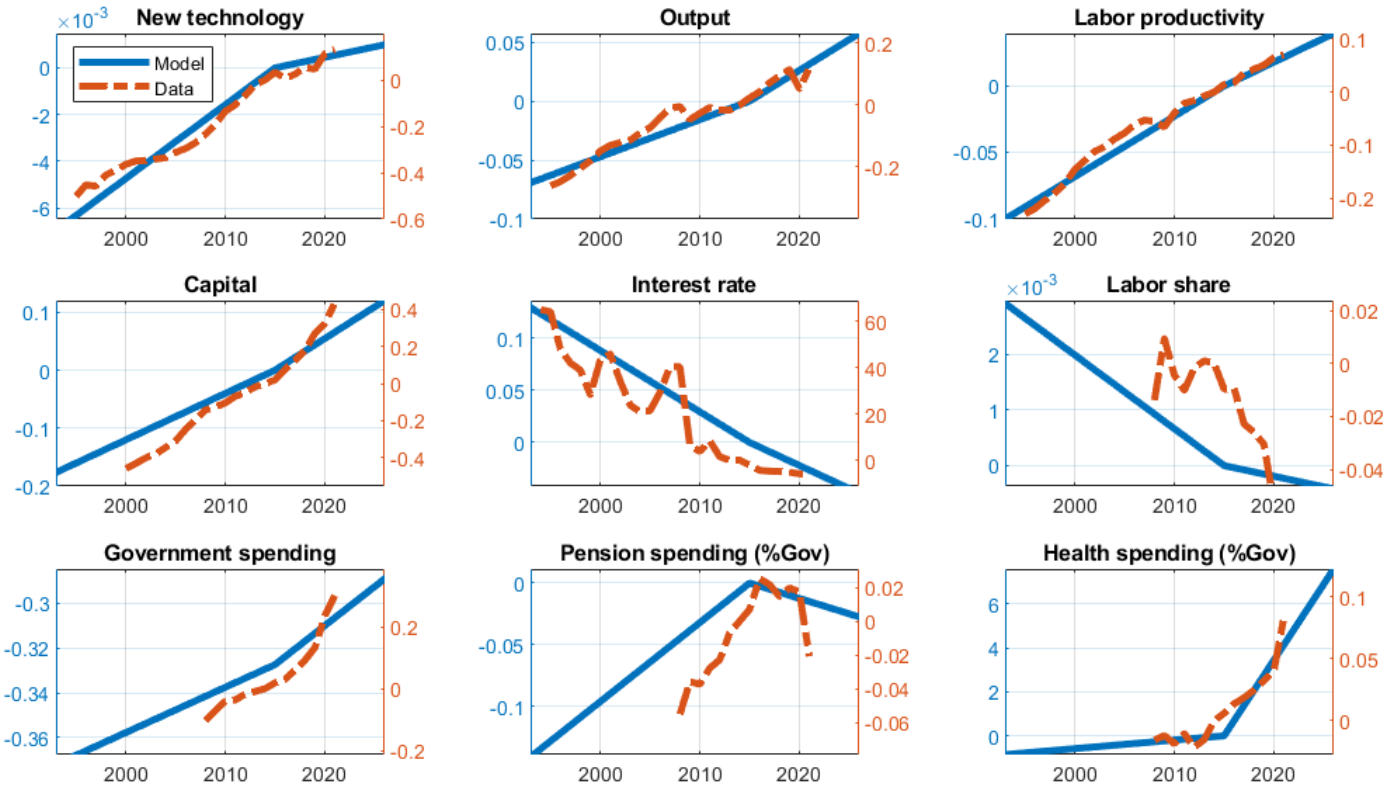
Empirics - Summary

The empirics support the theoretical model along 3 dimensions:

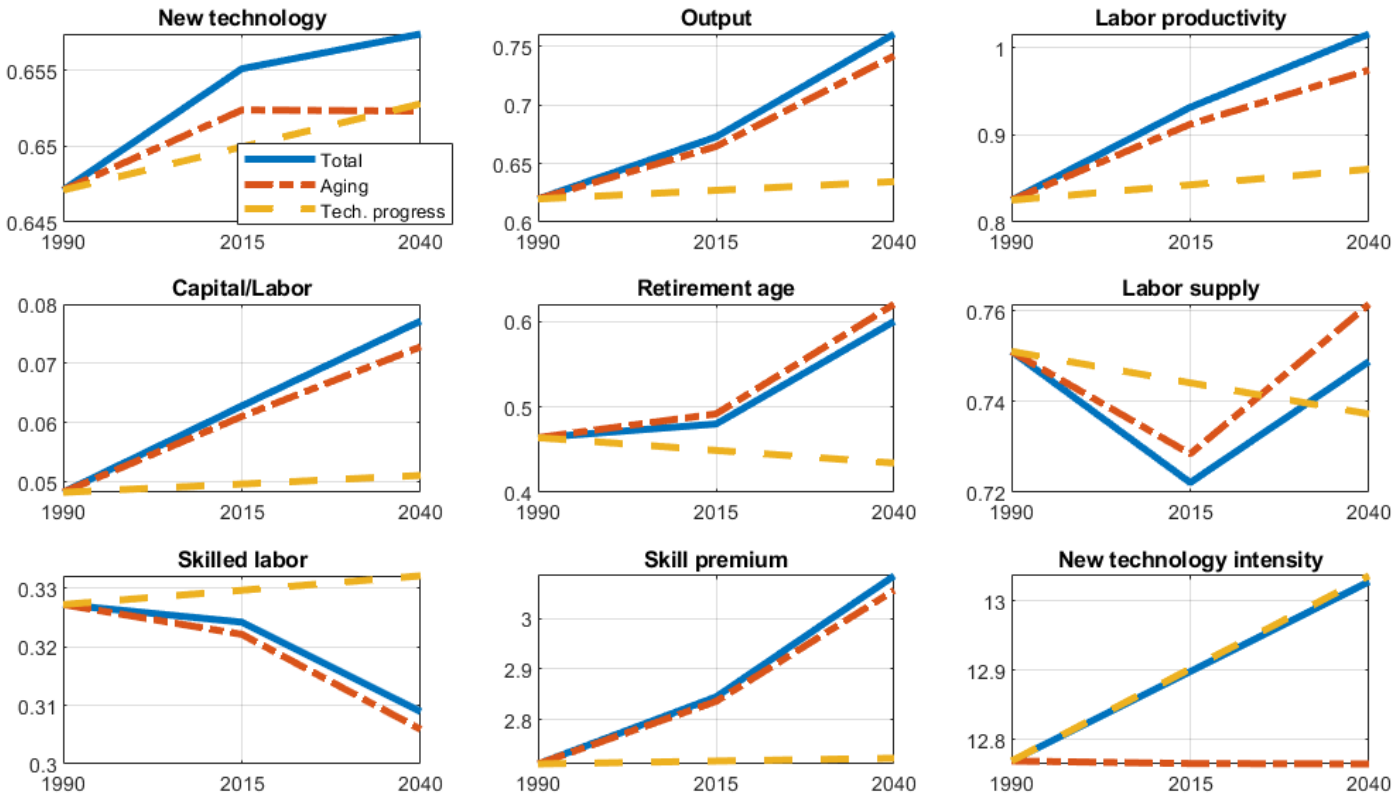
1. existence of a **hump-shaped** relationship between age and new technology
2. **skill- and young-technology complementarity**
   - new tech-intensive industries employ young, college-educated
   - within industries, the likelihood of engaging in IT tasks or participating in innovation declines with age
3. **depreciation of skills** complementary to evolving technology
   - aging increases wage premium only among college-educated
   - skill updating restores complementarity with new technology

Quantitative and Policy analysis

Calibration (EU27, 2015) and validation



Model predictions



- aging slows down new tech. and labor productivity
- aging explains the increase in the skill premium

Policy analysis - Increasing the retirement age

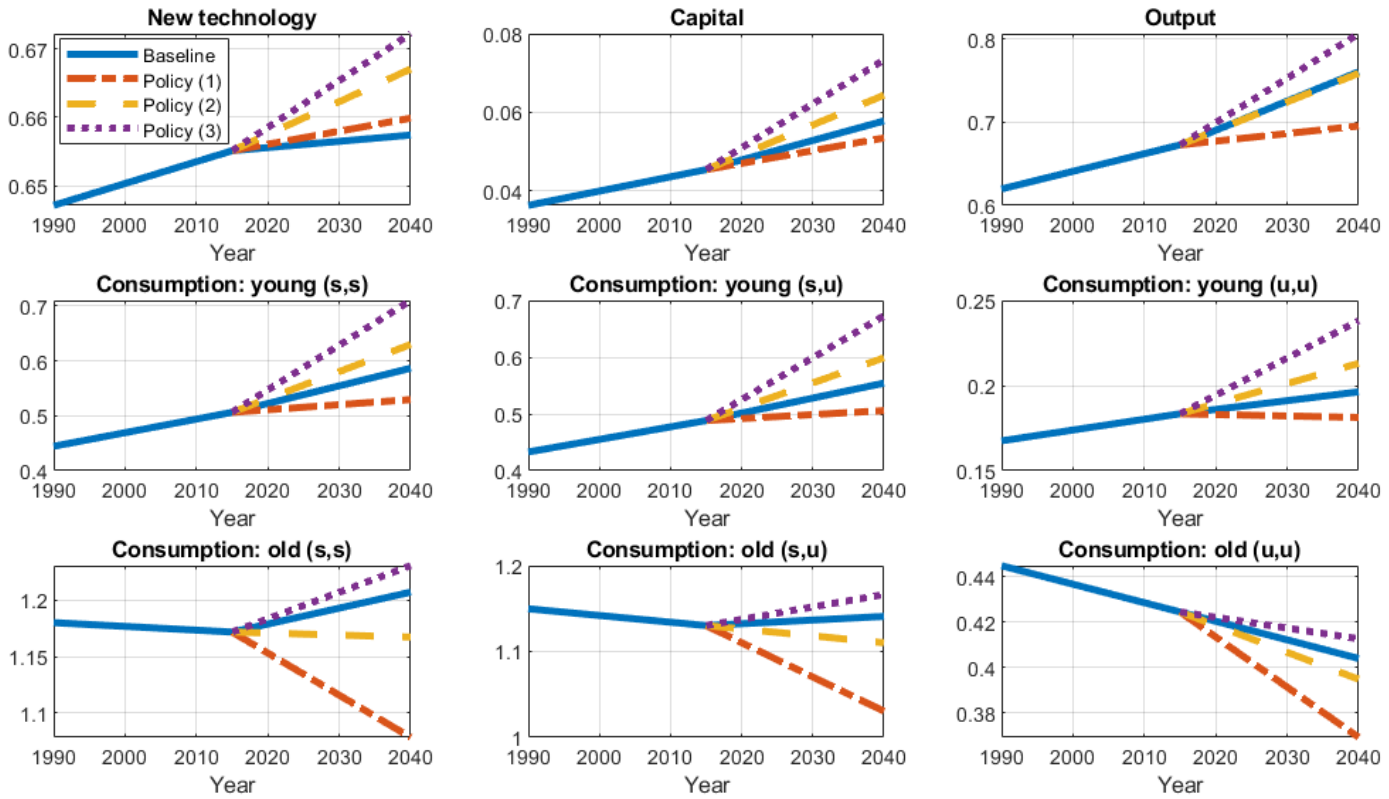
- Aging reduces labor supply & adds pressure to the gov. budget
- OECD countries have increased the retirement age
  $\Rightarrow$ lower capital accumulation and less new technology adoption
- Increasing the retirement age is not the only available policy (to maintain a balanced gov. budget):
  - increasing the labor tax
  - reducing pension benefits
- Can we find a *feasible* (i.e., Pareto improving) policy?

Policy analysis - Fixed retirement age & Balanced gov. budget

P1) increase in the labor tax (reduces savings)

P2) reduction in pension benefits (increases savings, unfeasible)

P3) reduction in the labor tax & in the pension replacement rate (increases savings, feasible)



Conclusion

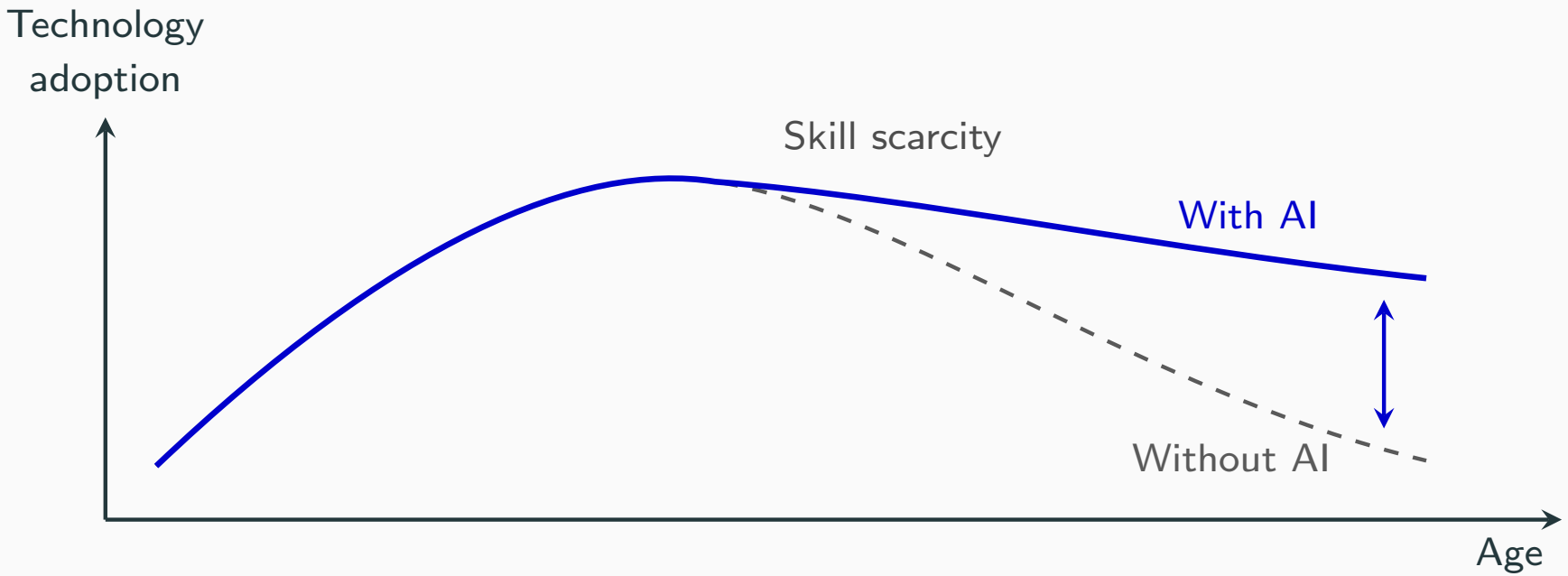
In this paper:

- **theoretical** analysis of the effect of population aging on tech.
- **empirical** hump-shaped relation between age and tech.
- **macroeconomic implications** of aging in Europe:
  a) slowing down in new tech. and labor productivity
  b) increase in wage inequality
- **retirement age** mitigation can lead to Pareto improvements

What about AI?

"AI embeds skills that would otherwise need to be acquired by workers"

- AI reduces the cost of complementarity to labor-saving tech.
- Skill scarcity redirects R&D toward ability-enhancing AI



"From Robots to AI? Aging-driven Directed Technological Change"

Thanks

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Appendix

(skip) Employment - Industry-level between-within analysis

	Between		*Within*	
	ICT	*Intangibles*	*ICT*	*Intangibles*
	(1)	(2)	(3)	(4)
YoungCollege	0.914***	1.30***	-0.045	0.081
	(0.124)	(0.148)	(0.171)	(0.081)
YoungNoCollege	-0.081	0.757***	-0.083	0.034
	(0.114)	(0.169)	(0.163)	(0.074)
OldCollege	-1.08***	0.312	-0.008	-0.112
	(0.185)	(0.236)	(0.195)	(0.147)
Fixed Effects (t)	-	-	✓	✓
FE Interaction (c, i)	-	-	✓	✓
Observations	482	432	6,327	5,880
R^2	0.341	0.269	0.446	0.909

Clustered (by country) standard errors

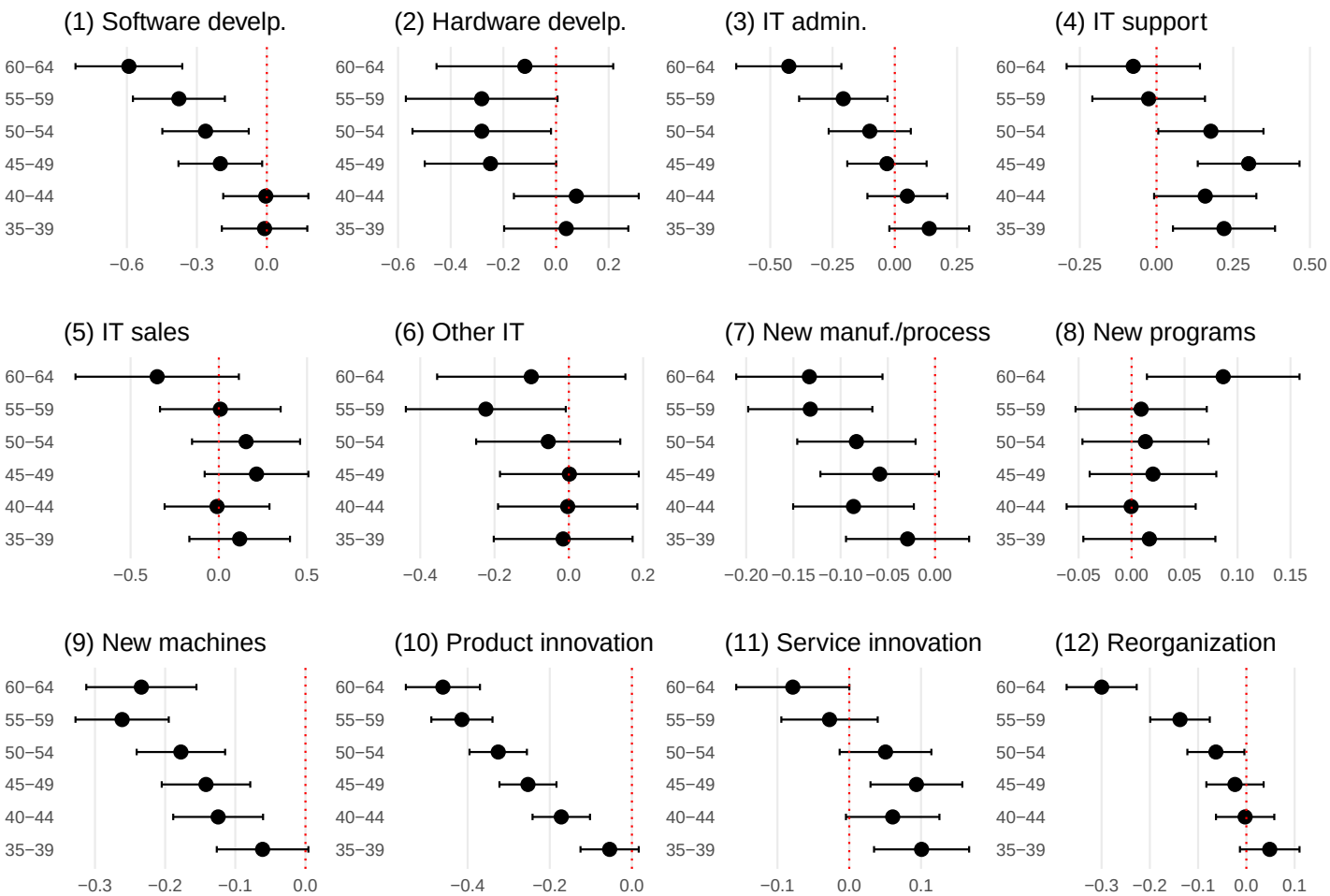
- significant results only when exploiting **between** (c,i) variation

$\Rightarrow$ ICT/Intangibles-intense sectors use more *YoungCollege*

$\Rightarrow$ ICT-intense sectors use less *OldCollege* (suggesting depreciation of college skills)

(skip) Employment - Within-industry Employment analysis

$$\log\left(\frac{P(Z_j=1)}{1-P(Z_j=1)}\right) = \beta_0 + \sum_k \beta_k \cdot Age_k + \gamma_t + \gamma_i + \gamma_e + \varepsilon$$



(skip) Wage - Age premium

	$AgePremium_{c,t}$	
	College	*NoCollege*
	(1)	(2)
$Age_{c,t}$	1.689***	0.292
	(0.604)	(0.615)
Fixed Effects (c, t)	✓	✓
Observations	392	392
R^2	0.948	0.857

Heteroskedasticity- and autocorrelation-robust standard errors

Aging increases relative young wages only among *College*:

$\Rightarrow$ young-technology complementarity (higher wages of young)

$\Rightarrow$ skill depreciation (obsolescence of old college skills)

(skip) Wage - Skill updating

	Wage			
	(1)	(2)	(3)	(4)
Training	0.124***	0.112***	0.104***	0.097***
	(0.015)	(0.015)	(0.016)	(0.015)
IT tasks (1-6)	-	✓	-	✓
Innovation (7-12)	-	-	✓	✓
Controls	✓	✓	✓	✓
Observations	5,585	5,585	5,585	5,585
R^2	0.243	0.257	0.254	0.265

- *Training* (up-to-date skills) increase wages
- the increase is mediated by *IT tasks* (10.5% of total wage increase) and *Innovation* (31.5%)

AI and Labor Markets Session

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IMF, OECD, PIIE and World Bank
Washington, DC 17 November 2026

AI adoption and labor market policy

As firms adopt AI, who will have a harder time finding good work, what will hold back adoption, and where can policy help?

Khosravi and Liu	**Who gets hired?** If firms need fewer entry-level workers, where will new workers get their first job and build experience?
Tavares et al	**What happens to workers in exposed jobs?** When employment in jobs falls, is it because fewer people enter, because workers move into other jobs, or because more workers spend time out of work? What happens to earnings?
Angelini	**What holds back adoption?** If firms lack workers with the skills to deploy new technology, can training existing workers ease that constraint?

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Angelini	**What holds back adoption?** If firms lack workers with the skills to deploy new technology, can training existing workers ease that constraint?

What do we want to know to steer policy?

A decline in employment in an exposed occupation could imply very different policy responses.

Fewer first jobs point toward *apprenticeships* or other routes into the profession.

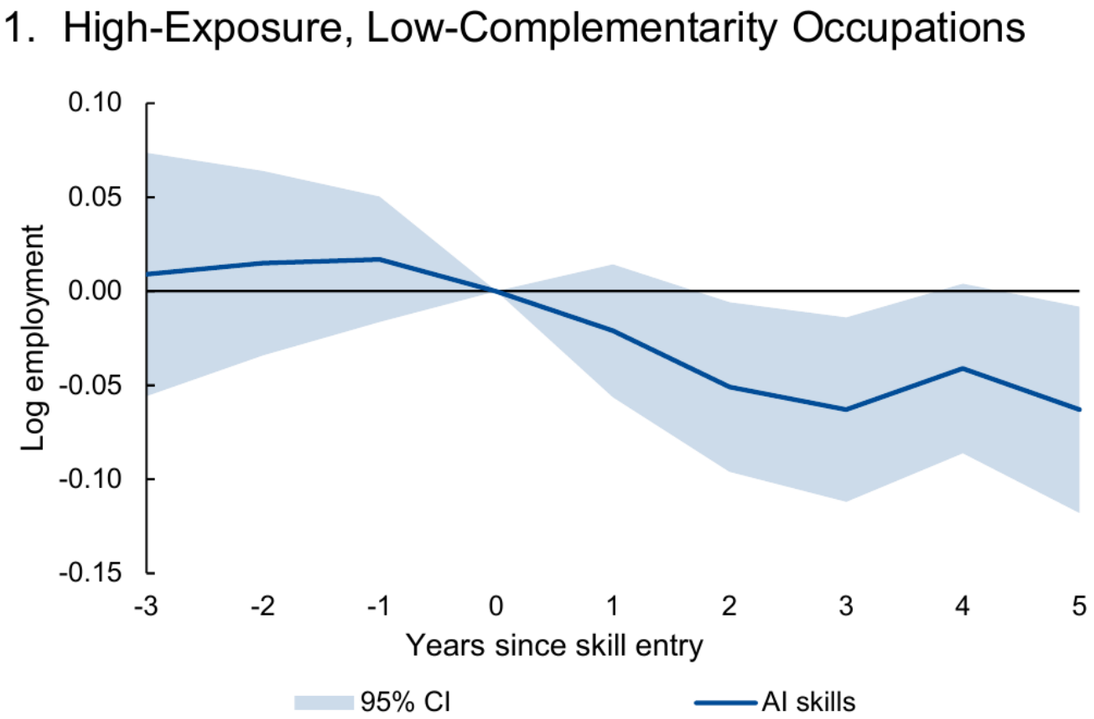
Displacement with lasting earnings losses point toward support for *job transitions*.

A skills bottleneck at adopting firms points toward *training tied to deployment*.

What drives the fall in employment?

- Fewer people enter the occupation
- Incumbents move to other jobs or places
- Incumbents lose work

Which of these explains the decline? What happened to earnings?



Jaumotte et al. (IMF), Figure 9, panel 1

Q1. What should we read into falling employment levels?

Tavares et al. (IMF)

Falling employment in exposed jobs could reflect fewer new entrants, more job switching, or more time out of work.

Can we follow workers over time?

Link records on occupation, employment, and earnings

Track entry, job changes, time out of work, and what workers earn after leaving an exposed job.

How should we support worker transitions?

Paid training (Amazon, Anthropic)

New role (Ikea)

Job search and income support

New job with wage support

2. AI and occupational demand

Khosravi and Liu

More-exposed firms changed their recruiting after ChatGPT launched. Did these firms deploy AI?

Rollout timing

They link deployment dates to job ads and compare entry-level postings in exposed jobs before the delayed rollout.

Did AI reduce advertised openings in some occupations?

Is AI the driver?

Jaumotte et al

When employers start asking for new AI skills in local job ads.

Khosravi and Liu

ChatGPT’s launch and how exposed each firm’s 2019 vacancy mix was to AI substitution.

When did employers (really) start giving tasks to AI?

AI timing is unfortunate …

The hiring pullback

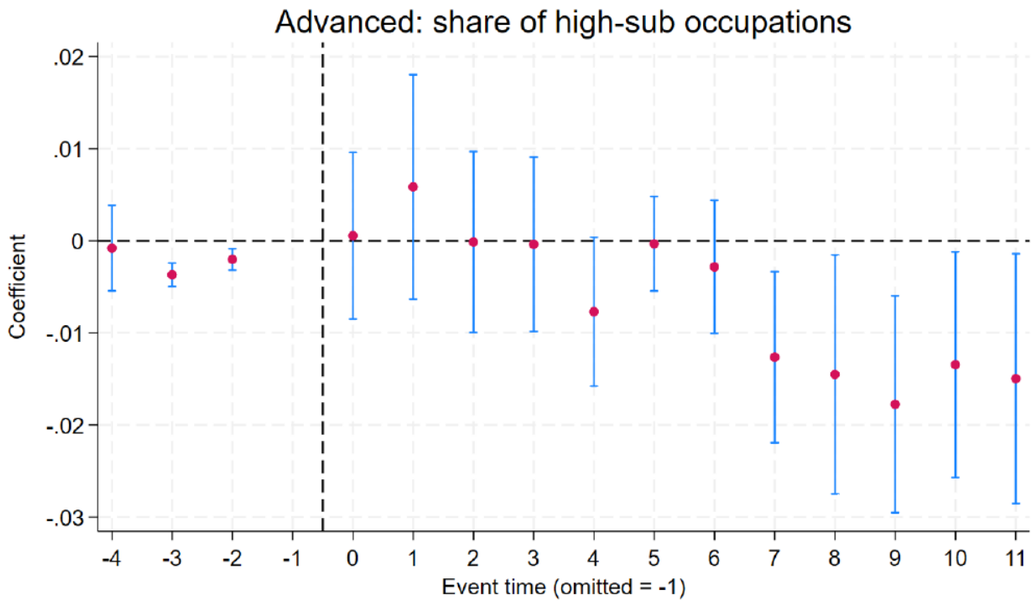
Firms that hired faster during the pandemic may also have pulled back faster.

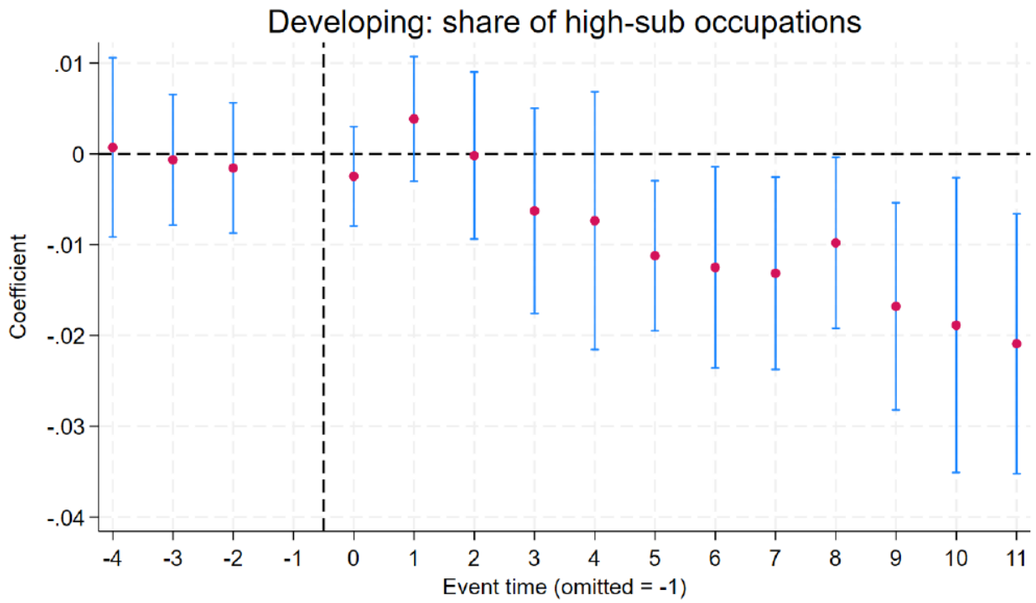
Remote work

Remote work changes where firms advertise and where workers live.

Does the gap persist among firms when accounting for these trends?

Q2. Is this LLM adoption or capabilities?





Khosravi and Liu, Figure 2(a–b). Bars show 95% confidence intervals.

Is this model improvement? Or firms taking time to adapt? And what does this mean for how we interpret these results?

Can we provide new workers with expertise?

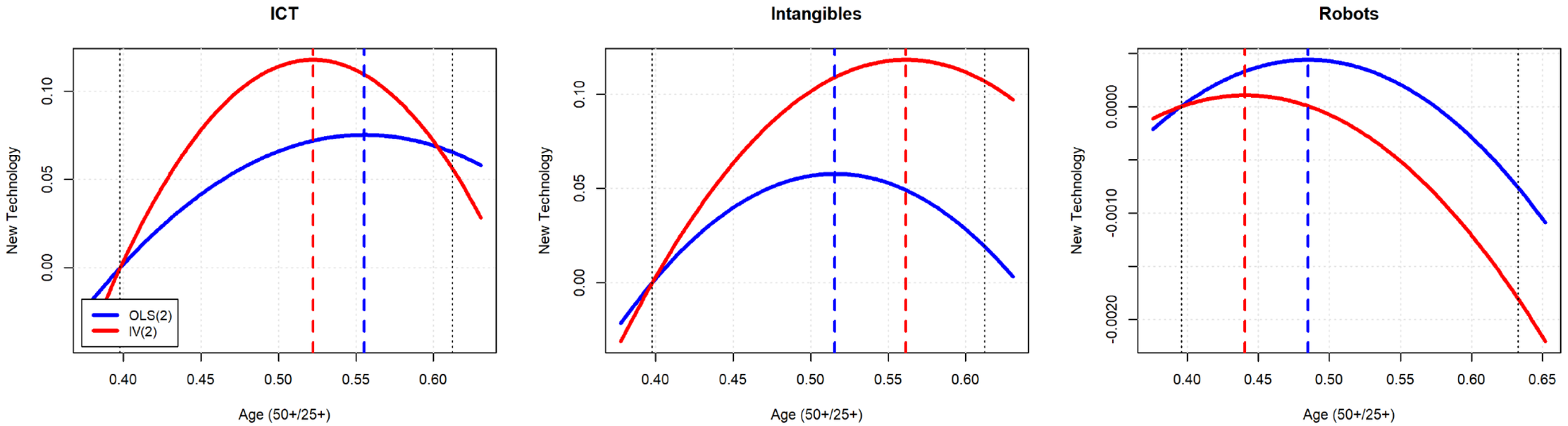
AI takes on occupational tasks

Knowledge work jobs combine output and learning in the same workflow – that's a design choice!

How will new workers gain experience?



3. Skill scarcity and technical deployment



Angelini, Figure 1 (top row). Quadratic fits. Blue is OLS, red is IV.

Labor scarcity makes automation more valuable

Skill scarcity can make it harder to deploy

Skills and technology adoption

Angelini

As populations age, technology investment rises and then falls. A shortage of technical skills is one possible explanation.

Training subsidies

What's the role of training?

Would subsidizing training increase adoption?

Q3. Does skill scarcity drive the downturn?

> Industries with more young college graduates invest more in ICT and intangibles. Estimates within the same country and industry over time are imprecise.

Within country, is the downturn steeper in industries that rely on more complementary skills?

Can we retrain experienced workers?



What if experienced workers can learn the new tools quickly?

How would cheaper retraining change adoption and the effect of raising the retirement age?

A decline in employment in an exposed occupation could imply different policy responses.

Is AI driving fewer first jobs? -> points toward *apprenticeships* or other routes into the profession.

What's happening to workers -> Displacement with lasting earnings losses point toward support for *job transitions*.

Can firms find the workers they need -> A skills bottleneck at adopting firms points toward *training tied to deployment*.

Thanks!

AI adoption

Workers

Skills



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