Labor Market Exposure to AI: Cross-country Differences and Distributional Implications

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Motivation

- AI-driven structural transformation could lead to "winners" and "losers" in the labor market
- But most discussion so far has focused on:
  - **Exposure** to AI → agnostic about substitution or complementarity
  - US and Advanced Economies → implications for Emerging Markets and Developing Economies could differ
- **Questions**:
  - How does exposure differ when accounting for AI's potential for complementarity?
  - How does AI exposure vary across and within countries? Are EMDEs different from AEs?

This paper

1. Expand workhorse AI occupational exposure (AIOE) index with occupation-specific factors affecting the likelihood of AI being a substitute or a complement to workers

2. Analysis of exposure and complementarity to AI using labor force microdata for 6 countries, four of which are EMDEs

This paper

1. Expand workhorse AI occupational exposure (AIOE) index with occupation-specific factors affecting the likelihood of AI being a substitute or a complement to workers
   - High exposure, high complementarity: e.g., Professionals, Managers
   - High exposure, low complementarity: e.g., Clerical support workers
   - **Early** evidence: predictions validated by US job vacancies data
     - **Caveat: Empirical results being updated**

2. Analysis of exposure and complementarity to AI using labor force microdata for 6 countries, four of which are EMDEs

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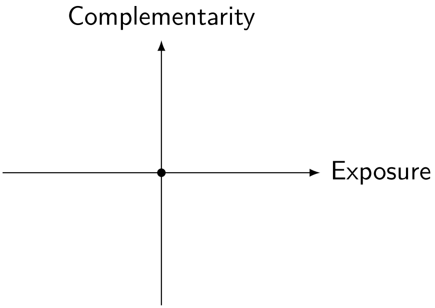
2. Analysis of exposure and complementarity to AI using labor force microdata for 6 countries, four of which are EMDEs
   - Between countries: higher share of HEHC and HELC jobs in AEs
   - Within countries: common patterns across gender, education, and income in both AEs and EMDEs

Conceptual framework: Exposure & Complementarity



- Exposure: overlap between human skills in an occupation and AI applications (Felten et al., 2021)
- Complementarity: technical / societal need for AI application to be supervised by human
- HEHC: positive effect of AI on labor demand more likely
- HELC: negative effect of AI on labor demand more likely

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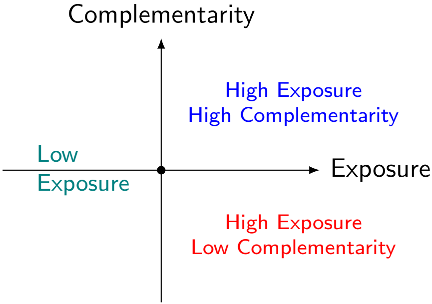

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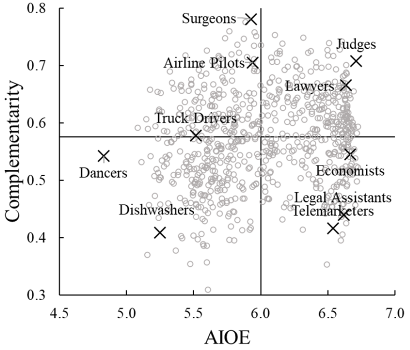
Felten et al. (2021) AIOE methodology

- Based on judgment of crowd-sourced experts, construct a matrix of the overlap A_{kj} between 10 AI applications (e.g., image recognition, text composition), and 52 human skills listed in O*NET (e.g., hand-eye-coordination)
- Using O*NET's "Level" and "Importance" scores of each skill j in occupation i, compute AI Occupational Exposure as follows

$$AIOE_i = \frac{\sum_{j=1}^{52} \sum_{k=1}^{10} A_{kj} \cdot L_{ji} \cdot I_{ji}}{\sum_{j=1}^{52} L_{ji} \cdot I_{ji}}$$

Complementarity: Implementation with O*NET

AIOE and Complementarity



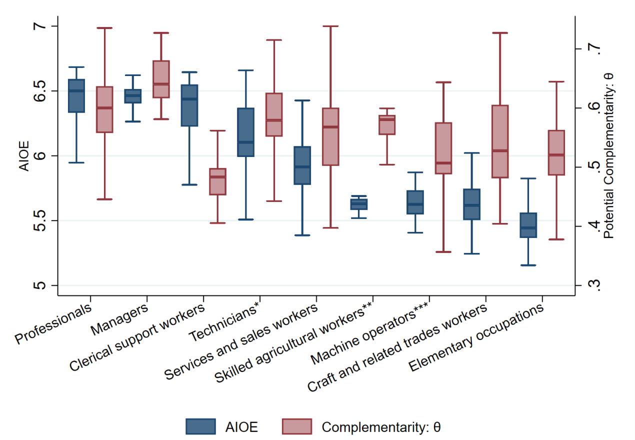
Use "work contexts" and "skills" components; Group into 6 categories, with scores from 0 to 100; take average

1. Communication: 1) Face-to-Face, 2) Public Speaking
2. Responsibility: 3) Responsibility for outcomes, 4) Responsibility for others' health
3. Physical Conditions: 5) Outdoors Exposed, 6) Physical Proximity
4. Criticality: 7) Consequence of Error, 8) Freedom of Decisions, 9) Frequency of Decisions
5. Routine: 10) Degree of Automation, 11) Unstructured vs Structured Work
6. Skills: 12) "Job Zone" (training and education needed)

AIOE and Complementarity by Major Occupation Groups

- Larger variance in complementarity than in exposure within major (1-digit ISCO-08) occupation groups

AIOE and Complementarity within Major Occupation Groups



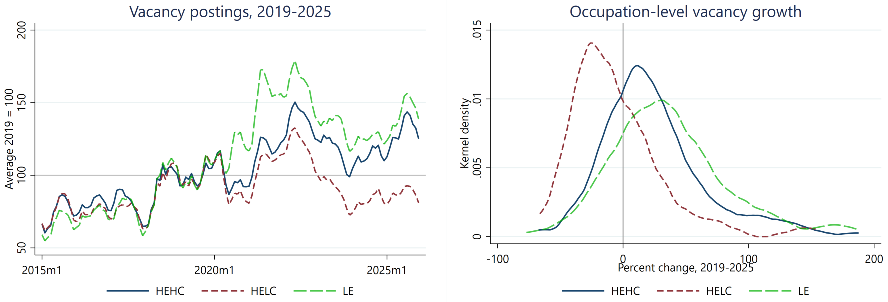
Robustness Checks to θ

- Principal Component Analysis
  - First two principal components only explain 66 percent of variance
- Sensitivity to each dimension of θ
  - Leave-one-out analysis: overall, no individual dimension strongly sways the results
- Compare θ against other measures of exposure: subsets of Felten et al. (2021), Eloundou et al. (2023), Webb (2020), Gmyrek et al. (2023)
  - Similar results
- Create a single comprehensive measure of Complementarity-Adjusted AIOE (C-AIOE)

Testing prediction on US job vacancies from Lightcast

- $\sim$ 250+ million individual job adverts between 2019 and 2025, matched with 4-digit ISCO-08
- HELC vacancies have been falling more pronouncedly since 2022

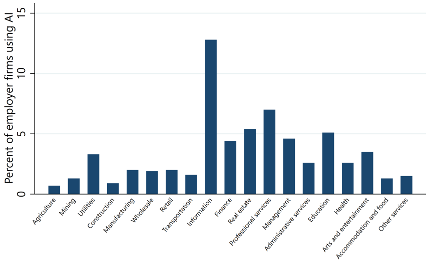
Vacancies by Exposure and Complementarity in the US.



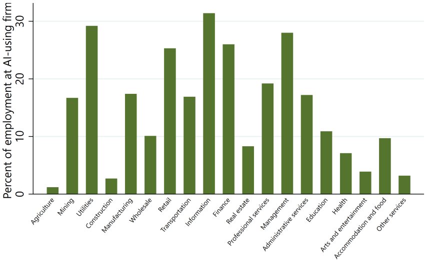
Regression Analysis: AI adoption by Industry

AI adoption by sector in the US Census 2022 Annual Business Survey

Firm-weighted



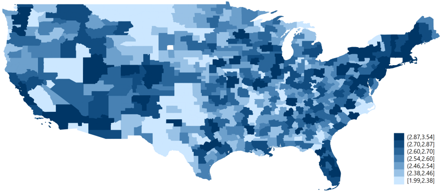
Employment-weighted



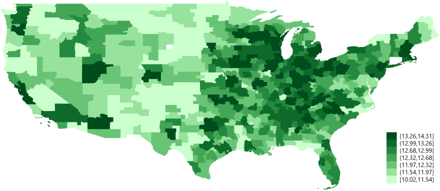
AI Adoption across the US

Geographical Distribution of AI Adoption by CZ

Firm-weighted



Employment-weighted

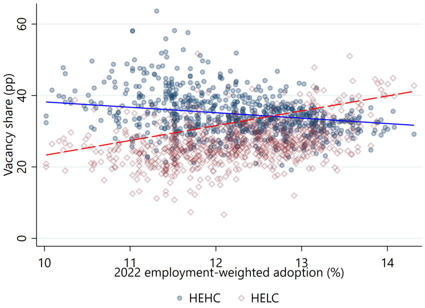


AI Adoption and Vacancies by US Commuting Zones

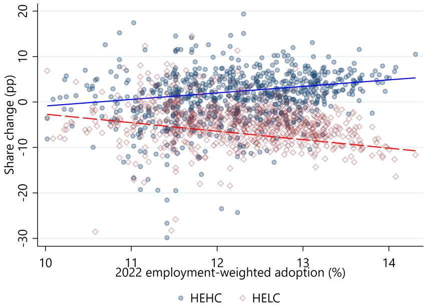
- Local AI adoption proxied by national industry-level adoption in 2022 from Annual Business Survey (ABS) and Commuting Zone employment shares

2022 AI adoption and vacancies at the CZ level

Vacancies Shares 2019



Change in Vacancies Shares 2019-2025



Regression Specification

$$\Delta_{2019-2025} v^{o}_{i,s,r} = \alpha + \beta \, Adopt_{i,s,r,2022} + \gamma X_{i,s,r,2019} + \delta_r + \epsilon_{i,s}$$

- $\Delta_{2019-2025} v^{o}_{i,s,r}$ is the change in vacancies in CZ i in state s and region r of occupation type o between 2019 and 2025
- $Adopt_{i,s,r2015}$ is the industry-based employment-weighted AI adoption measure for CZ i
- $X_{i,2019}$ characteristics of the CZ in 2019
- δ_r is a region-level fixed effect

Regression Details

- All models: Census-region fixed effects, 2018 CZ population analytic weights; state-clustered standard errors
- Demographic controls: log population; share of female, White, college, older-worker, unemployment, and technology-sector employment
- Full controls: share of employment in teleworkable occupations (Dingel and Nieman, 2022), digital jobs (Muro et al., 2017), routine-task intensity (Autor et al., 2023), the COVID employment shock (Soh et al., 2024), offshorability (Binder, 2007), and the pre-period China shock (Autor et al., 2013)

Results: Employment-Weighted 2022 Adoption, Vacancies shares 2019-2025

2022 employment-weighted AI adoption; vacancy share change 2019-2025

	(1) Region FE	(2) Demographic controls	(3) Full controls
Panel A: HELC			
2022 AI exposure	-2.091***	-0.854***	-1.105***
	(0.275)	(0.284)	(0.270)
R-squared	0.443	0.603	0.625
Panel B: HEHC			
2022 AI exposure	1.531***	0.718**	0.721**
	(0.196)	(0.290)	(0.283)
R-squared	0.201	0.291	0.297
Panel C: LE			
2022 AI exposure	0.560**	0.136	0.384
	(0.220)	(0.378)	(0.356)
R-squared	0.234	0.303	0.332
Observations	740	740	721
Region fixed effects	Yes	Yes	Yes
Demographic controls	No	Yes	Yes
Full additional controls	No	No	Yes

Results: Firm-Weighted Adoption

2019 firm-weighted AI adoption; vacancy share change 2019-2025

	(1) Region FE	(2) Demographic controls	(3) Full controls
Panel A: HELC			
2022 AI exposure	-7.547***	-6.546***	-6.342***
	(0.524)	(1.196)	(1.195)
Observations	740	740	721
R-squared	0.571	0.622	0.631
Panel B: HEHC			
2022 AI exposure	4.741***	1.806	1.492
	(0.682)	(1.595)	(1.690)
Observations	740	740	721
R-squared	0.234	0.278	0.285
Panel C: LE			
2022 AI exposure	2.806***	4.740**	4.849**
	(0.769)	(1.850)	(1.809)
Observations	740	740	721
R-squared	0.267	0.322	0.347
Region fixed effects	Yes	Yes	Yes
Demographic controls	No	Yes	Yes
Full additional controls	No	No	Yes

Results: 2019 Adoption

2019 employment-weighted AI adoption; vacancy share change 2019-2025

	(1) Region FE	(2) Demographic controls	(3) Full controls
Panel A: HELC			
2019 AI exposure	-5.727***	-2.204***	-3.270***
	(0.426)	(0.782)	(0.887)
R-squared	0.490	0.597	0.618
Panel B: HEHC			
2019 AI exposure	3.980***	1.501*	1.149
	(0.441)	(0.882)	(0.996)
R-squared	0.218	0.281	0.285
Panel C: LE			
2019 AI exposure	1.747***	0.703	2.121*
	(0.445)	(1.057)	(1.219)
R-squared	0.243	0.303	0.336
Observations	740	740	721
Region fixed effects	Yes	Yes	Yes
Demographic controls	No	Yes	Yes
Full additional controls	No	No	Yes

Results: 2019 Adoption + 2019-2022 Incremental Adoption

2019 and Δ2019-2022 employment-weighted adoption; Δ2019-25 vacancy shares

	(1) Region FE	(2) Demographic controls	(3) Full controls
Panel A: HELC			
2019 AI adoption	-5.890***	-1.395	-2.023*
	(0.968)	(0.914)	(1.052)
D 2019-2022 adoption	0.148*	-0.551*	-0.796*
	(0.794)	(0.524)	(0.467)
R-squared	0.490	0.599	0.622
Panel B: HEHC			
2019 AI adoption	3.294***	-0.342	-1.132
	(0.562)	(0.855)	(1.000)
D 2019-2022 adoption	0.624*	1.255***	1.457***
	(0.377)	(0.391)	(0.387)
R-squared	0.224	0.298	0.307
Panel C: LE			
2019 AI adoption	2.596***	1.737	3.156**
	(0.867)	(1.060)	(1.267)
D 2019-2022 adoption	-0.773***	-0.704***	-0.660***
	(0.618)	(0.568)	(0.530)
R-squared	0.249	0.307	0.340
Observations	740	740	721
Region fixed effects	Yes	Yes	Yes
Demographic controls	No	Yes	Yes
Full additional controls	No	No	Yes

Cross-country Analysis

- Microdata from 2 AEs and 4 EMs
- Post-COVID waves or latest pre-COVID
- 4-digit ISCO-08 occupation codes (400+ occupations)

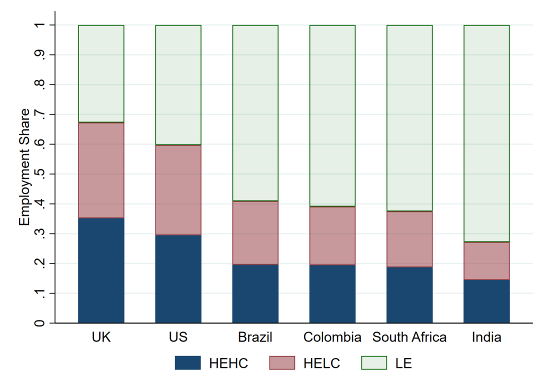
Data Sources

Country	**Survey**	**Year**	**ISCO-08 Digits**
Brazil	Pesquisa Nacional por Amostra de Domicílios Contínua	2022	4
Colombia	Gran Encuesta Integrada de Hogares	2022	4
India	Period Labour Force Survey	2018-19	3
South Africa	Labor Market Dynamics in South Africa Survey	2019	4
UK	Labour Force Survey	2022	4
US	American Community Survey	2019	4

Aggregate cross-country differences

- AEs on average have higher shares of both HEHC and HELC jobs

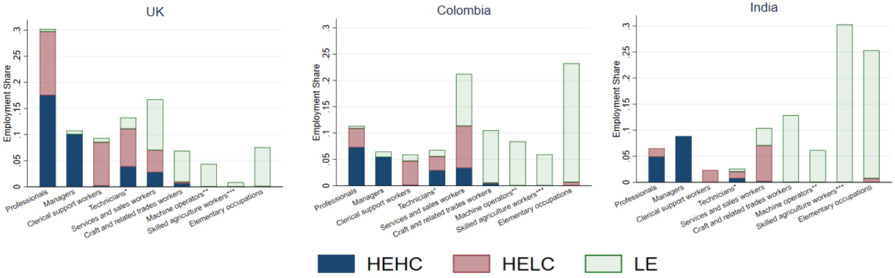
Employment Share by AI Exposure and Complementarity



Breaking it down by occupations

- Occupational (and industrial) structure of the economy explains cross-country variation

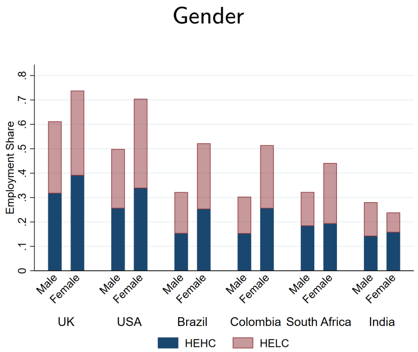
Employment Share by Exposure and Complementarity across Occupation Groups

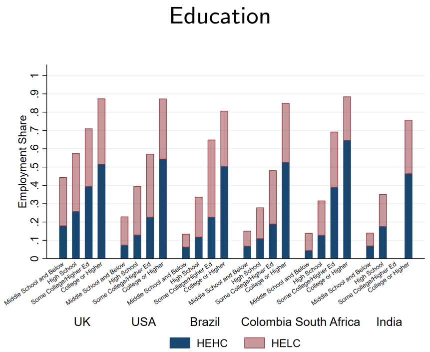


Within Country Variation - Part 1

- Broadly similar heterogeneity across gender (except for India) and education within countries

Share of Employment in High-Exposure Occupations by Demographic Characteristics



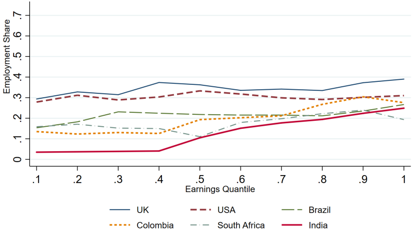


Within Country Variation - Part 2

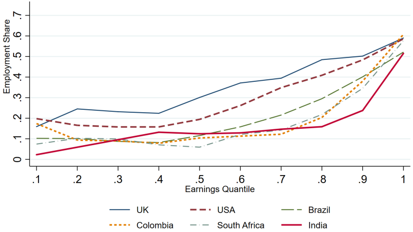
- Similar patterns across countries
- HELC share roughly constant over the income distribution
- HEHC share higher in upper deciles of the income distribution

Share of Employment in High Exposure Occupations by Earnings Decile

High Exposure, Low Complementarity



High Exposure, High Complementarity



Conclusion

Results

- Complementarity is a salient dimension within highly exposed occupations
- Cross-country differences in HEHC and HELC employment shares
  - AEs have higher shares of both $\rightarrow$ in short-run more vulnerable but also better placed to reap benefits
- Similar within-country patterns: high-education and high-income workers more positively exposed

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- Similar within-country patterns: high-education and high-income workers more positively exposed

Caveats

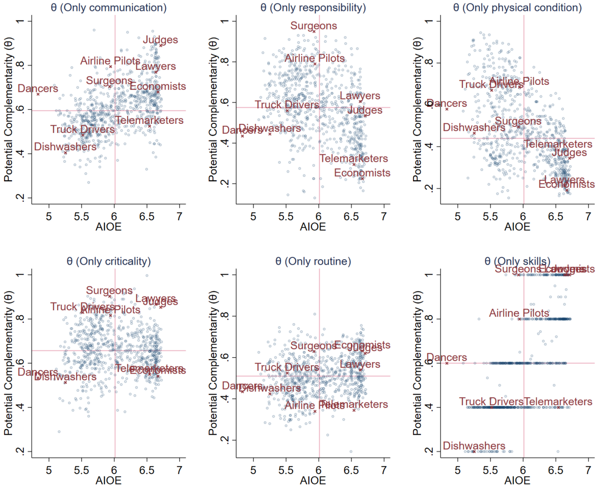
- Complementarity dependent on social preferences that could change
- Labor market adjustment will be dynamic and affected by policies
- Country characteristics like level of digital infrastructure affect exposure

Thank you!

Appendix

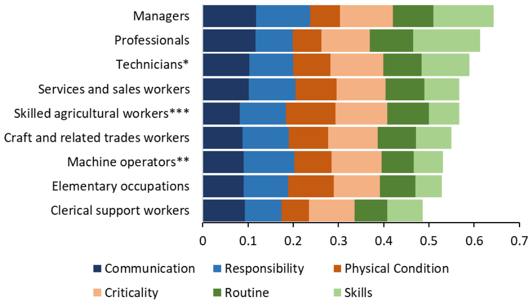
Individual components of θ

Association between Individual θ Component and AIOE



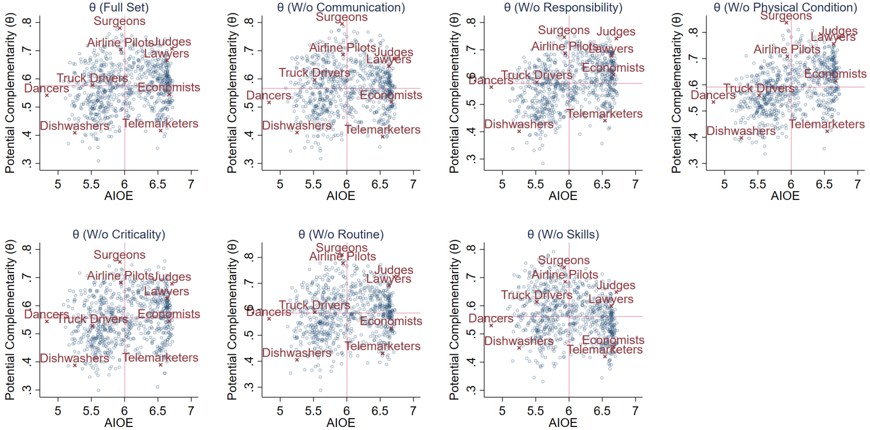
Average Contribution of Each Component

Average Contribution of Each Component to θ by Occupation Group



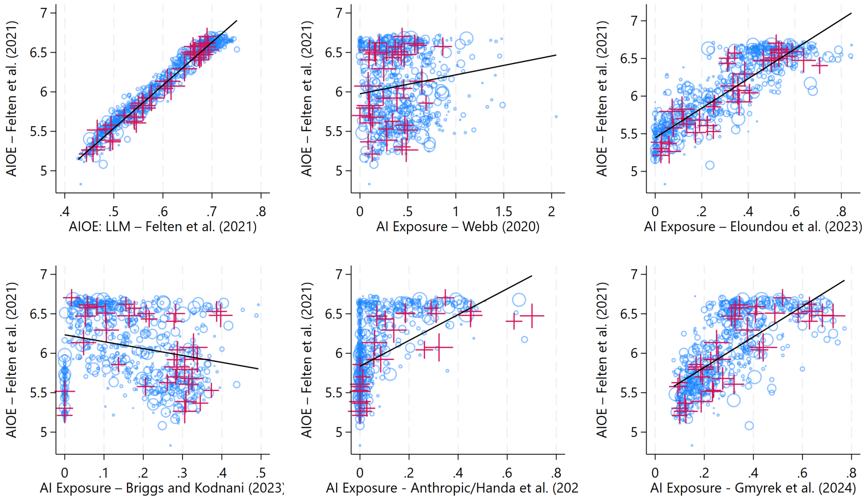
Leave-one-out analysis

Figure: Association between Potential Complementarity and AIOE: Leaving-one-out Sensitivity Analysis (A)

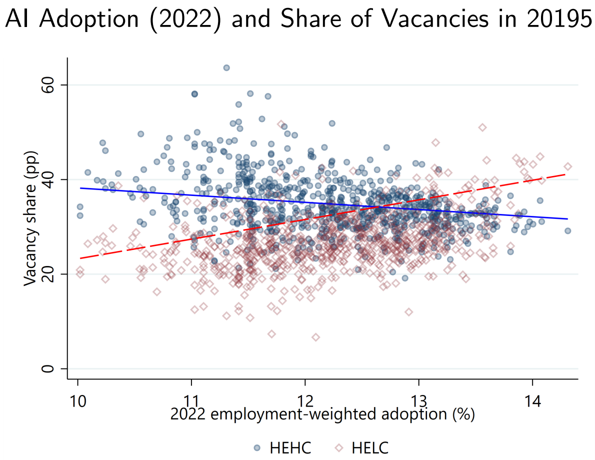


Comparison of exposure measures

Felten et al. (2021) vs. other measures of occupational AI exposure

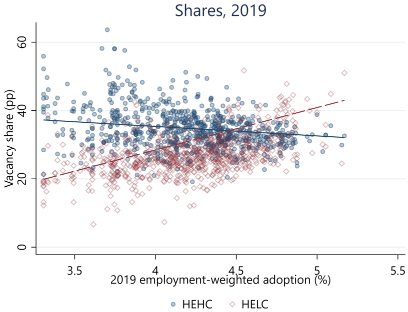


AI Adoption and Vacancies by US Commuting Zones

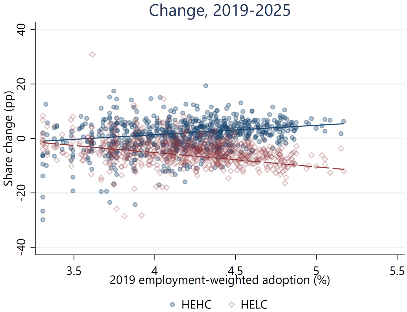


AI Adoption (2019) and Vacancies by US Commuting Zones

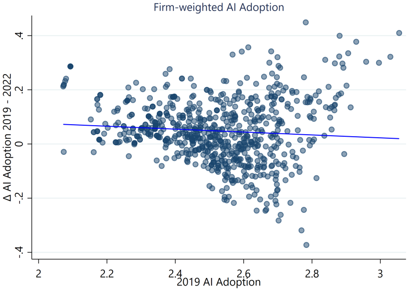
2019 Share

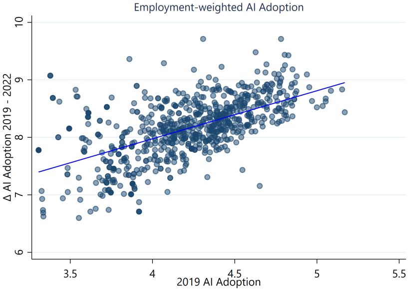


Change in Share 2019-2025

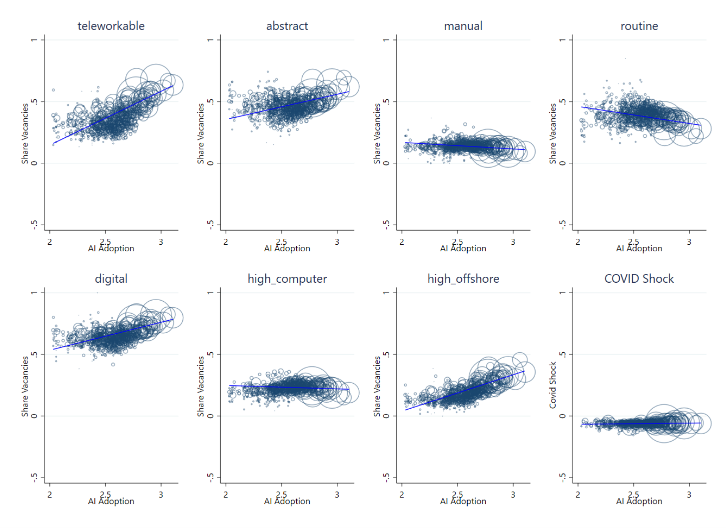


AI adoption by CZ 2019 and Δ 2019-2022

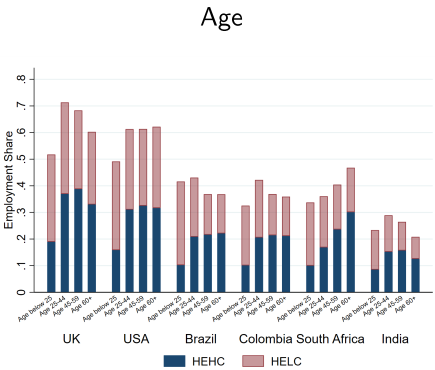




AI Adoption and other characteristics of labor demand by commuting zone



Exposure and Complementarity by Age

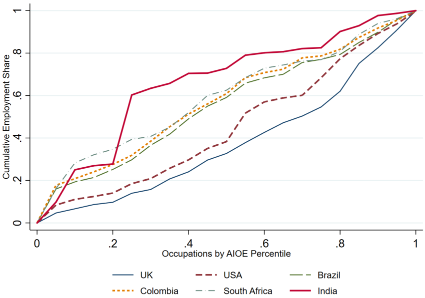


Complementarity-Adjusted AIOE

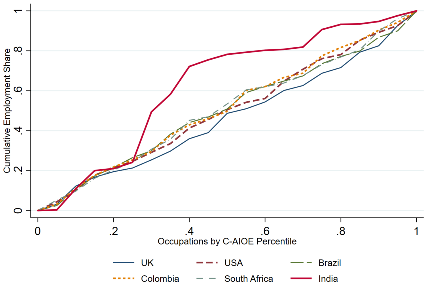
- Single measure: $\text{C-AIOE}_i = \text{AIOE}_i * (1 - w * (\theta_i - \theta_{MIN}))$
- Baseline $w = 1$
- Higher C-AIOE implies higher substituion potential

Cumulative Employment Distribution: AIOE and C-AIOE.

(a) AIOE

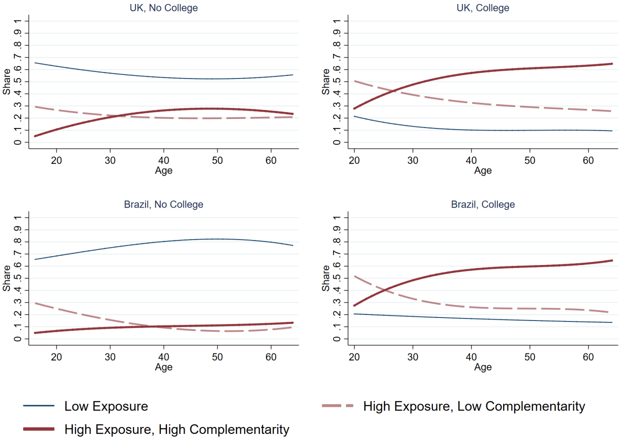


(b) C-AIOE



Bonus slide from companion paper Cazzaniga et al. (2024)

Life-cycle Profile of Employment Shares



Note: the y-axis represents the estimated share of workers in each category for a given age, represented in the x-axis. Shares are estimated according to a cubic age polynomial. The equation is estimated by country and level of education.