# Exposure to Artificial Intelligence and Occupational Mobility: A Cross-Country Analysis

Mauro Cazzaniga, **Carlo Pizzinelli**, Emma Rockall,
Marina M. Tavares

SEPTEMBER 4, 2024

WORLD BANK – GEORGETOWN CONFERENCE ON AI

# Motivation

- **Structural transformation** from AI may trigger a **reallocation of labor** both for currently employed workers and for new generations of entrants into the labor market
- Labor demand for some **existing occupations** may fall and for other will rise
- **New occupations** being created: we do not know what they are, but we can make informed guesses on what they may be like and what skills they may require
- Need to look at structural transformation through a **life-cycle** lens

## Questions

1. How does AI-induced reallocation interact with workers' career growth?
   - Which workers (age, education) are more exposed to risks of disruption and which are more able to move into growing occupations? Impact on earnings throughout the career?

2. Variation across countries in these prospects? E.g.., AEs vs EMDEs?

# In this paper

1. Panel microdata from 2 labor force surveys: one Advanced Economy, **UK**, and one Emerging Market, **Brazil**.

2. Use classification of occupations by **AI exposure** (Felten et al., 2021) and **complementarity** (Pizzinelli et al., 2023)

3. Examine historical life-cycle patterns of workers' transitions across types of jobs
   - Identify more at-risk groups of workers and those with greater ability to adjust to structural change, by age and education

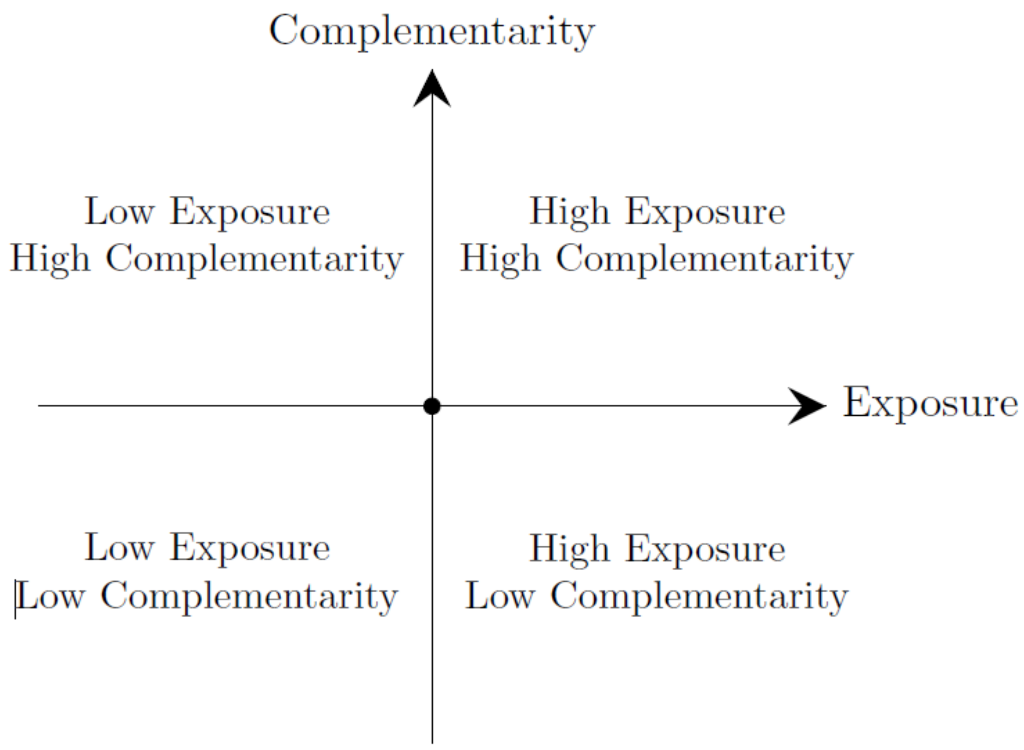
4. Draw implications for **expected lifetime earnings**
   - Simple scenarios with different assumptions on job destruction, reallocation, wage growth

# Main Findings

- **College educated** workers in both **UK and Brazil** make more “upward” transitions toward high-exposure high-complementarity (HEHC) job
- Among the **non-college educated**, in Brazil they make more “downward” transitions towards low-exposure (LE) jobs
- **Young college educated** in both countries make the most transitions from high-exposure low-complementarity (HELC) to HEHC jobs as part of their career growth
  - This group is the most likely to benefit from growing jobs but also whose careers may be most disrupted by shrinking jobs
- For each scenario, effects on lifetime earnings depend on shares of LE, HELC, HEHC employment and relative wages in each country and education group

# Occupational exposure and complementarity

- Felten et al. (2021): Exposure as overlap between AI capabilities and human skills needed to carry out a job
- High complementarity: greater likelihood of AI functioning as a supporting technology
  - Lower risk of falling labor demand and job destruction
  - Higher productivity growth
- Complementarity still requires worker to have to skills
- Complementarity is relevant conditional on a level of exposure
- **New occupations more likely to be high exposure and high complementarity**



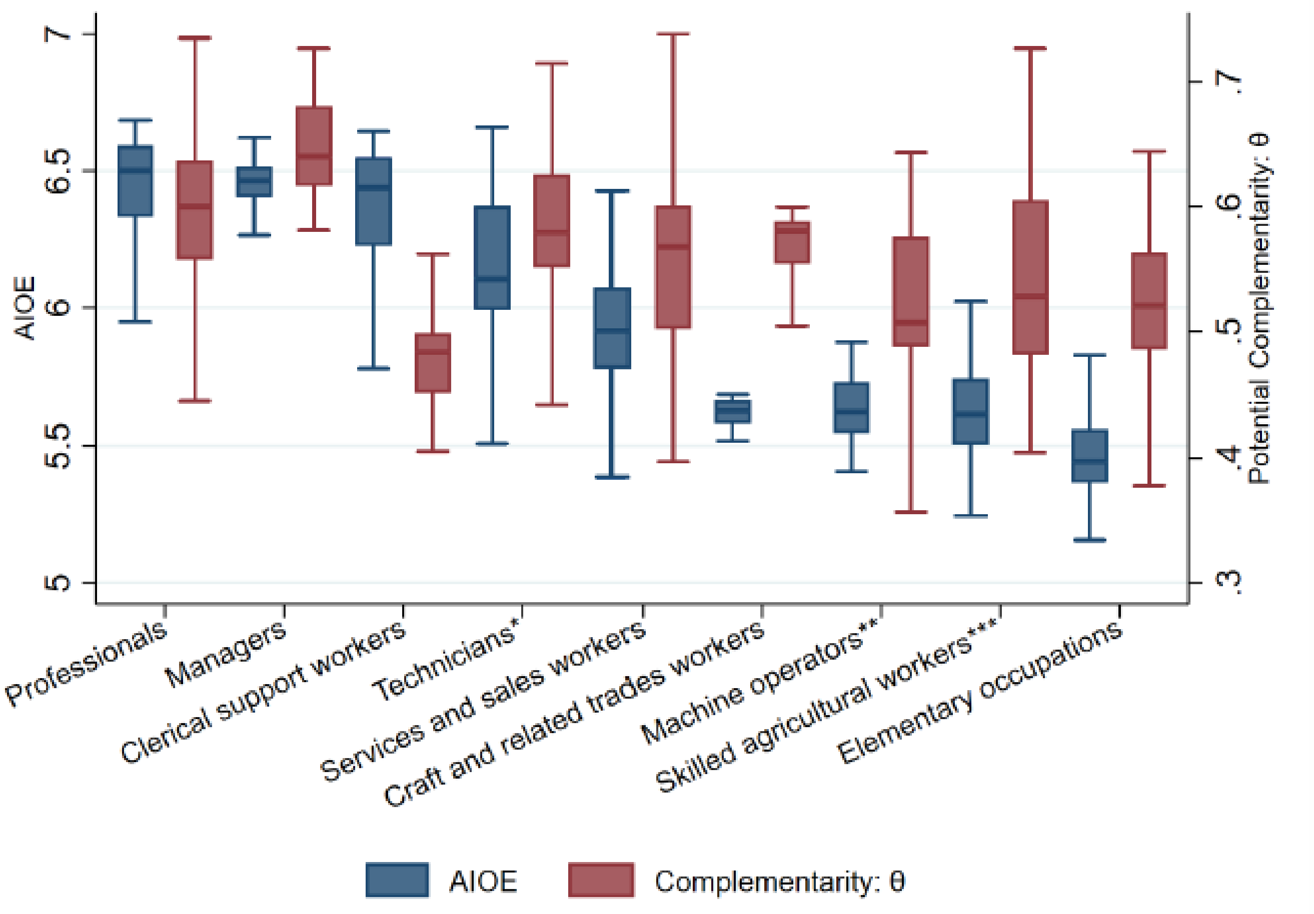
# Computing a potential complementarity measure

- Leverage two lesser used parts of the O*NET capturing
  "work context" and "skills."
- Group into 6 categories, with scores from 0 to 100.

**a. Communication:** 1) Face-to-Face, 2) Public Speaking
b. **Responsibility:** 3) Responsibility for outcomes, 4) Responsibility for others' health
c. **Physical Conditions:** 5) Outdoors Exposed, 6) Physical Proximity
d. **Criticality:** 7) Consequence of Error, 8) Freedom of Decisions, 9) Frequency of Decisions
e. **Routine:** 10) Degree of Automation (inverted scale), 11) Unstructured vs Structured Work
f. **Skills:** 12) Job Zone ("job zone" measures the level of education, training and skills needed for a job. )

$\theta$ computed as: (a + b + c + d + e + f ) / (6*100)

**AI Complementarity and Exposure across Major Occupation Groups**



# Data

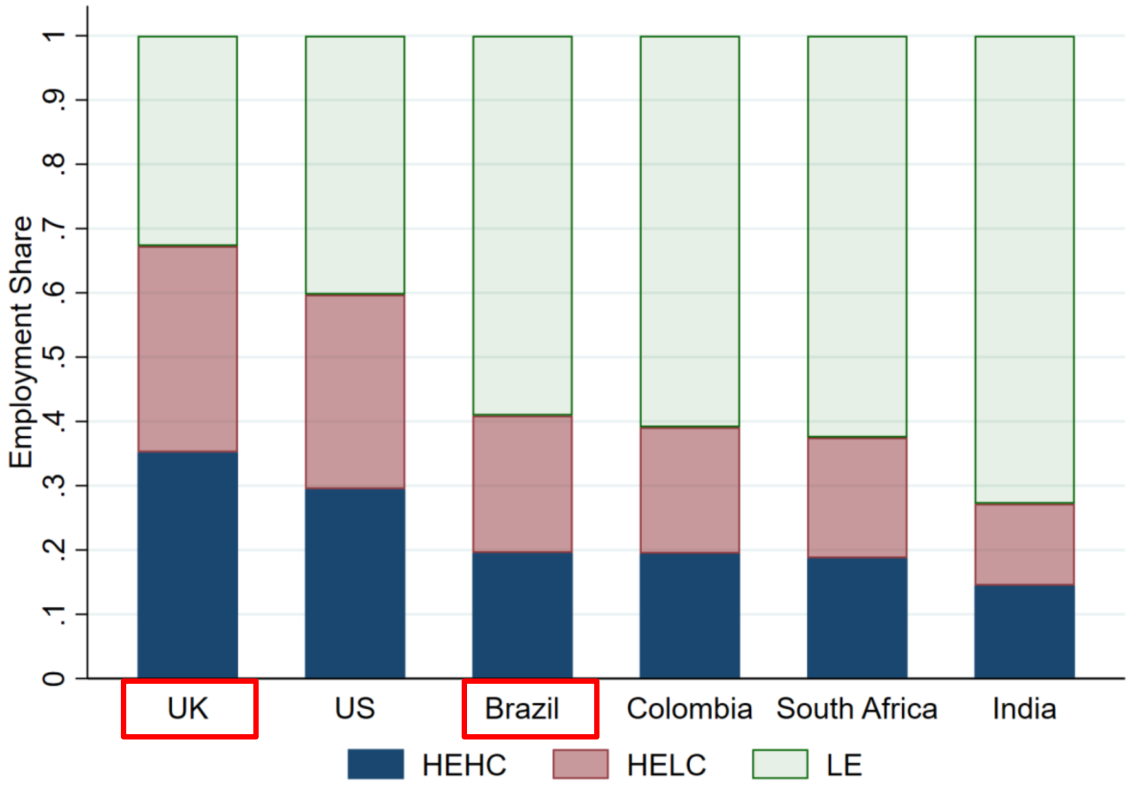
- Microdata with one-year panel dimension for two countries: 2014-2022
  - Brazil: Pesquisa Nacional por Amostra de Domicílios Contínua
  - United Kingdom: Quarterly Labour Force Survey

- Classification of occupations by AI occupational exposure (AIOE) from Felten et al. (2021) and complementarity from Pizzinelli et al. (2023).
- Divide occupations into three groups:
  - Low exposure (**LE**)
  - High exposure, low complementarity (**HELC**)
  - High exposure, high complementarity (**HEHC**)

# Composition by exposure and complementarity

AEs, like the UK have a higher share of high-exposure jobs both with high and low complementarity than EMDEs like Brazil

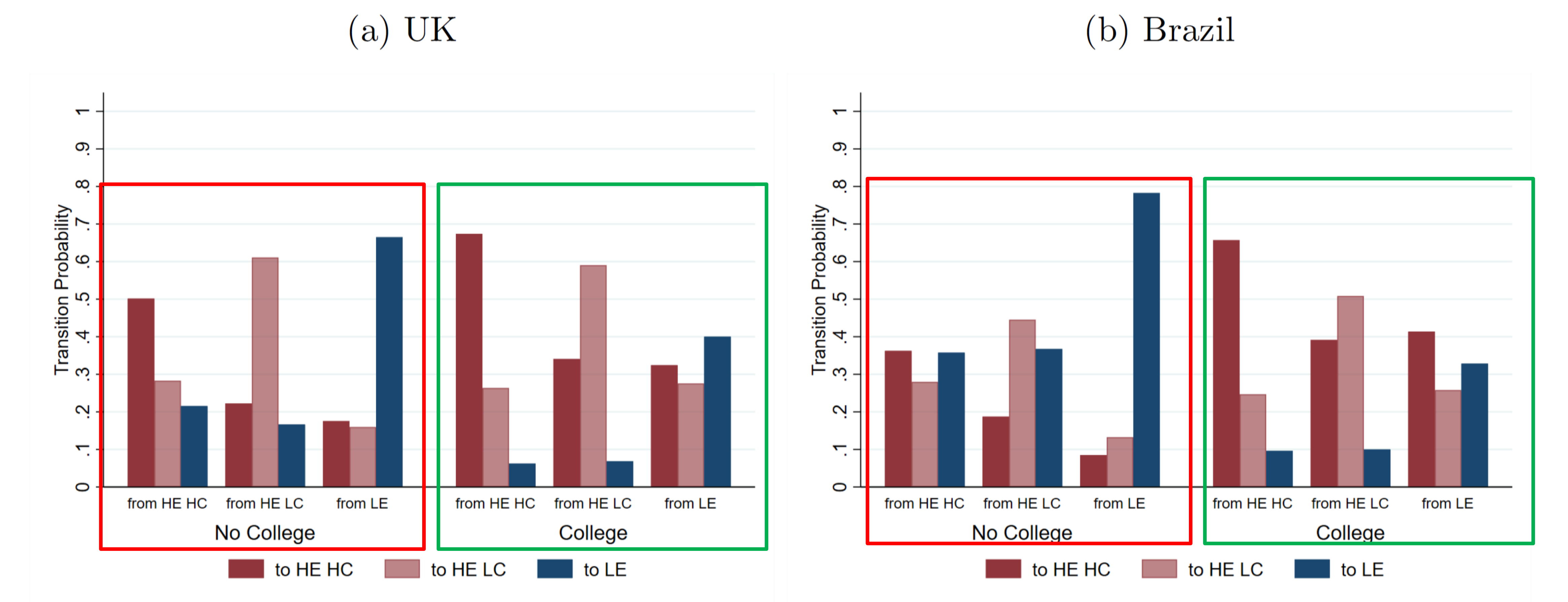
**Employment Share by AI Exposure and Complementarity**



# Transition probabilities across occupation types

- Higher probability of moving to HEHC jobs across quarters for the college educated in both countries and lower probability of "moving down the ladder" to LE and HELC

- Robust to controlling for other demographic characteristics



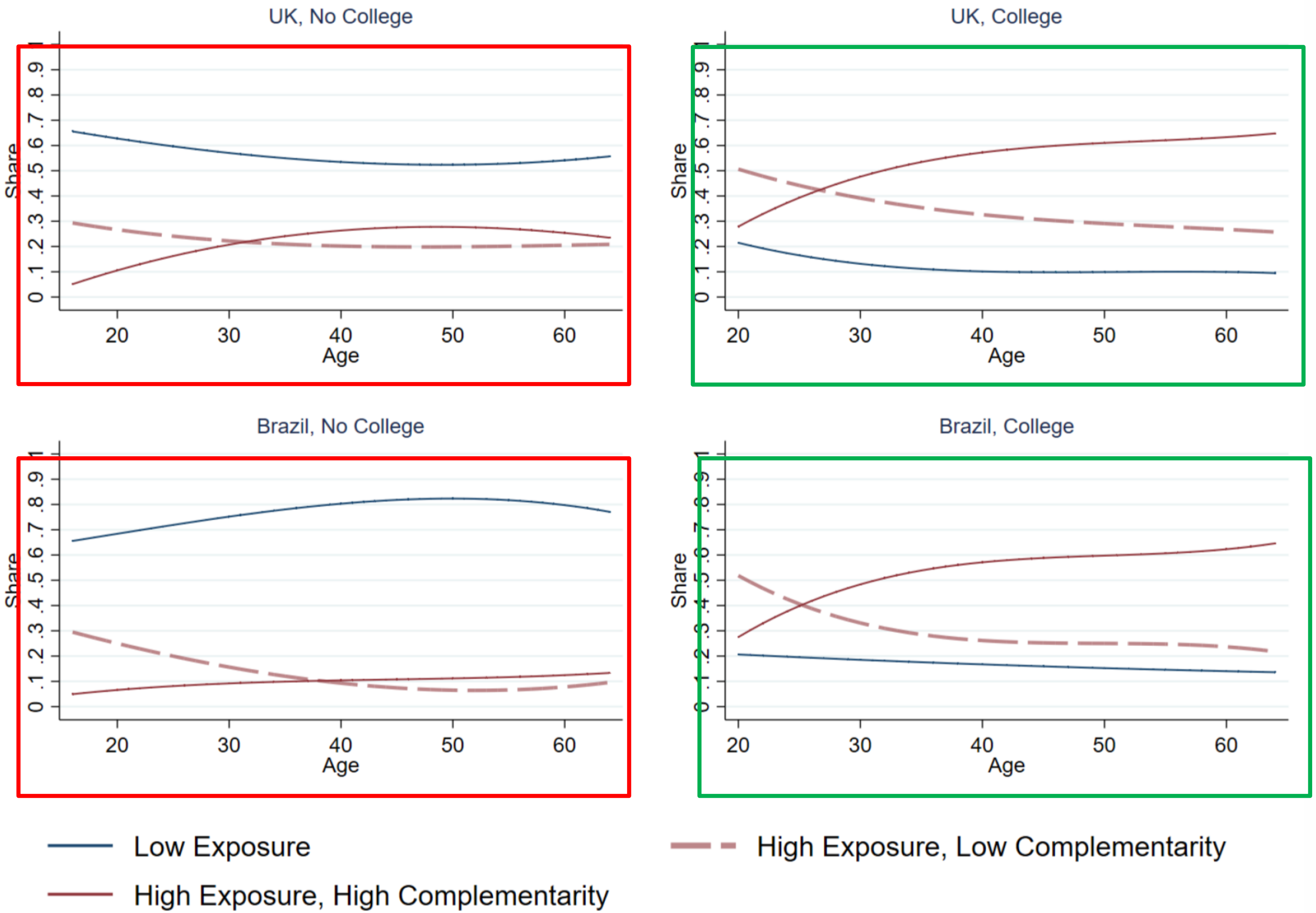
# Simple life-cycle specification

- For worker *i,* probability of employment in occupation *k* in year *t* is a cubic polynomial of age, plus demographic controls and time fixed effects

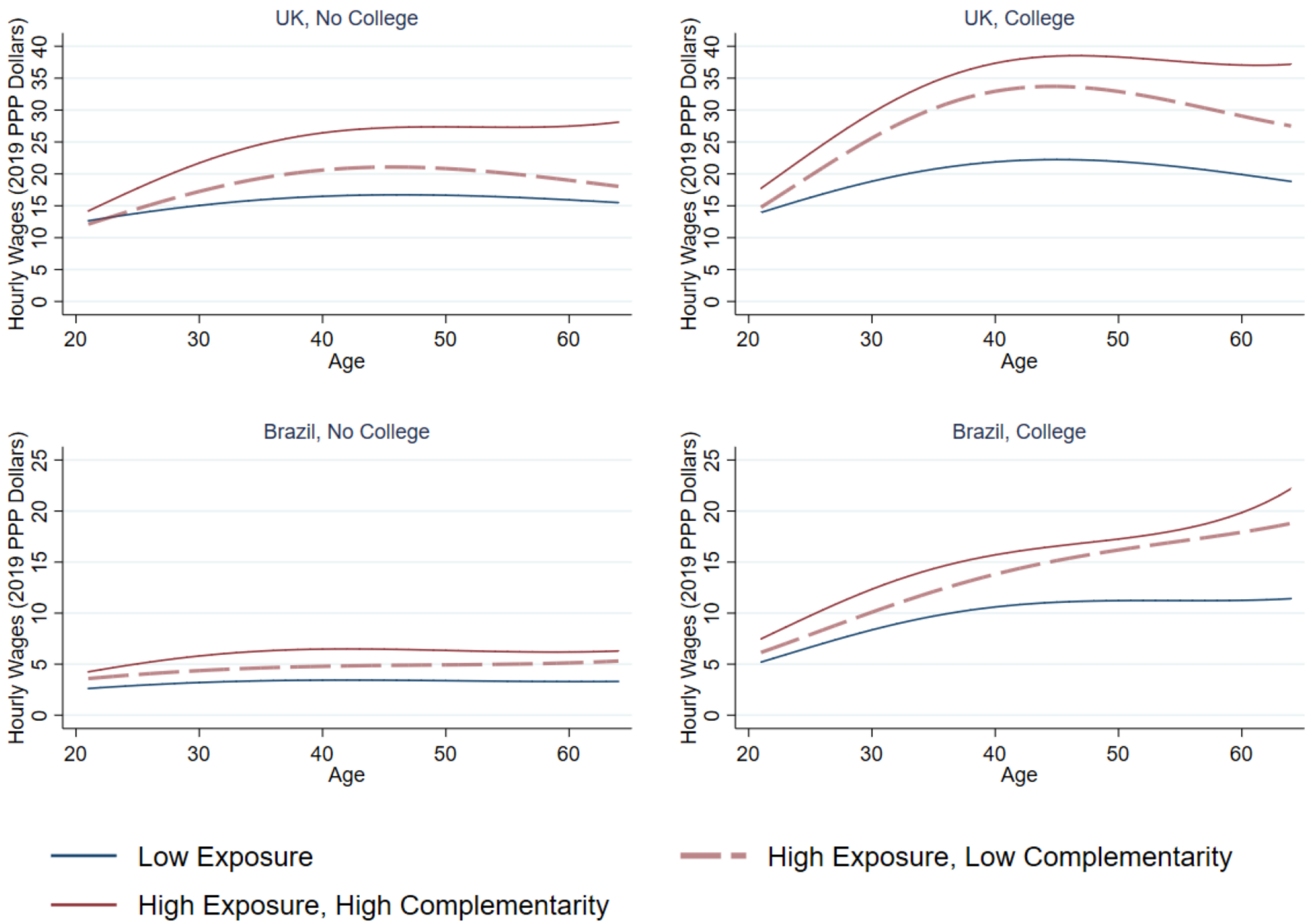
$$C_{it}^{k} = \beta_0 + \beta_1 age_{it} + \beta_2 age_{it}^2 + \beta_3 age_{it}^3 + \delta female_{it} + \gamma_t + \varepsilon_{it}$$

- Age polynomial traces average life-cycle path of employment in a given occupation
- Given short time period, exclude cohort effects
- Similar specification for log wages in occupation *k*

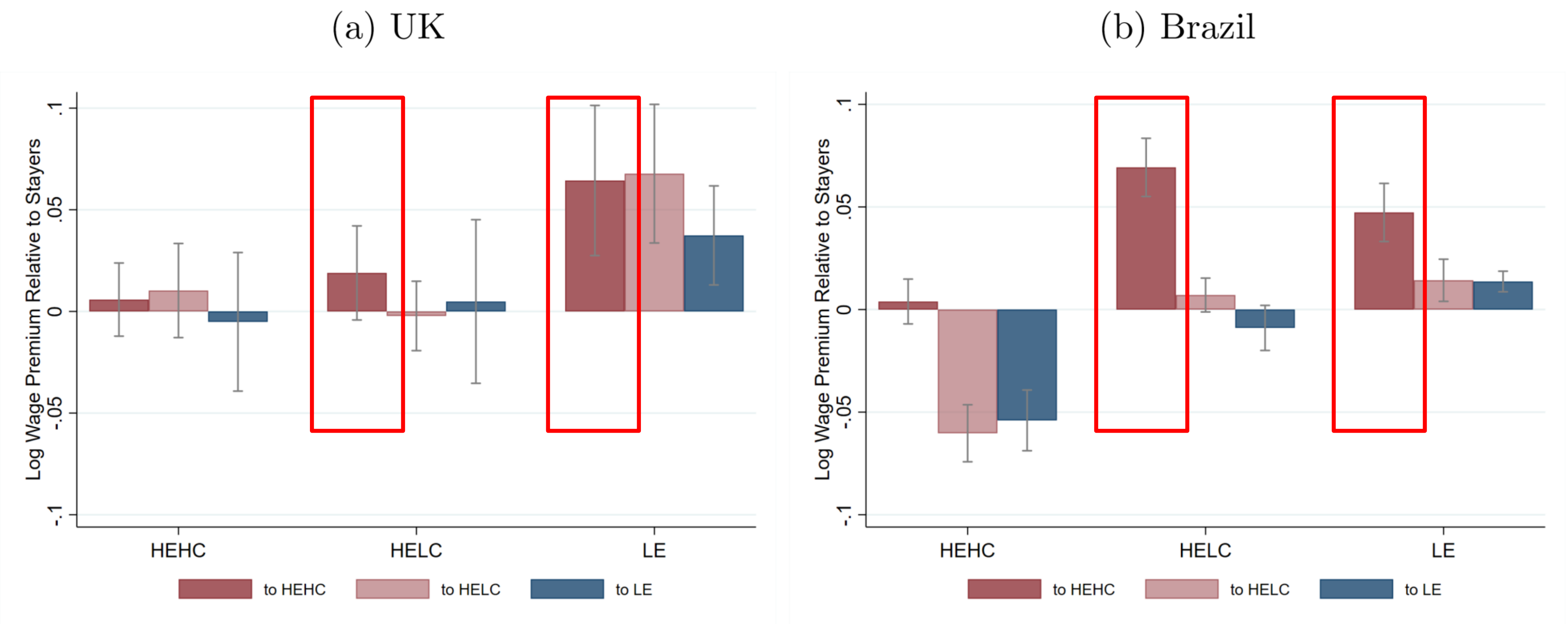
# Life-cycle profiles of employment by occupation type



# Life-cycle profiles of wages by occupation type



# Wage gains from switching to HEHC jobs




$$\Delta \log(y_{irt}) = \delta_1 J2J_{irt} + \delta_2 OS_{irt} \times J2J_{irt} + \delta_3 EUE_{irt} \quad + \sum_k \theta_k C^k_{ir(t-1)} C^k_{irt}$$

$$+ \sum_k \sum_j OS_{irt} \phi_{kj} C^k_{ir(t-1)} C^j_{irt} + \beta X_{irt} + \gamma_t + \eta_r + \varepsilon_{irt}$$

# Impact on lifetime earnings: alternative scenarios

PDV of expected future earnings for new labor market entrants in 2024 depends on the probability of employment in each occupation *k* at age *a* and the expected wage therein

$$\hat{W}_{a_0} = \sum_{a \geq a_0} \beta^{a-a_0} \sum_k \hat{p}_a^k \hat{w}_a^k$$

**AI-driven structural change scenarios:**

1. 10% of HELC jobs destroyed and workers move to unemployment
2. 10% of HELC jobs destroyed and workers move to LE
3. 10% of HELC jobs destroyed and workers move to HEHC
4. 10% wage rise in HEHC jobs

Can think of further scenarios as combinations of these 4

# Scenarios

Impact on lifetime earnings of each scenario depends on relative shares of employment and wages in HELC, HEHC, and LE occupations

Table 11: Changes in Expected Lifetime Earnings

| Scenario | College | | No College | |
|---|---|---|---|---|
| | Brazil | UK | Brazil | UK |
| Baseline (2019 Thousand PPP Dollars) | 423.3 | 1567.5 | 251.5 | 1128.8 |
| HELC to Unemployment (% Change) | -29.3 | -24.1 | -33.6 | -28.5 |
| HELC to LE (% Change) | -6.5 | -6.6 | -2.2 | -2.7 |
| HELC to HEHC (% Change) | 5 | 4 | 11.4 | 10.8 |
| HEHC Wage Increase (% Change) | 5.8 | 6.9 | 3.9 | 4.9 |

# Conclusion and discussion

- Important to consider not only exposure but also complementarity

- Dynamic view of structural change
  - Focus on transitions from/to different occupations
  - Consider full impact on careers and lifetime earnings

- College educated workers in UK and Brazil look more similar to each other than the non-college educated do

- Young college educated make most transitions from HELC to HEHC
  - Potential for growth of new jobs jobs but also disruption of “stepping stone” jobs

- Total impact on careers will depend on ability to reallocate and wage differentials
  - Different for those who have not entered the labor market and those already in it

- Big **caveat of using historical patterns** for forward looking analysis

# Appendix

# Occupational shares by education level

| | UK | | | | Brazil | | | |
|---|---|---|---|---|---|---|---|---|
| | LE | HELC | HEHC | Total | LE | HELC | HEHC | Total |
| No College | 29 | 19.1 | 14.9 | 63 | 57.7 | 15.8 | 9.2 | 82.7 |
| College | 4.3 | 12.6 | 20.1 | 37 | 2.6 | 5.0 | 9.7 | 17.3 |
| Total | 33.3 | 31.7 | 35 | | 60.3 | 20.8 | 18.9 | |

# Quarterly transitions

Table A.1: Employment Flows by Gender: Females

| Status in the quarter | UK | | | Brazil | | |
|---|---|---|---|---|---|---|
| | Employed | Unemployed | NLF | Employed | Unemployed | NLF |
| Employed | 97.4 | 0.8 | 1.8 | 88.4 | 3 | 8.6 |
| Unemployed | 24.5 | 55.8 | 19.7 | 26 | 43.4 | 30.6 |
| NLF | 4 | 3.3 | 92.7 | 11.4 | 6.1 | 82.5 |

Status in the subsequent quarter

Note: The table shows the transition flows for the UK for the three states considered for male individuals. Each cell represents the share of people with the status in the column in the subsequent quarter that were in the status in the row in the current quarter.

# Quarterly transitions by exposure and complementarity

## UK

| Status in the quarter | Status in the subsequent quarter: Employed (HE) | Employed (LE) | Unemployed | NLF |
|---|---|---|---|---|
| Employed (HE) | 96.2 | 1.7 | 0.8 | 1.3 |
| Employed (LE) | 3.3 | 94.2 | 1.1 | 1.4 |
| Unemployed | 13.7 | 10.8 | 60.1 | 15.4 |
| NLF | 2.6 | 1.4 | 3.7 | 92.3 |

## Brazil

| Status in the quarter | Status in the subsequent quarter: Employed (HE) | Employed (LE) | Unemployed | NLF |
|---|---|---|---|---|
| Employed (HE) | 81.4 | 11 | 2.7 | 4.9 |
| Employed (LE) | 7.1 | 82.3 | 3.7 | 6.9 |
| Unemployed | 10.2 | 21.7 | 42.9 | 25.2 |
| NLF | 4.3 | 7 | 7 | 79.7 |

# AI Exposure in the literature

- AI exposure measures: Felten et al. (2021, 2023), Eloundou et al. (2023), Briggs and Kodnane (2023), Gmyrek et al. (2023), Webb (2020), Brynjolfsson et al. (2018)
  - Mostly look at exposure in an agnostic way
  - Based on O*NET, mostly using a “task-based” framework
  - **Contribution**: look at complementarity through a different dimensions of job characteristics

- Exposure in EMDEs:
  - Briggs and Kodnane (2023) extrapolate exposure based on industry composition and US industry-occupation cross-tabulation
  - Gmyriek et al. (2023) closest to ours but still use tabulations.
  - **Contribution**: microdata allows for more granular and deeper analysis of cross- and within-country differences

# The Felten et al. (2021) AIOE measure

- Measure "overlap" between 11 AI applications and 52 human abilities based on expert judgment
- $A_{kj}$ is the correspondence between AI applications and ability *j*
- Using O*NET, this is weighted by the total Prevalence $L_{ji}$ and Importance $I_{ji}$ of ability *j* in occupation *i* to compute the AI Occupational Exposure measure
- *Relative* interpretation: not an absolute measure of exposure

$$AIOE_i = \frac{\sum_{j=1}^{52} A_j \cdot L_{ij} \cdot I_{ij}}{\sum_{j=1}^{52} L_{ij} \cdot I_{ij}}$$

# Computing a potential complementarity measure

- Leverage two lesser used parts of the O*NET capturing "work context" and "skills."
- Group into 6 categories, with scores from 0 to 100.

**a. Communication:** 1) Face-to-Face, 2) Public Speaking

b. **Responsibility:** 3) Responsibility for outcomes, 4) Responsibility for others' health

c. **Physical Conditions:** 5) Outdoors Exposed, 6) Physical Proximity

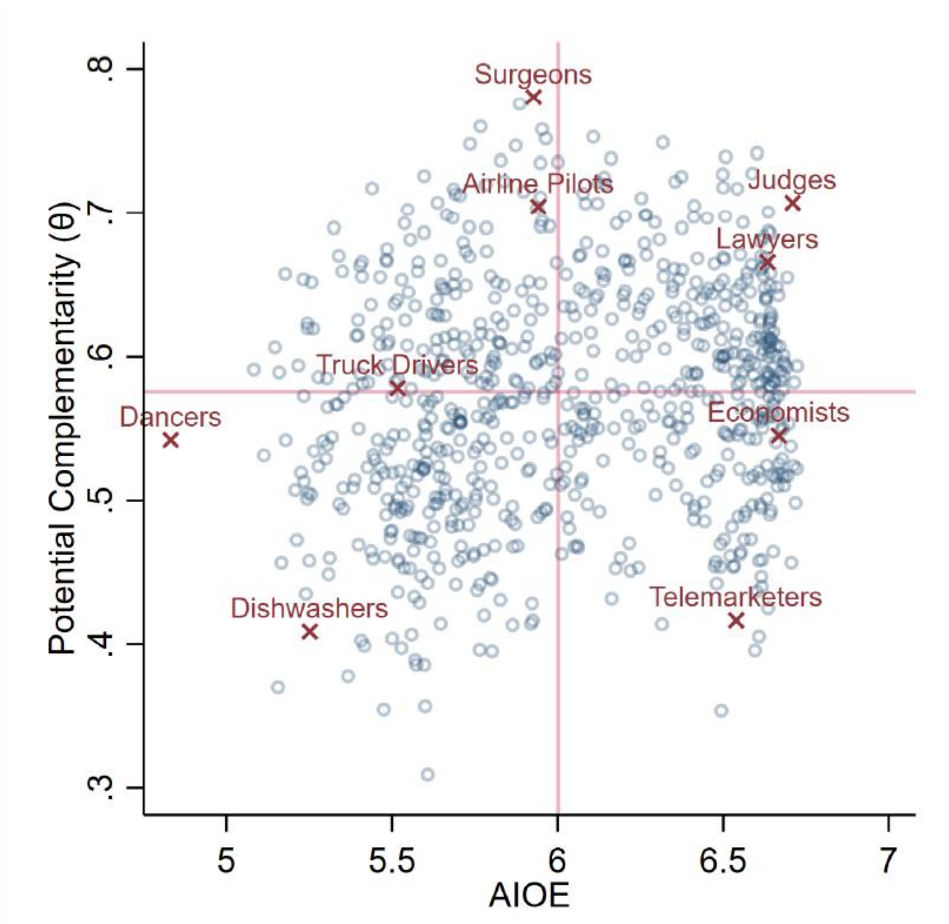
d. **Criticality:** 7) Consequence of Error, 8) Freedom of Decisions, 9) Frequency of Decisions

e. **Routine:** 10) Degree of Automation (inverted scale), 11) Unstructured vs Structured Work

f. **Skills:** 12) Job Zone ("job zone" measures the level of education, training and skills needed for a job. )

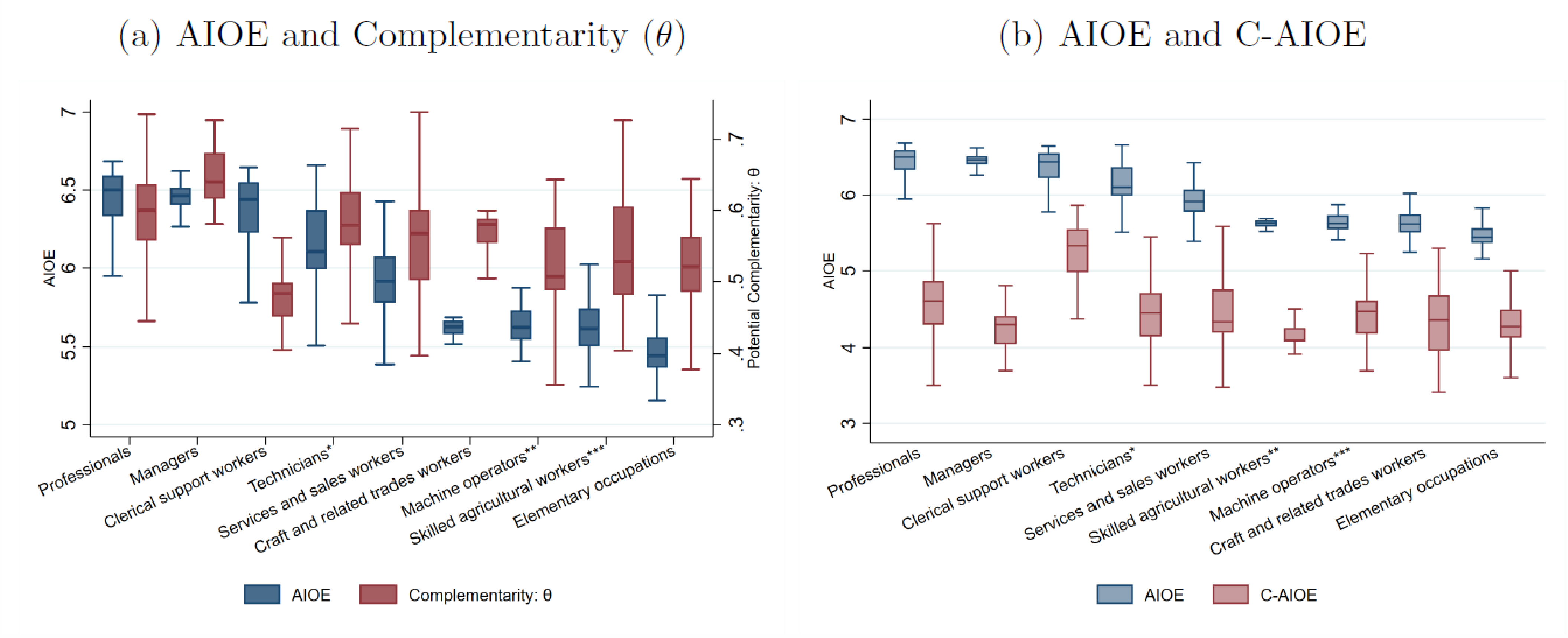
$\theta$ computed as: (a + b + c + d + e + f ) / (6*100)

**AI Exposure (AIOE) and Potential Complementarity (θ)**



# AIOE, Complementarity, and C-AIOE by Occupation Groups

**AI Complementarity and Exposure across Major Occupation Groups**



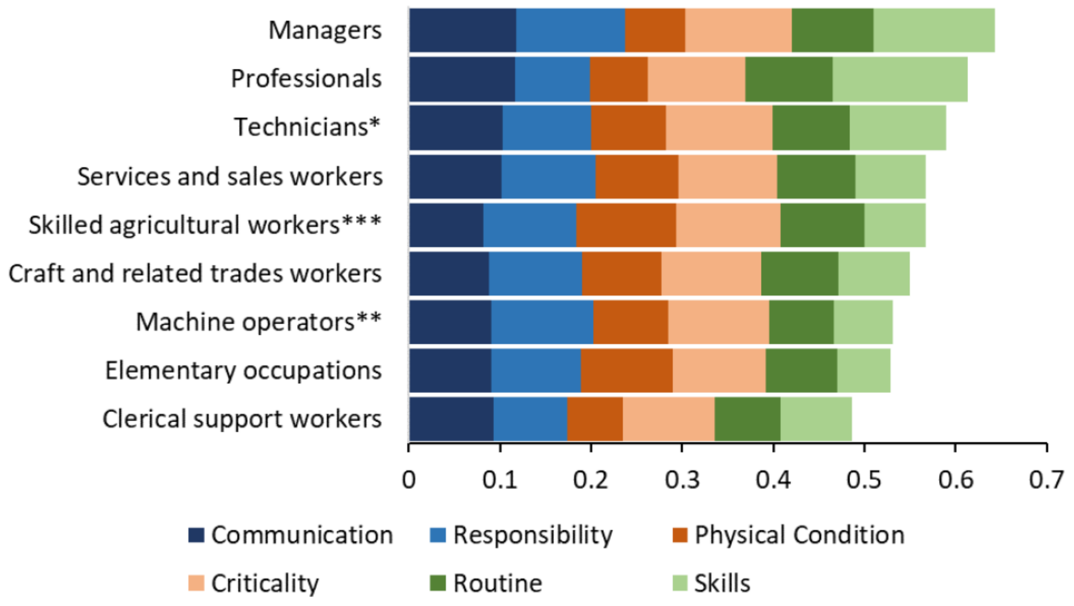
# Robustness checks to θ

- 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
  - Similar results except for the measure of Briggs and Kodnane (2023)

# Contribution of individual components

- Overall, no component individually drives the cross-occupation differences
- But "skills" clearly plays a role for Managers, Professionals, and Technicians

**Average contribution of individual components to θ by Major Occupation Groups**

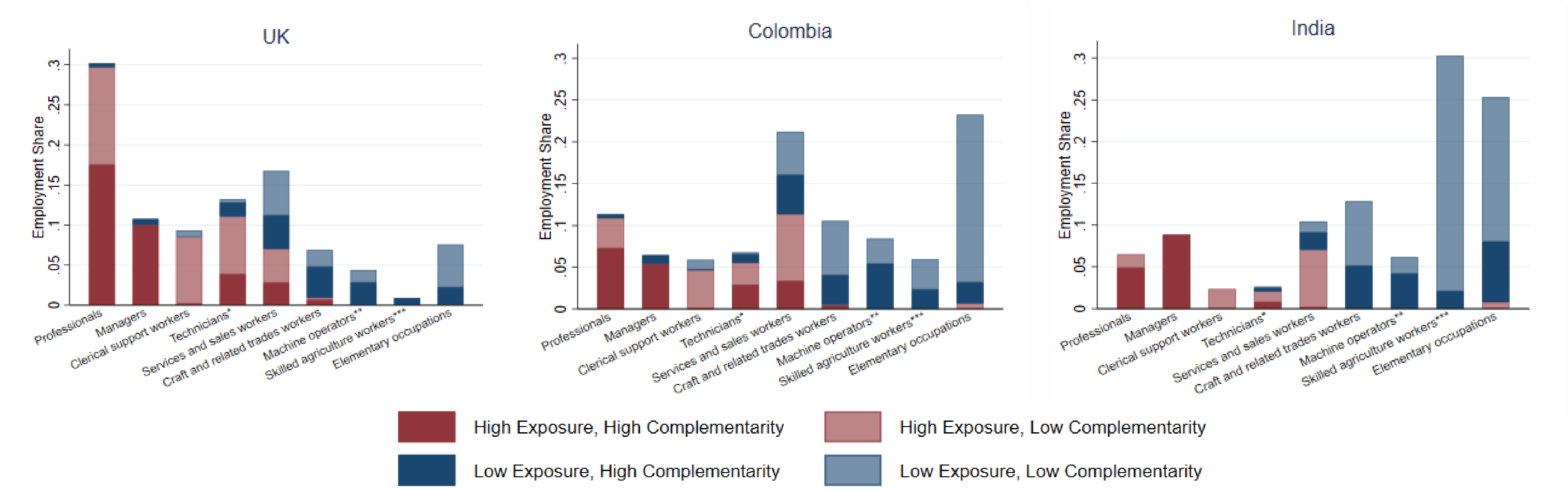



Note: The figure plots the average contribution of each component of $\theta$ among occupations in each 1-digit ISCO-08 occupation code. *: Technicians and associate professionals. **: Plant and machine operators and assemblers. ***: Skilled agricultural, forestry and fishery workers.

# Differences explained by overall economic structure

- UK, US - concentration in high-exposure: professional, managerial, and clerical support
- India - concentration in low-exposure : skilled agricultural and elementary occupations

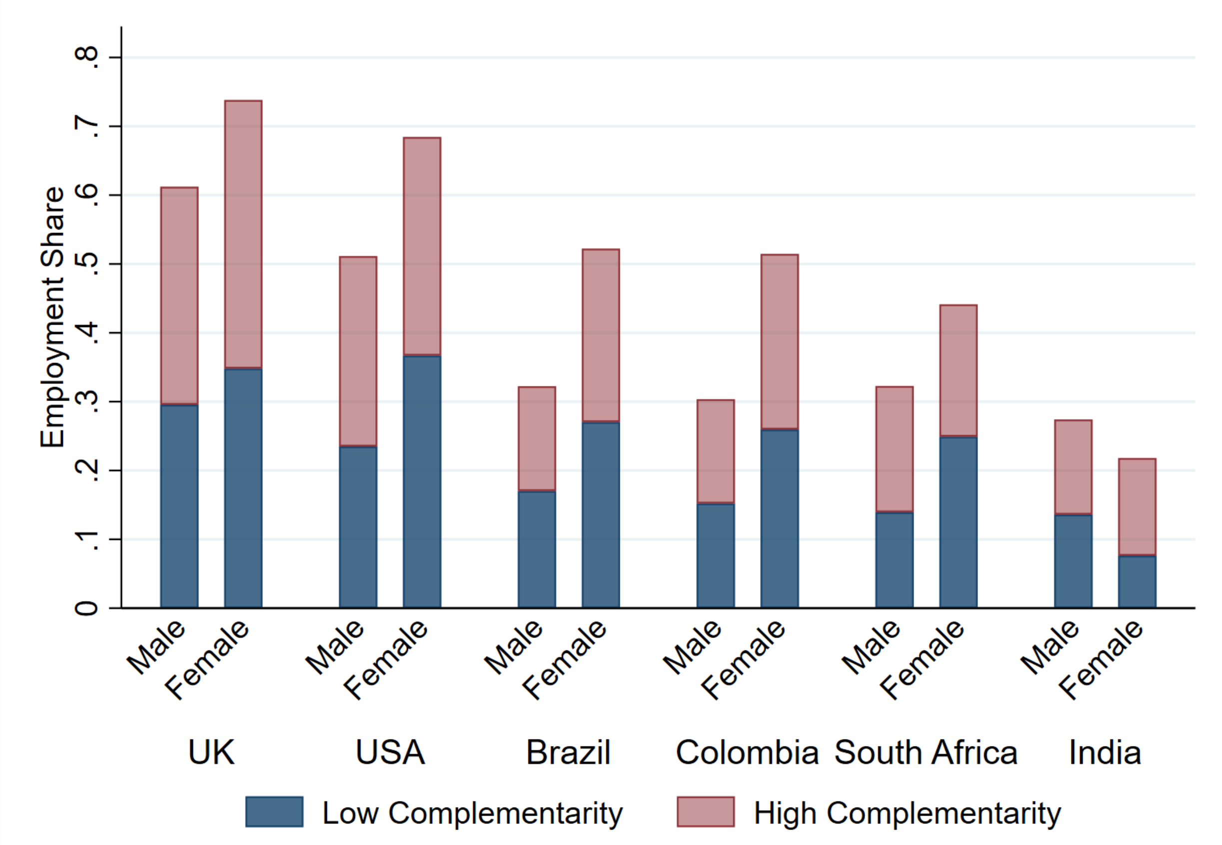
**Employment Share by AI Exposure and Complementarity by Occupation Groups**



# Within-country differences: Gender

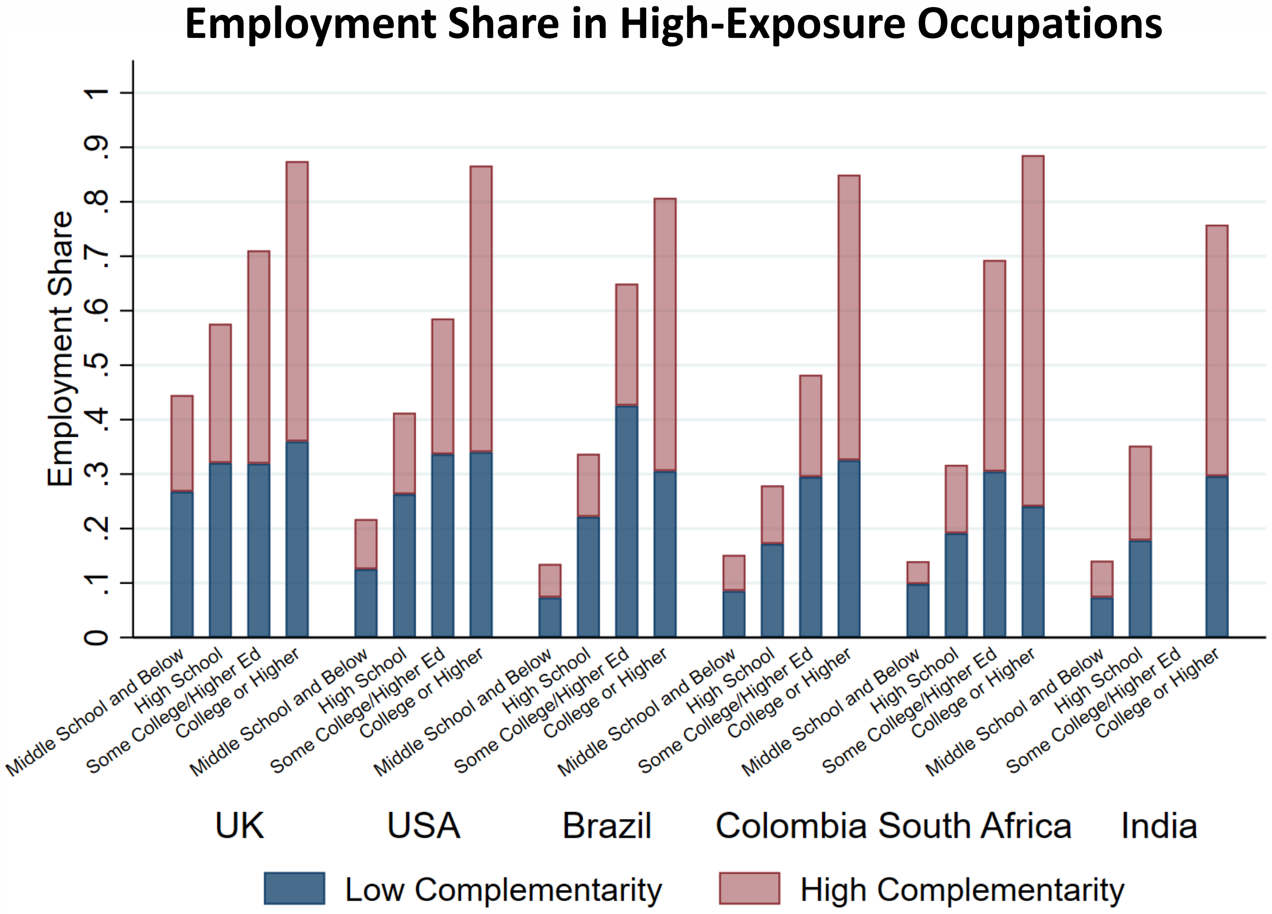
- Females are more likely to work in high exposure occupations.

Employment Share in High-Exposure Occupations



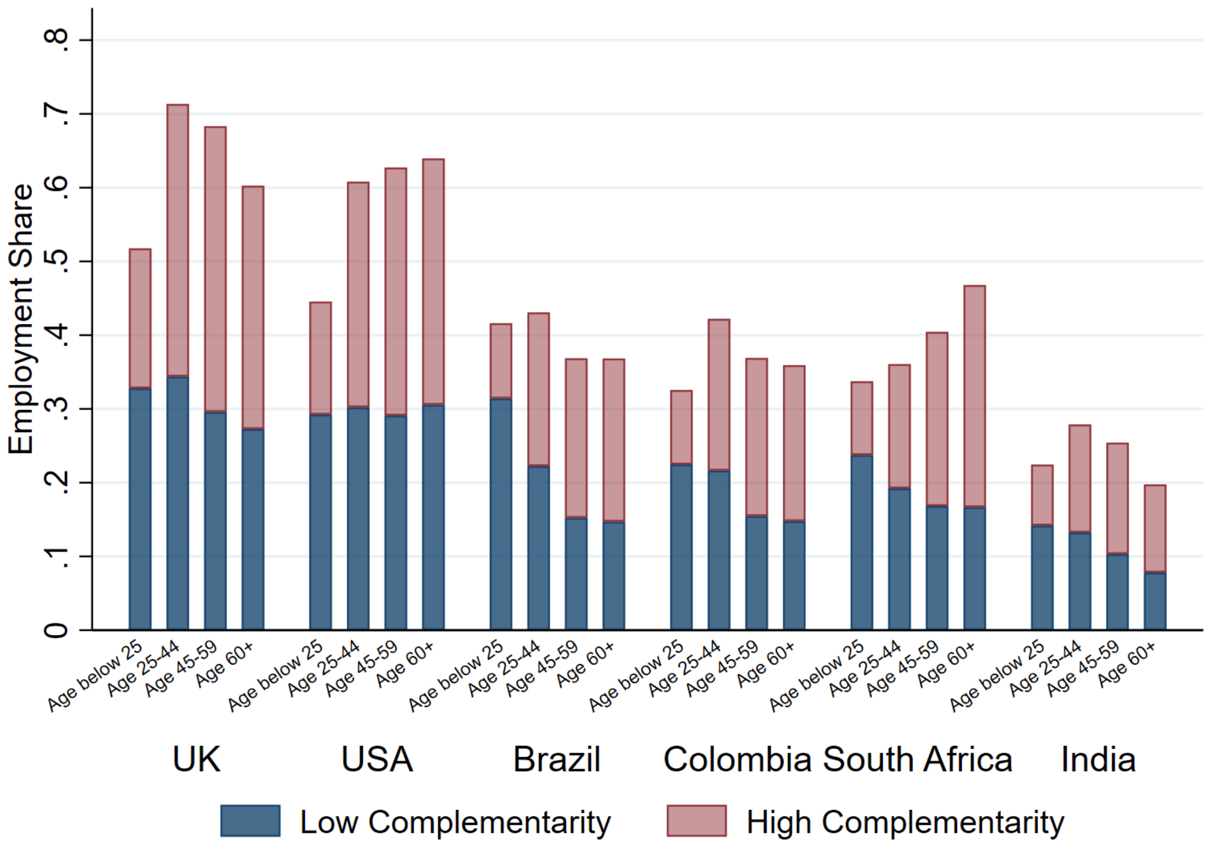
# Within-country differences: Education

- High-educated workers are more likely to work in high exposure occupations.



# Within-country differences: Age

**Employment Share in High-Exposure Occupations**



# Within-country differences: Income

- When controlling by complementarity, the risk of AI displacement are equally distributed across the income distribution, while the gains are concentrated at the top.