GEN-AI: ARTIFICIAL INTELLIGENCE AND THE FUTURE OF WORK

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Motivation and Questions

- Artificial Intelligence (AI) is set to profoundly change the global economy, with some commentators seeing it as akin to a new industrial revolution.
- The SDN examines the implications of AI adoption across AEs and EMDEs, exploring its potential to displace and complement human labor. The SDN also assesses the potential effects of AI on inequality and productivity and evaluates countries' preparedness to adopt AI.

Question 1:

Which countries are more exposed to AI adoption? Which countries are likely to benefit most?

Question 2:

How differently will AI impact workers within countries? Which segments of workers are likely to thrive, and which face more risks?

Question 3:

Historically, how frequently did workers shift between roles now facing varying AI-exposure? What insights do these shifts reveal about labor adaptability?

Question 4:

In what ways could AI reshape income and wealth inequality?

Question 5:

What is the potential impact for growth and productivity?

Question 6:

Which countries appear better prepared for the AI transition? How can policies maximize gains and mitigate likely AI-related challenges?

Main findings

Almost 40% percent of global employment is exposed to AI.

- 60% of AE jobs are exposed to AI, 40% in EMs (same as in the Arab League), and 26% in LICs, mostly cognitive roles.
- AI may negatively affect half of these jobs; the other half could gain productivity.
- AEs are generally at greater risk but also better poised to exploit AI benefits than EMDEs.

AI may lead to higher income and wealth inequality.

- AI complementarity is highly correlated with income.
- AI may increase capital returns.

To harness AI's potential fully, priorities depend on countries’ development levels.

- AEs and some EMs are ahead in AI readiness compared to LICs.
- AEs and some EMs should focus on AI regulation and invest in AI innovation and integration.
- EMDEs need digital infrastructure and training.

AI Exposure and Complementarity

Measuring exposure to and complementarity with AI

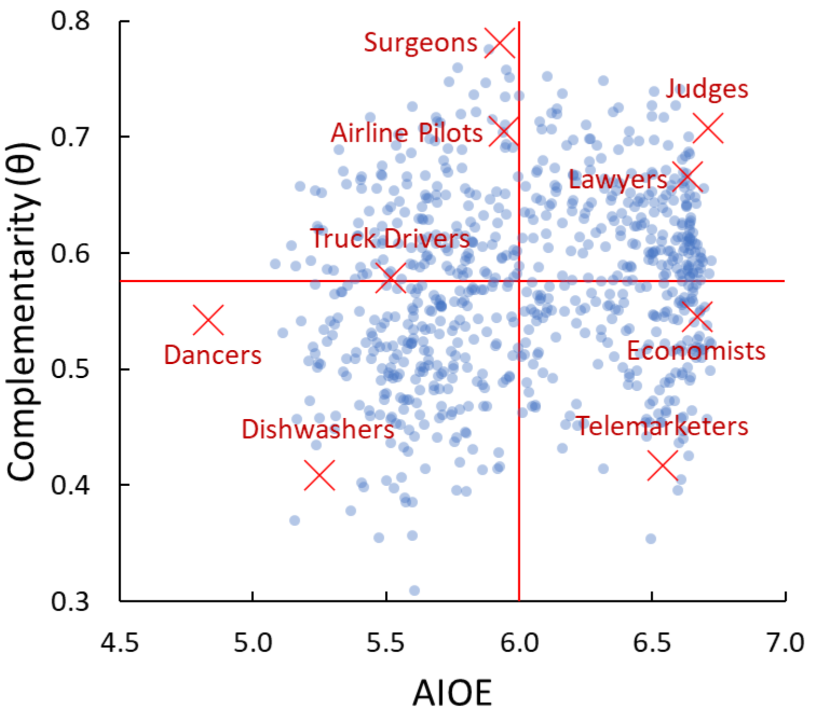
- **Exposure to AI:** Degree of overlap between AI applications and human abilities in occupations (Felten et al., 2021;2023).

- **Complementarity (or Shielding) Index:** Leverage two parts of the O*NET capturing "work context" and "skills." Group into 6 categories:

- **a. Communication:** Face-to-Face, and public speaking
- **b. Responsibility:** Responsibility for outcomes and others' health
- **c. Physical Conditions:** Outdoors exposed, and physical proximity
- **d. Criticality:** Consequence of error, freedom and frequency of decisions
- e. **Routine:** Degree of automation, and unstructured vs structured Work
- **f. Skills:** Job zone (level of education, training and skills needed)

- **Examples:**
  - Judges: High AI exposure yet shielded by societal norms and laws—AI may complement their work, enhancing productivity.
  - Clerical Workers: High AI exposure with low shielding—higher displacement risk.

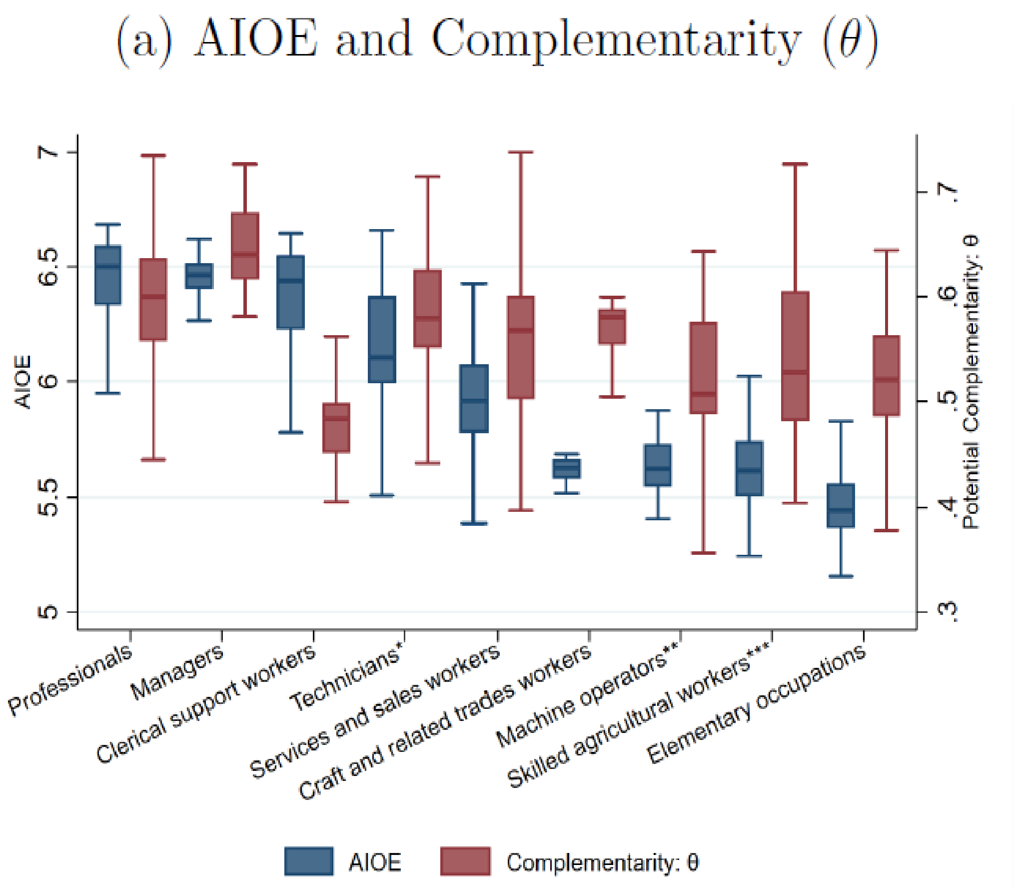
Conceptual Diagram of AI Exposure (AIOE) and Complementarity (θ)



Sources: Felten, Raj, and Seamans (2021); Pizzinelli and others (2023); and IMF staff calculations.
Note: Red reference lines denote the median of AIOE and complementarity.

AI Exposure and Complementarity by Occupations

AI Complementarity and Exposure across Major Occupation Groups



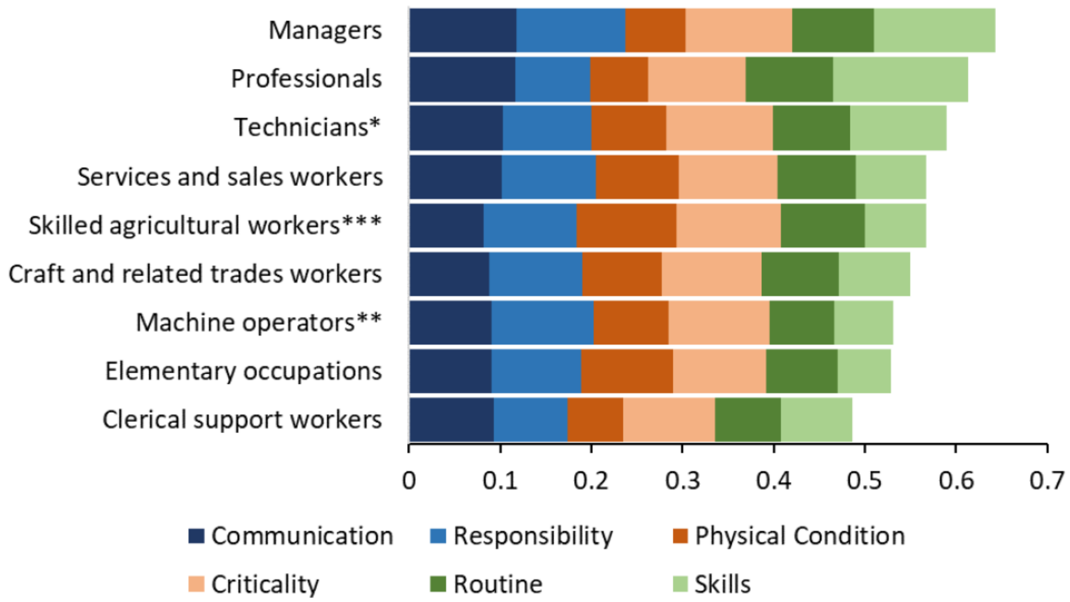
Robustness Checks

- 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

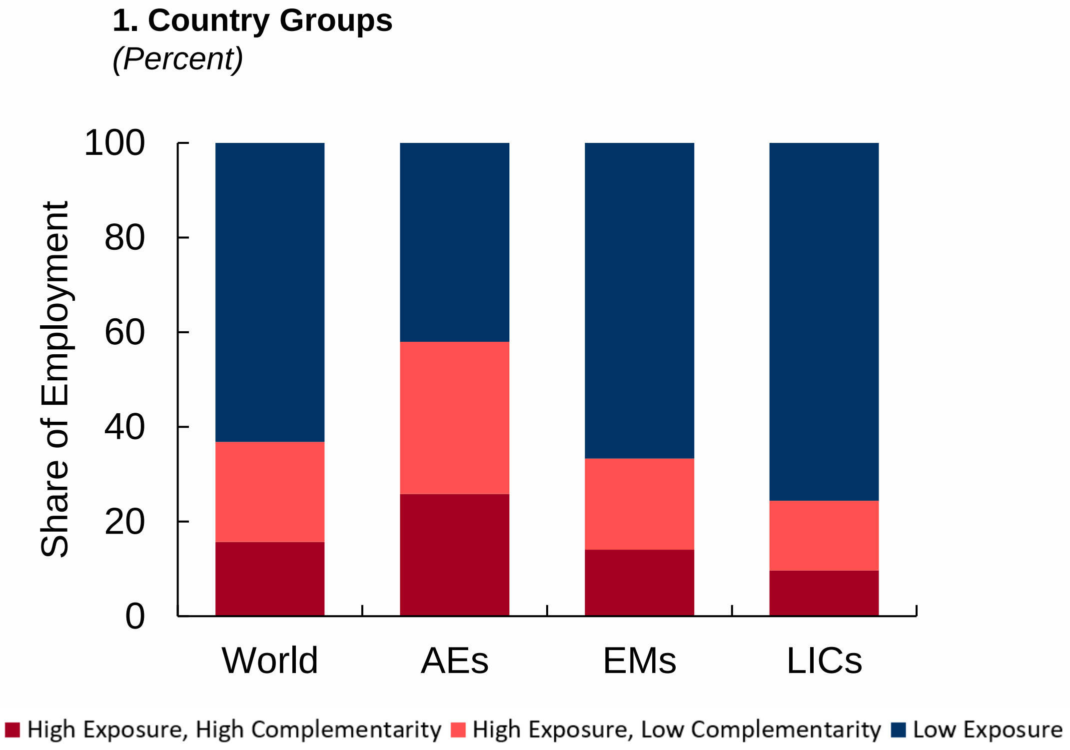


Note: The figure plots the average contribution of each component of θ among occupations in each 1-digit ISCO-08 occupation code. *: Technicians and associate professionals. **: Plant and machine operators and assemblers. ***: Skilled agricultural, forestry and fishery workers.

AI and Labor Markets across Countries

About forty percent of workers worldwide and sixty percent in AEs is in high-exposure occupations

Employment Shares by AI Exposure and Complementarity

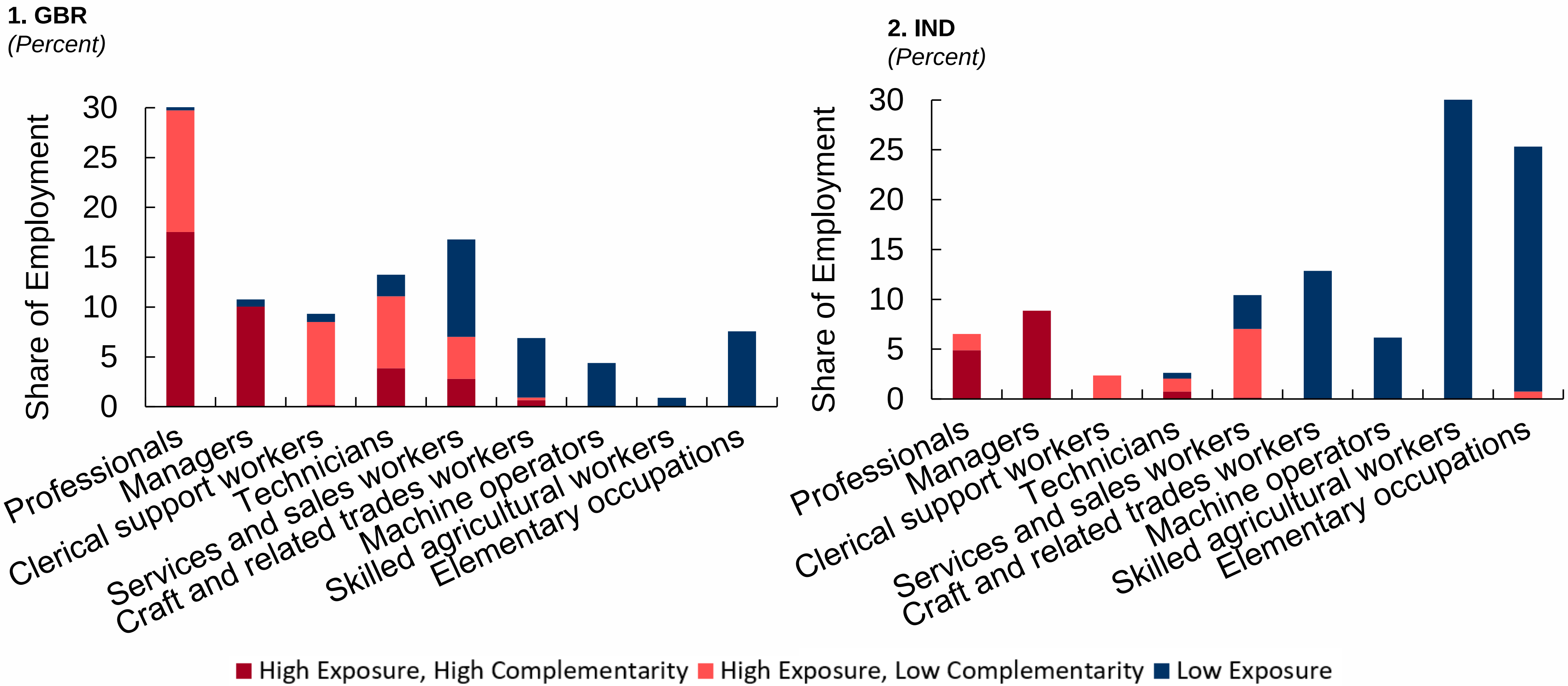


Sources: American Community Survey (ACS); Gran Encuesta Integrada de Hogares (GEIH); India Periodic Labour Force Survey (PLFS); International Labour Organization (ILO); Labour Market Dynamics in South Africa (LMDSA); Pesquisa Nacional por Amostra de Domicílios Contínua (PNADC); UK Labour Force Survey (LFS); and IMF staff calculations.
Note: Country labels use International Organization for Standardization (ISO) country codes. ISCO stands for International Standard Classification of Occupations. AEs = advanced economics; EMs = emerging markets; LICs = low-income countries; World = all countries in the sample. Share of employment within each country group is calculated as the working-age-population-weighted average.

- AI exposure and complementarity varies by income group:
  - AEs: 27% high-complementarity; 33% low complementarity jobs;
  - EMs: 16% high-complementarity; 24% low complementarity jobs;
  - LICs: 8% high-complementarity; 18% low complementarity jobs.
- AEs dominate in cognitive-intensive roles, potentially facing more immediate AI job disruption.
- However, AEs also have a stronger position to harness AI's growth potential.
- With appropriate digital infrastructure, AI could help EMDEs mitigate skill shortages.

Labor force composition in terms of broad occupational groups largely explains the differences in exposure and complementarity across countries

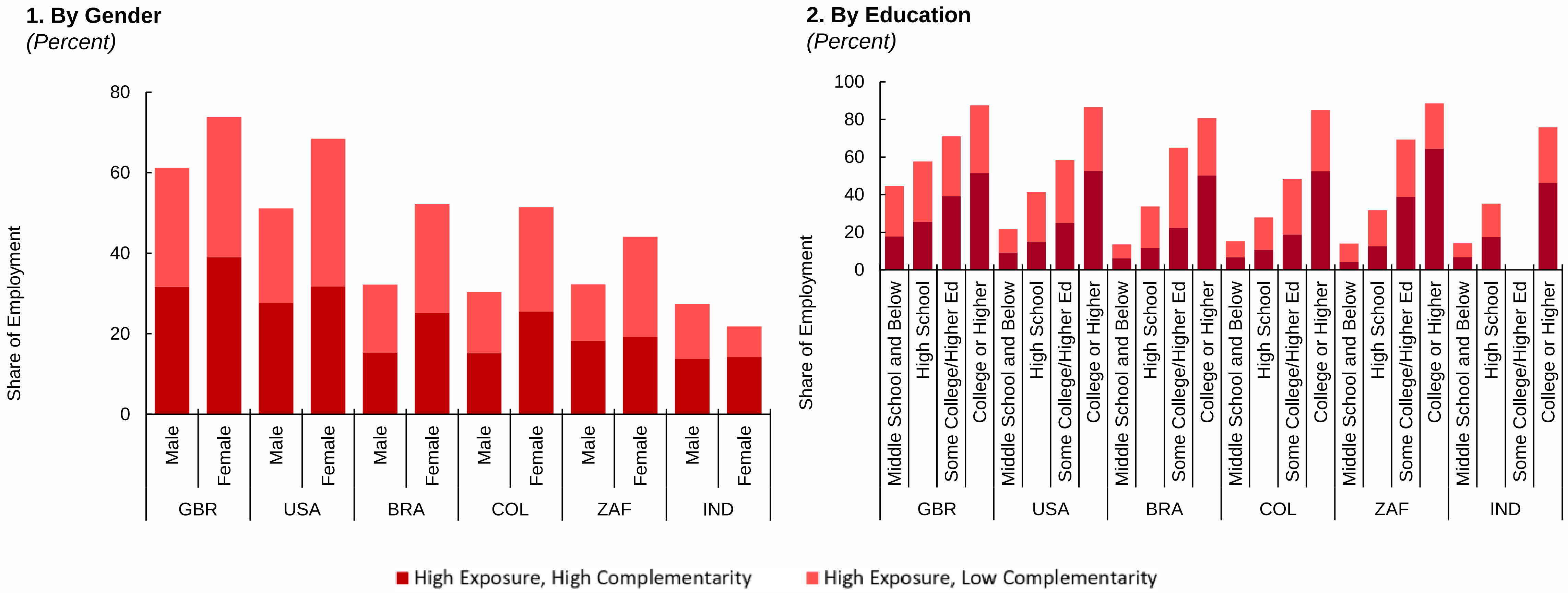
Employment Share by Exposure and Complementarity



Sources: India Periodic Labour Force Survey (PLFS); Pesquisa Nacional por Amostra de Domicílios Contínua (PNADC); UK Labour Force Survey (LFS); and IMF staff calculations.
Note: The charts plot the total employment share by each of the nine 1-digit ISCO-08 occupation codes. Country names use International Organization for Standardization (ISO) country codes. ISCO stands for International Standard Classification of Occupations.

Exposure is higher for women and for more educated workers, but is mitigated by a higher potential for complementarity with AI

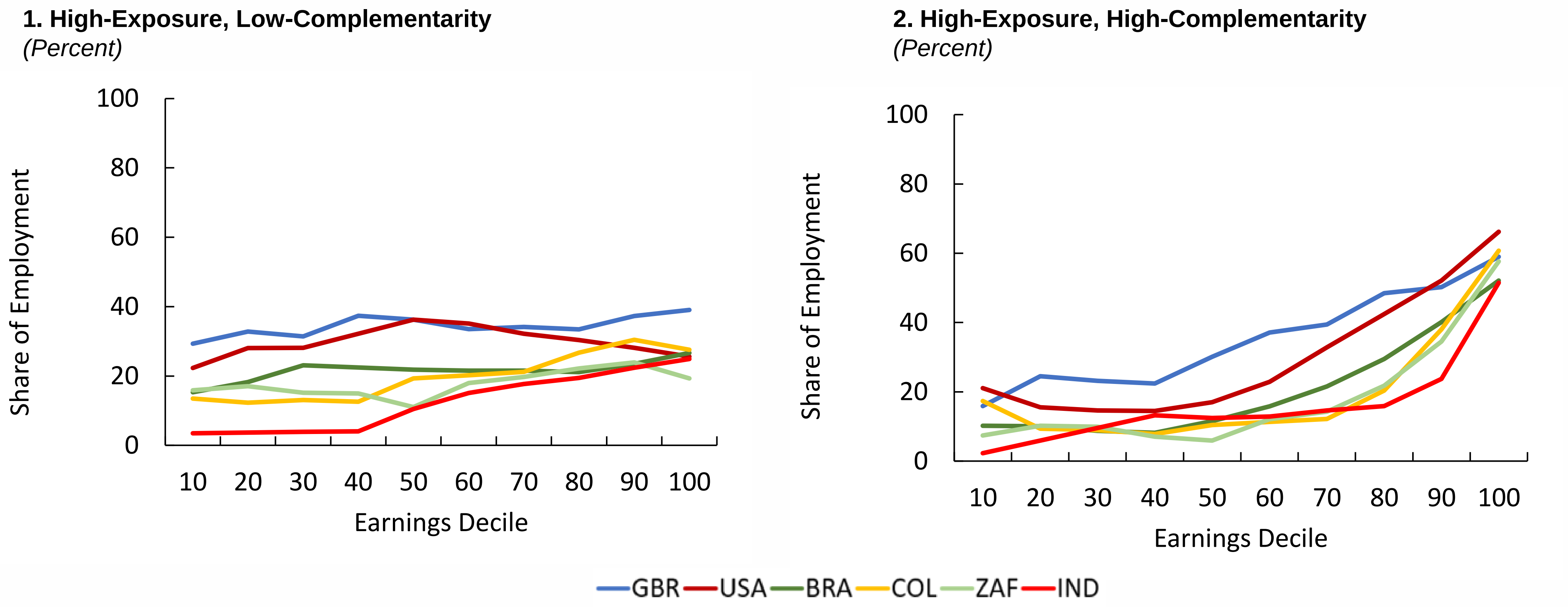
Share of Employment in High-Exposure Occupations by Demographic Groups



Sources: American Community Survey (ACS); Gran Encuesta Integrada de Hogares (GEIH); India Periodic Labour Force Survey (PLFS); Labour Market Dynamics in South Africa (LMDSA); Pesquisa Nacional por Amostra de Domicílios Contínua (PNADC); UK Labour Force Survey (LFS); and IMF staff calculations.
Note: The bars in both plots represent employment shares in high-exposure occupations. In plot 1, employment shares are conditional on each gender category. In plot 2, employment shares are conditional on each of the four education categories (Middle School and Below, High School, Some College and College). In plot 3, employment shares are conditional on each of the four age intervals. Country labels use International Organization for Standardization (ISO) country codes.

Exposure is spread along the labor income distribution but potential gains from AI are positively correlated with income

Share of Employment in High-Exposure Occupations and Potential Complementarity by Income Deciles



Sources: American Community Survey (ACS); Gran Encuesta Integrada de Hogares (GEIH); India Periodic Labour Force Survey (PLFS); Labour Market Dynamics in South Africa (LMDSA); Pesquisa Nacional por Amostra de Domicílios Contínua (PNADC); Pizzinelli and others (2023); UK Labour Force Survey (LFS); and IMF staff calculations.
Note: Panel 1 shows the employment share in jobs with high exposure but low complementarity, and Panel 2 presents the employment share in jobs with high exposure and high complementarity, each categorized by income deciles. Panel 3 shows the potential AI occupational complementarity from Pizzinelli and others (2023), averaged and grouped by income deciles. Country labels use International Organization for Standardization (ISO) country codes.

Potential for Worker Reallocation in the AI-Induced Transformation: Evidence from Historical Transitions

Brazil has more dynamic labor market than the UK

Overview:

- Quarterly employment flow and job mobility analysis.
- Focus on transitions between employment statuses and within employed workers.

UK Highlights:

- High employment stability: 97.8% remain employed.
- Job and occupation persistence: 87.3% keep same job and occupation, 11% experience occupation switching.

Brazil Highlights:

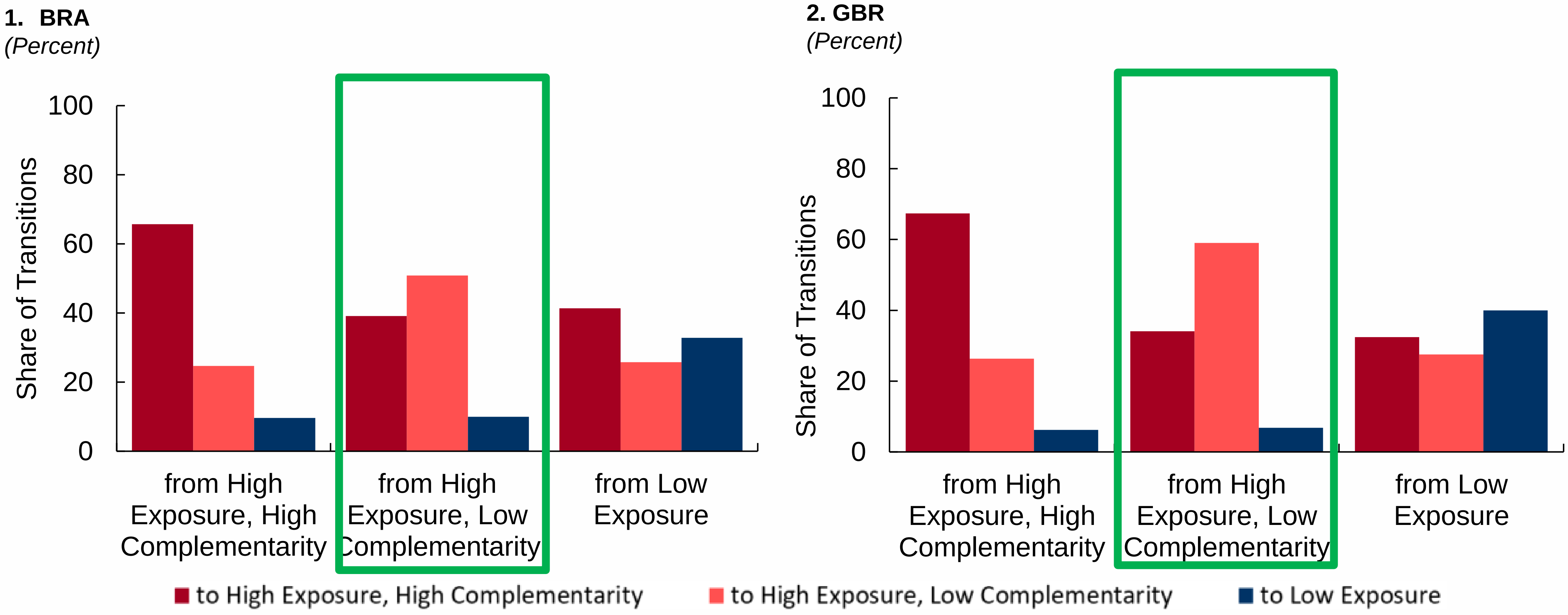
- Lower employment stability: 90.7% remain employed.
- Greater occupational mobility: 65% keep same job and occupation, 34% experience occupation switching .

Comparative Insights:

- UK: Greater status persistence and job stability.
- Brazil: Higher fluidity and occupational mobility, indicating a more dynamic labor market.

Workers with college education have historically shown a greater ability to transition into what are now jobs with high AI-complementarity potential

Occupational Transitions for College-Educated Workers



Sources: Pesquisa Nacional por Amostra de Domicílios Contínua (PNADC); UK Labour Force Survey (LFS); and IMF staff calculations.
Note: "From" indicates the exposure category of the occupation the individual had in the preceding quarter, while "to" indicates the exposure category of the occupation the worker transitioned to. The share of transitions represents the average share of transitions in the "from" category for college-educated workers that go to the "to" category. Country names use International Organization for Standardization (ISO) country codes.

Wage Impact of Occupational Change

1.Model Equation:

$$\Delta \log(y_{irt}) = \delta_1 J2J_{irt} + \delta_2 OS_{irt} \times J2J_{irt} + \delta_3 EUE_{irt}$$
$$+ \sum_k \theta_k C_{k,ir(t-1)} C_{k,irt} + \sum_k \sum_j OS_{irt} \phi_{kj} C_{k,ir(t-1)} C_{j,irt}$$
$$+ \beta X_{irt} + \gamma_t + \eta_r + \epsilon_{irt}$$

Variable Definitions:

- $yirt$: Hourly wages.
- OS: Dummy for occupation switches.
- $J2J$: Dummy for job switches.
- EUE: Dummy for transitions through unemployment.
- $Xirt$: Matrix of demographic covariates, including age-education interactions.
- γt,ηr: Year-quarter and region fixed effects.

2.Coefficients Explained:

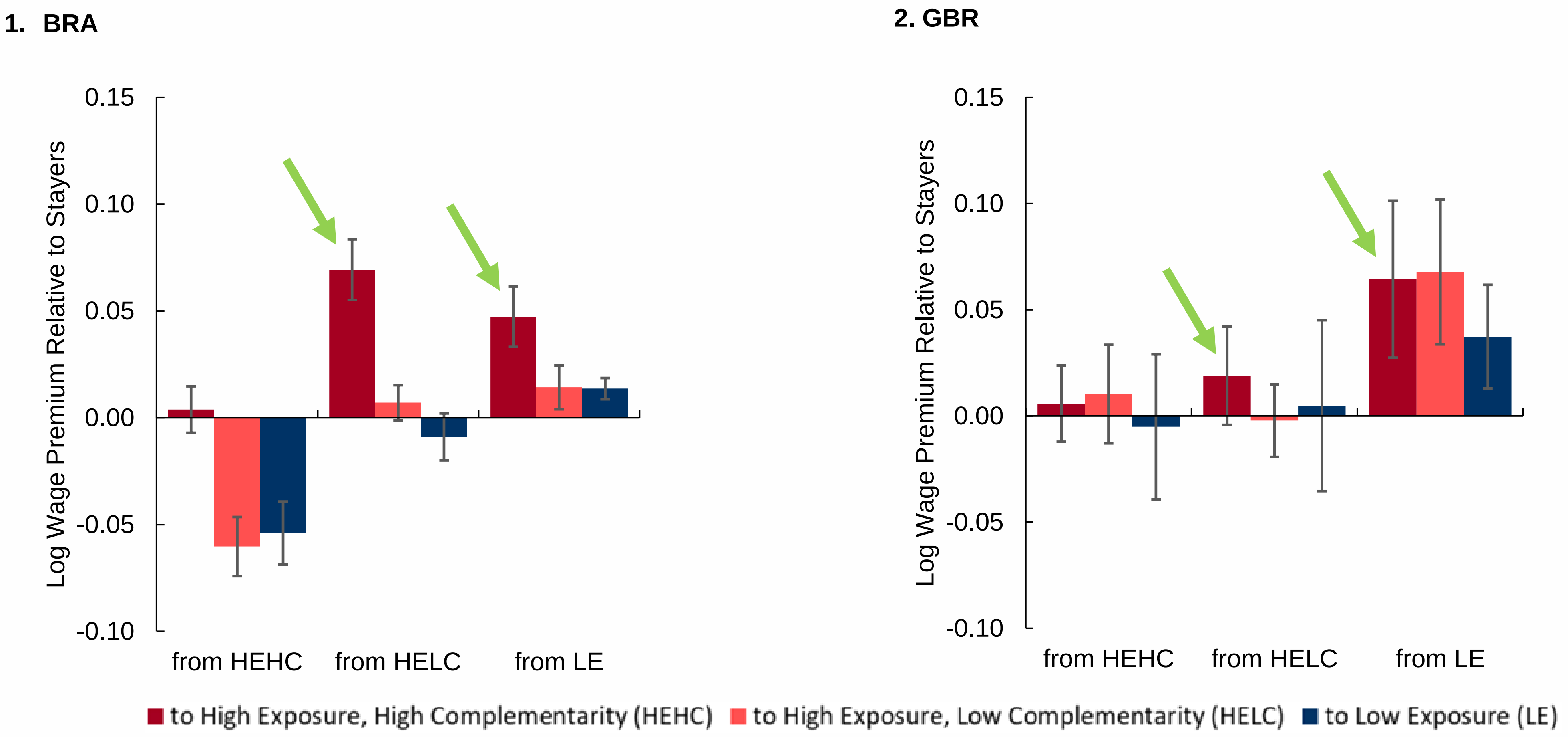
- θk: Average log wage change for workers who did not change occupation in category k.
- ϕkj: Average log wage change for workers switching from occupation k to j.

3.Key Insight:

- Focus on wage premium for workers switching exposure categories compared to "stayers".
- Example: Wage premium for switching from HELC to HEHC computed as $\phi HELC,HEHC - \theta HELC$.

Occupation switches also affect workers' incomes

Estimated Wage Premia from Occupation Changes



Sources: Pesquisa Nacional por Amostra de Domicílios Contínua (PNADC); UK Labour Force Survey (LFS); and IMF staff calculations.
Note: "From" indicates the exposure category of the occupation the individual had in the preceding year, while "to" indicates the exposure category of the occupation the worker transitioned to. The premia are "relative to stayers", that is, they represent the increase or decrease in wages in relation to workers in the "from" category that did not switch occupations over a year. Wage premia are calculated according to the regression specification in Annex 2. 95% confidence intervals for the point estimates are shown in bars. Country names use International Organization for Standardization (ISO) country codes.

Modeling Employment Across The Life-Cycle

Objective:

- Estimate the probability of employment in occupations as a function of worker's age (Dabla-Norris et al. (2023).

Methodology:

- Employ cubic polynomial regression to model employment probability.

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

1. *$C_{k,it}$*: Employment status in occupation exposure category k (HEHC, HELC, LE).
2. Age effect modeled through linear, quadratic, and cubic terms.
3. Includes gender and year-quarter fixed effects.

Parameters Explained:

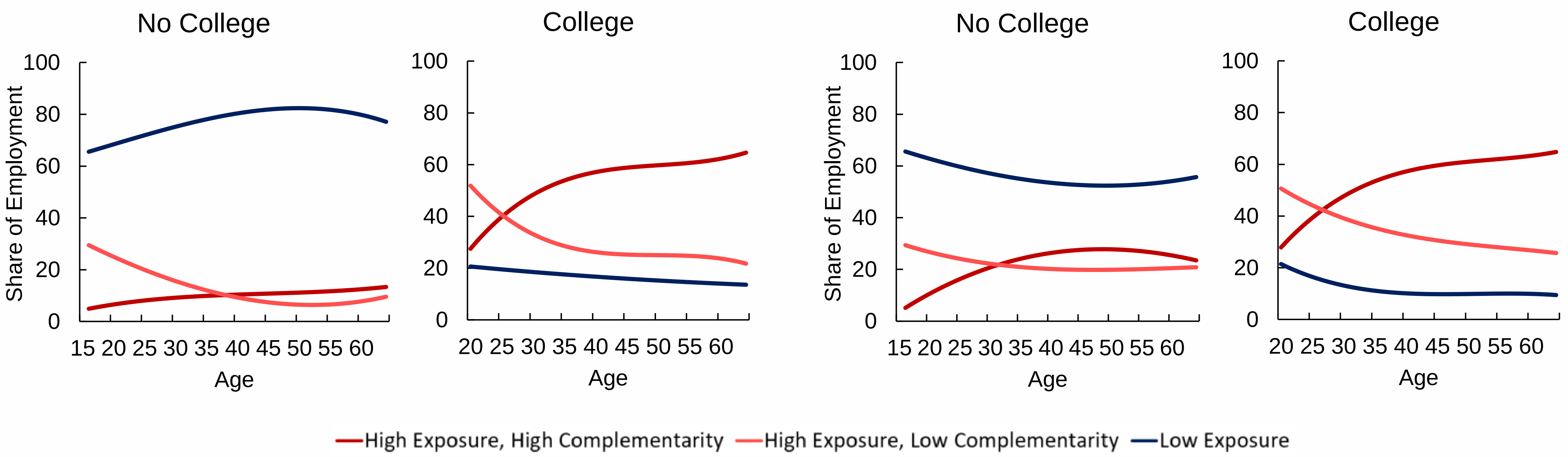
1. $\beta_0, \beta_1, \beta_2, \beta_3$: Coefficients for baseline probability and age effects.
2. δ: Gender dummy variable.
3. γ_t: Year-quarter fixed effects to control for time-specific variations.

AI adoption both poses challenges and represents an opportunity for young college-educated workers' careers

Life Cycle Profiles of Employment Shares by Education Level

1. BRA
(Percent)

2. GBR
(Percent)



Sources: Pesquisa Nacional por Amostra de Domicílios Contínua (PNADC); UK Labour Force Survey (LFS); and IMF staff calculations.
Note: The figures plot the estimated share of employment by age for each exposure category for college and non-college educated workers, according to the calculations described in Annex 3. Country names use International Organization for Standardization (ISO) country codes.

AI, Productivity, and Inequality

Model-based analysis of AI's economic impact

- **Task-based model** by Rockall, Pizzinelli and Tavares (2023) assesses effects on income distribution and wider economic impacts stemming from AI adoption. The Model builds on the work of Moll, Rachel and Restrepo (2022) and Drozd, Taschereau-Dumoucheland, and Tavares (2023)

- Model incorporates differences in labor productivity, asset holdings, AI exposure, and complementarity.

- **Four critical channels of impact of AI** are identified:
  1. **Labor displacement**: Shift of tasks from human labor to AI capital, reducing labor income.
  2. **Complementarity**: Value added shifts to AI-complementary occupations, increasing labor demand for these occupations and reducing it for others.
  3. **Productivity gains**: Overall economic boost potentially offsets labor income losses.
  4. **Capital income:** AI adoption leads to increases in the return of capital, raising capital income further.

- Calibration to the UK Economy.

Model Intuition

- To be more specific, the model aggregates to the following Cobb-Douglas production function:

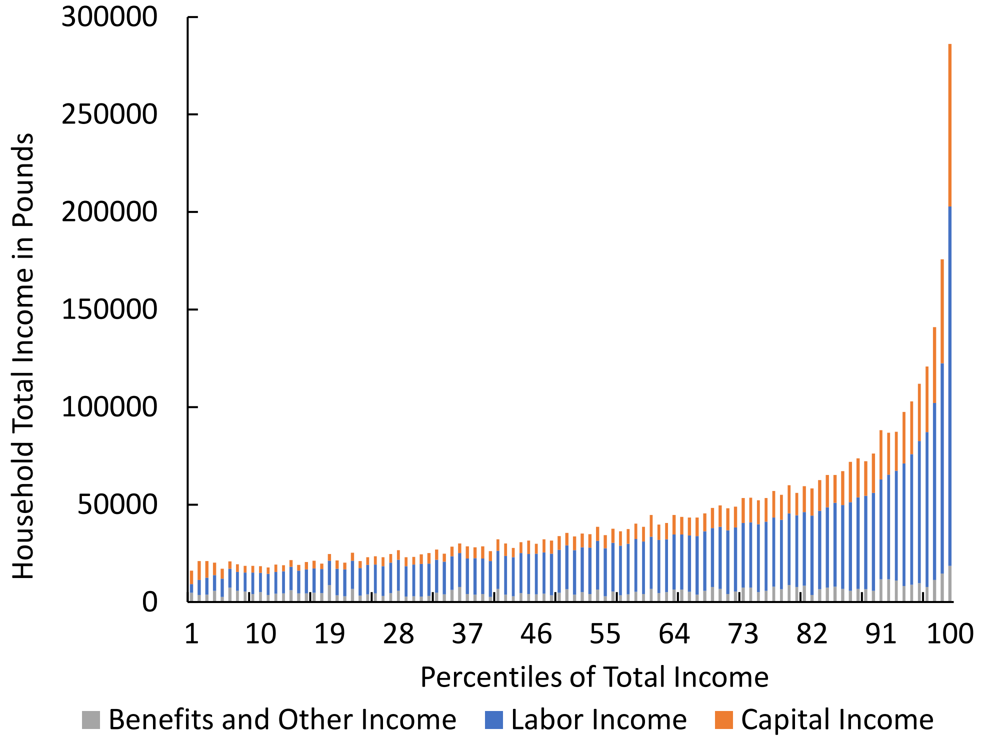
$$Y(K) := AK^{\sum_z \alpha_z \eta_z} \prod_z (\psi_z \ell_z)^{(1-\alpha_z)\eta_z},$$

- η_z denotes the importance in value added of the tasks performed by skill z
- ψ_z denotes the productivity of labor for these tasks
- K denotes the aggregate stock of capital in the economy
- α_z is the labor share at skill z

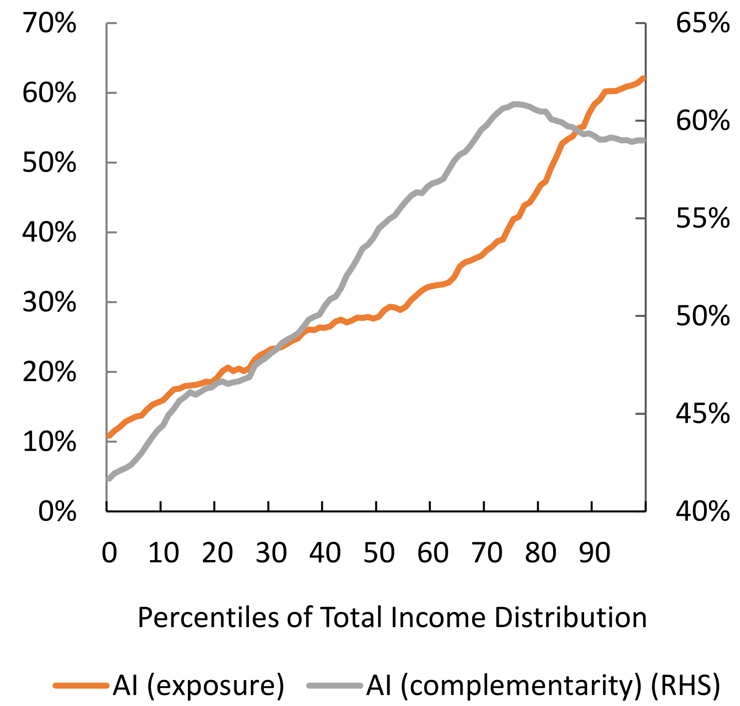
While middle and low-income workers' total income depends mostly on wage income, high-income workers have a large share of capital income.

Exposure to AI and to Automation and Income in the UK

1. Exposure of Income to AI
(Pounds Sterling)



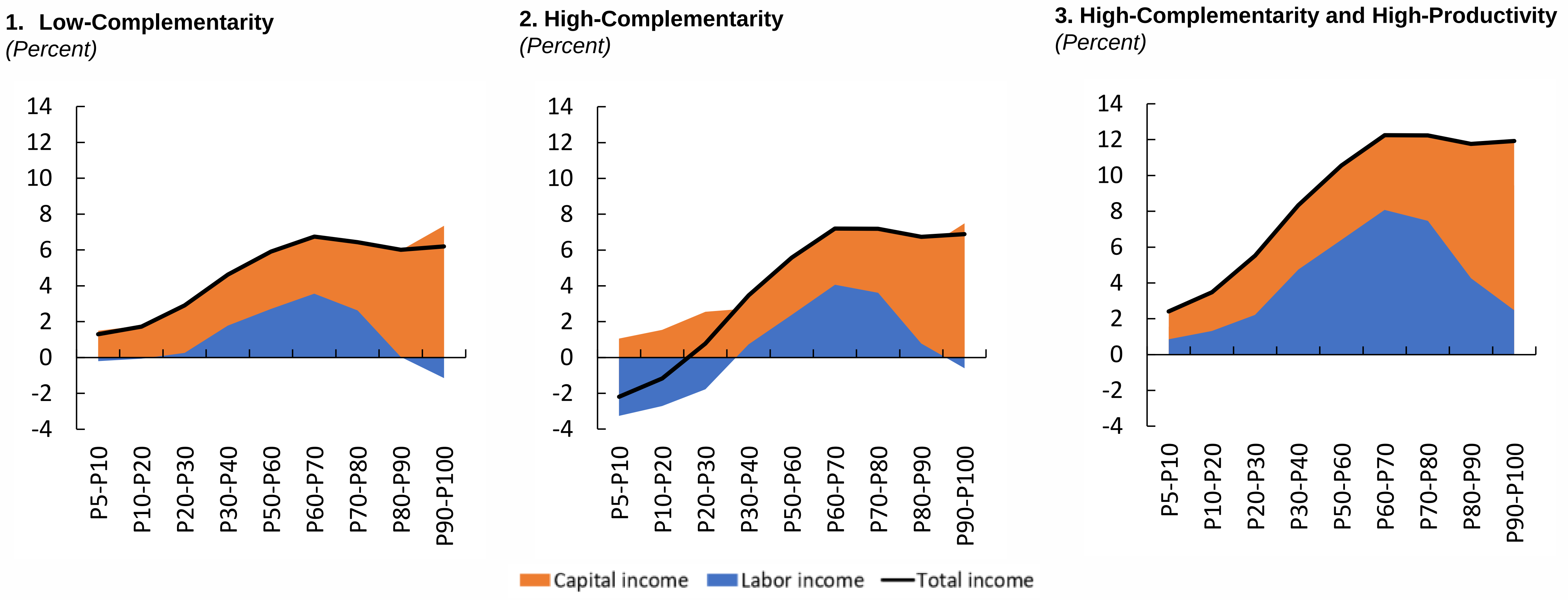
2. Exposure and Complementarity by Income Percentiles
(AI and Complementarity Index)



Sources: Wealth and Assets Survey (WAS); and IMF Staff calculations.
Note: Plot 1 reports three categories of workers' income by total income percentiles: (i) wage income, (ii) benefits, pensions, and other income, and (iii) capital income (rents and estimated investment income). In plot 2, AI exposure is measured as the share of total hours worked in a job in the top 30% of AI Occupational Exposure (AIOE) scores, from Felten, Raj, and Seamans (2021), weighted by hours worked. This threshold is chosen to make the analysis comparable to historical episodes of automation. AI complementarity is measured by considering the work contexts and skills, as discussed in Box 1 and in detail in Pizzinelli and others (2023). In the panel, we plot AI exposure and complementarity by total income percentiles.

The impact of AI on labor income inequality depends on the degree of exposure to, and complementarity with, AI and its boost to productivity

Change in Total Income by Income Percentile Under Three Scenarios



Sources: IMF staff calculations

Note: The plots represent three scenarios from the model: (i) low-complementarity, (ii) high-complementarity, and (iii) high- complementarity and high productivity. For all scenarios, the calibrated change in the capital share is the same: 5.5pp, based on the change in the capital share from 1980-2014. The plots show the change in total income by income percentile, decomposed into the change in labor income in blue and the change in capital income in red. For more details on the model see SDN Annex 4.

Under the high-complementarity-high-productivity scenario, the increase in total national income is largest and benefits all workers, although gains are larger for those at the top.

Impact on Aggregates
(Percentage Point on LHS; Percent on RHS)

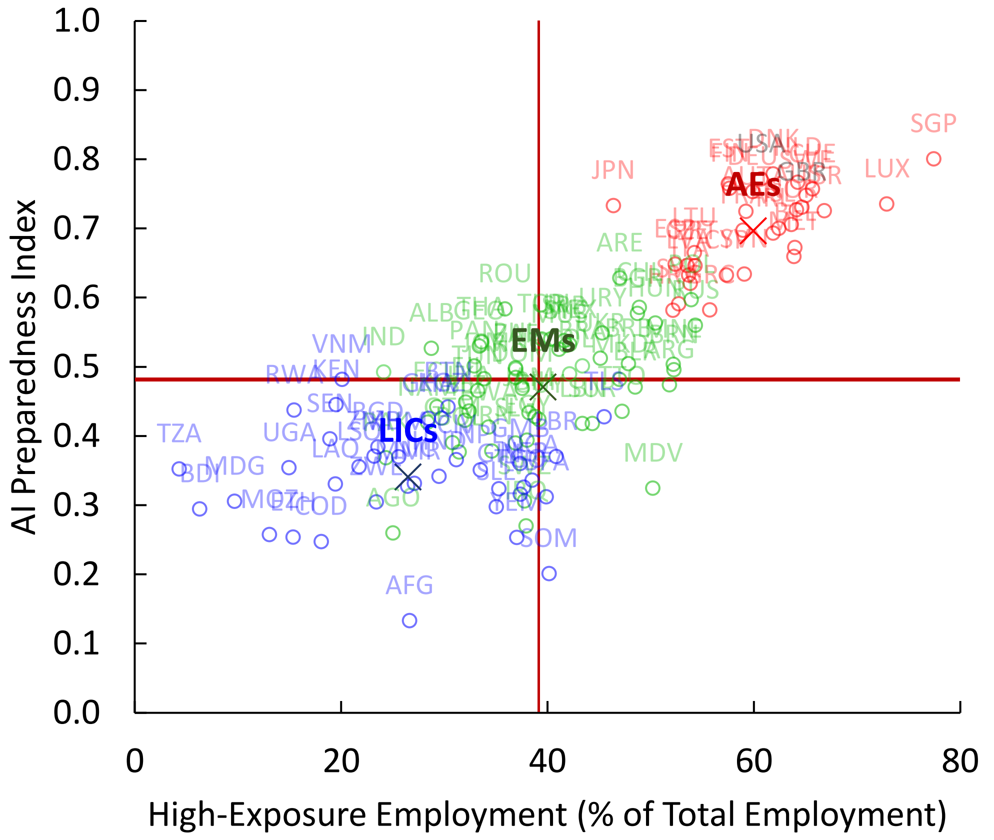
Sources: IMF Staff calculations.
Note: The figure shows the change in the aggregate wage and wealth Gini between the initial and final distribution in each scenario, as well as the change TFP and output. For more details on the model see SDN Annex 4. TFP = total factor productivity.

- **Scenario 1:** *Low AI Complementarity*
  - Output increases by nearly 10%
- **Scenario 2:** *High AI Complementarity*
  - Sectoral shift towards high-complementarity occupations.
  - Income increase is similar to first scenario; wage inequality rises.
- **Scenario 3***: High Productivity Impact*
  - Output surges by 16%.
  - Income level rises for all workers

AI Preparedness

Higher-income economies, including AEs and some EMs, are generally better prepared than LICs to adopt AI

AI Preparedness Index and Employment Share in High-Exposure Occupations



Sources: International Labour Organization (ILO); and IMF staff calculations.
Note: The plot includes 125 countries: 32 AEs, 56 EMs, and 37 LICs. The red reference lines are derived from the median values of the AI preparedness index and high-exposure employment. Circles represent the average values for each respective country group. Crosses denote the average values for each corresponding country group AEs = advanced economics; EMs = emerging markets; LICs = low-income countries. Country labels use International Organization for Standardization (ISO) country codes.

- **AI Preparedness Index (AIPI)** measures readiness across multiple strategic AI adoption areas.
- Builds on cross-country technology diffusion and adoption research (Keller, 2004; Nicoletti et al., 2020).
- Index includes macro-structural indicators under **four themes**:
  1. **Digital infrastructure:** basis for AI tech diffusion and application.
  2. **Innovation and economic integration:** promotes R&D and global trade, attracting investments.
  3. **Human capital and labor market policies:** digital skill distribution and policies for labor transitions.
  4. **Regulation and ethics:** legal framework's adaptability and governance for enforcement.

Dimensions of AI Preparedness & Data Requirements

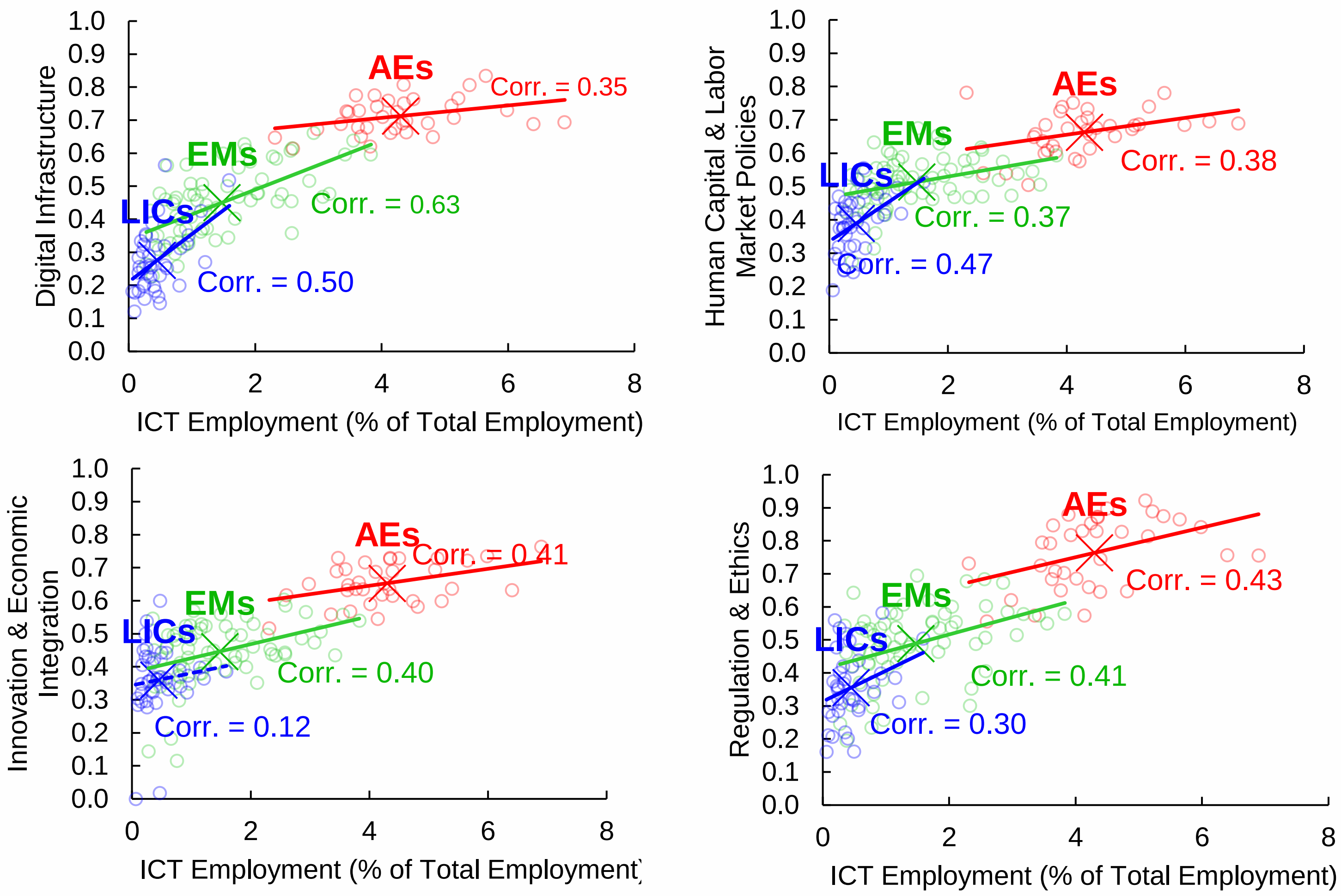
Dimension	Indicator
1. FOUNDATIONAL AI PREPAREDNESS	
I. Digital Infrastructure	
Accessible, Affordable, and secured Internet Access	- Estimated internet users per 100 inhabitants [UN] - Number of main fixed telephone lines per 100 inhabitants [UN] - Number of mobile subscribers per 100 inhabitants [UN] - Number of fixed broadband subscriptions per 100 inhabitants [UN] - Number of wireless broadband subscriptions per 100 inhabitants [UN] - Cost of internet access (percent of monthly GNI per capita) [ITU] - Secure Internet servers per 1 million people [WB]
Mature e-commerce infrastructure	- Private Sector's E-commerce Business Environment o Postal Reliability Index [UPU] o Use of mobile phone for online transactions (% of population ages 15+) [WB] - Public Sector's Online services Infrastructure [UN]
II. Human Capital and Labor Market Policies	
Education and digital skills	- Human Capital Index (i.e., mean years of schooling; expected years of schooling; gross enrolment ratio; adult literacy) [UN] - Public Education Expenditure (10-year average; %GDP) [WB] - Skillset of graduates (proxy for equality of education) [WEF] - Digital skills among active population (e.g., computer skills; basic coding, etc.) [UN] - Number of STEM graduates (10-year average; % of total graduates) [WB] - Number of female STEM graduates (10-year average; % of STEM graduates) [WB]
Labor Market Flexibility & Policies	- Flexibility of wage determination (centralized vs individual firm level) [WEF] - Social protection (% of population covered by social protection schemes) [ILO] - Internal labor market mobility [WEF] - Active labor market policies (e.g., skills matching, retraining) [WEF] - Pay and productivity (i.e., extent to which wages are market determined) [WEF]
2. SECOND-GENERATION AI PREPAREDNESS	
III. Innovation & Economic Integration	
Innovation	- R&D spending per unit of GDP [WB] - Frontier Technology Readiness (i.e., AI related R&D activity: number of scientific publications; number of patents on frontier technologies) [UN] - Domestic credit to private sector (%GDP) [WB]
Economic Integration	- Mean Tariff Rate [FI] - Non-tariff barriers [FI] - Free movement of capital and people (average of three indicators: financial openness; capital controls, and freedom of foreigners to visit) [FI]
IV. Regulation and Ethics	
Strong legal frameworks and enforcement mechanisms	- Legal framework's adaptability to digital business models [WEF] - Overall governance (proxy for enforcement/accountability) [WB]

Main Sources of Data for the AIPI Index

- International Labor Organization
- International Telecommunication Union
- United Nations
- Universal Postal Union
- World Bank
- World Economic Forum
- Fraser Institute

Reform prioritization should align with AI preparedness gaps, which vary across the development spectrum

ICT Employment Share and Individual Components of the AI Preparedness Index



Policy prioritization should distinguish between:

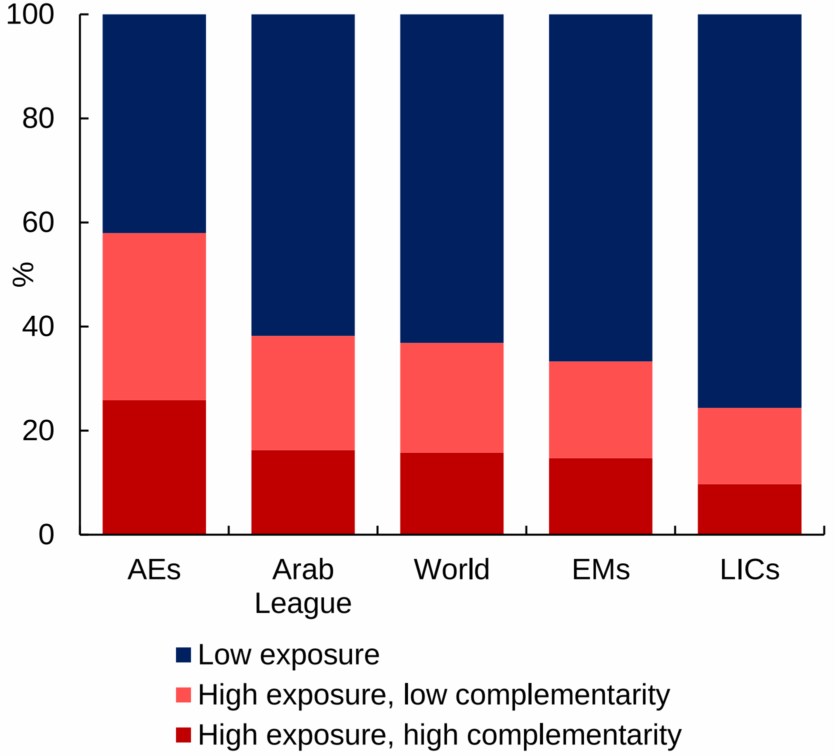
- **Foundational AI preparedness** (digital infrastructure and human capital that enable workers and firms for AI adoption) is crucial for LICs and many Arab League countries.

- **Second-generation preparedness** (innovation and legal frameworks) is crucial for AEs (and some EMs, including in the Arab League) with already strong foundational preparedness and digital skills.

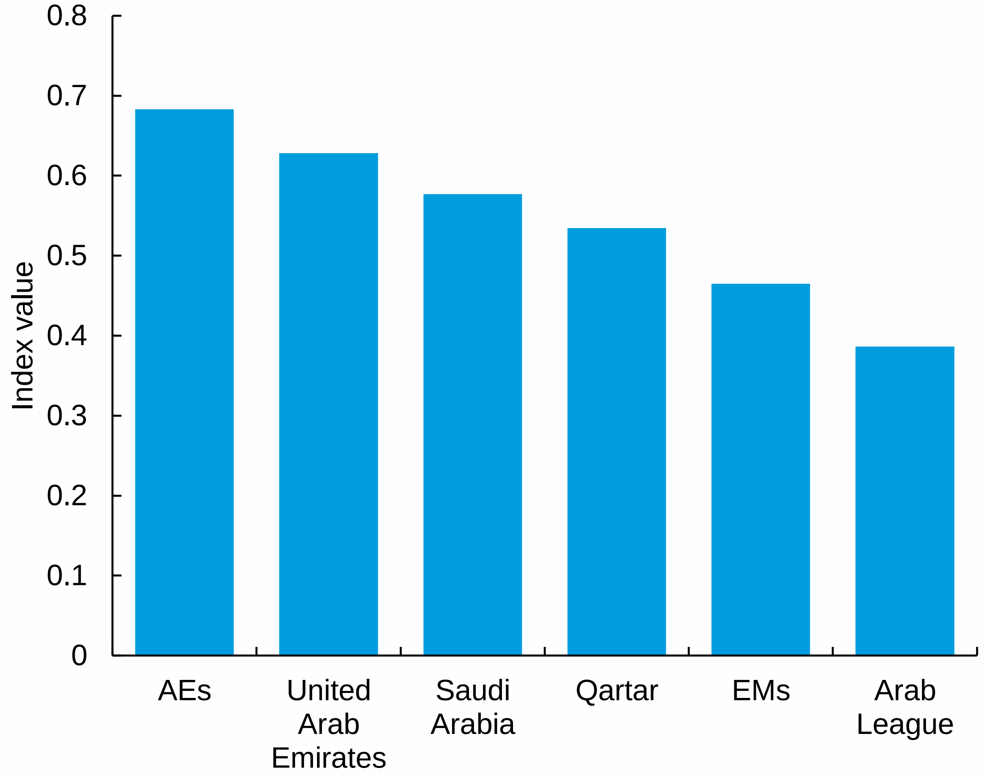
Sources: International Labour Organization (ILO); and IMF staff calculations.
Note: ICT employment refers to people working in the information and communication sector based on ISIC-Rev 4 classification. 142 countries are included: 35 AEs, 67 EMs, and 40 LICs. Circles represent the average values for each respective country group. Crosses denote the average values for each corresponding country group. Simple correlation ("Corr.") is also added for each country group. AEs = advanced economics; EMs = emerging markets; LICs = low-income countries; ISIC = International Standard Industrial Classification.

The Arab League has similar AI exposure but lower preparedness than EMs

1. Employment Share by AI Exposure and Complementarity
(percent)



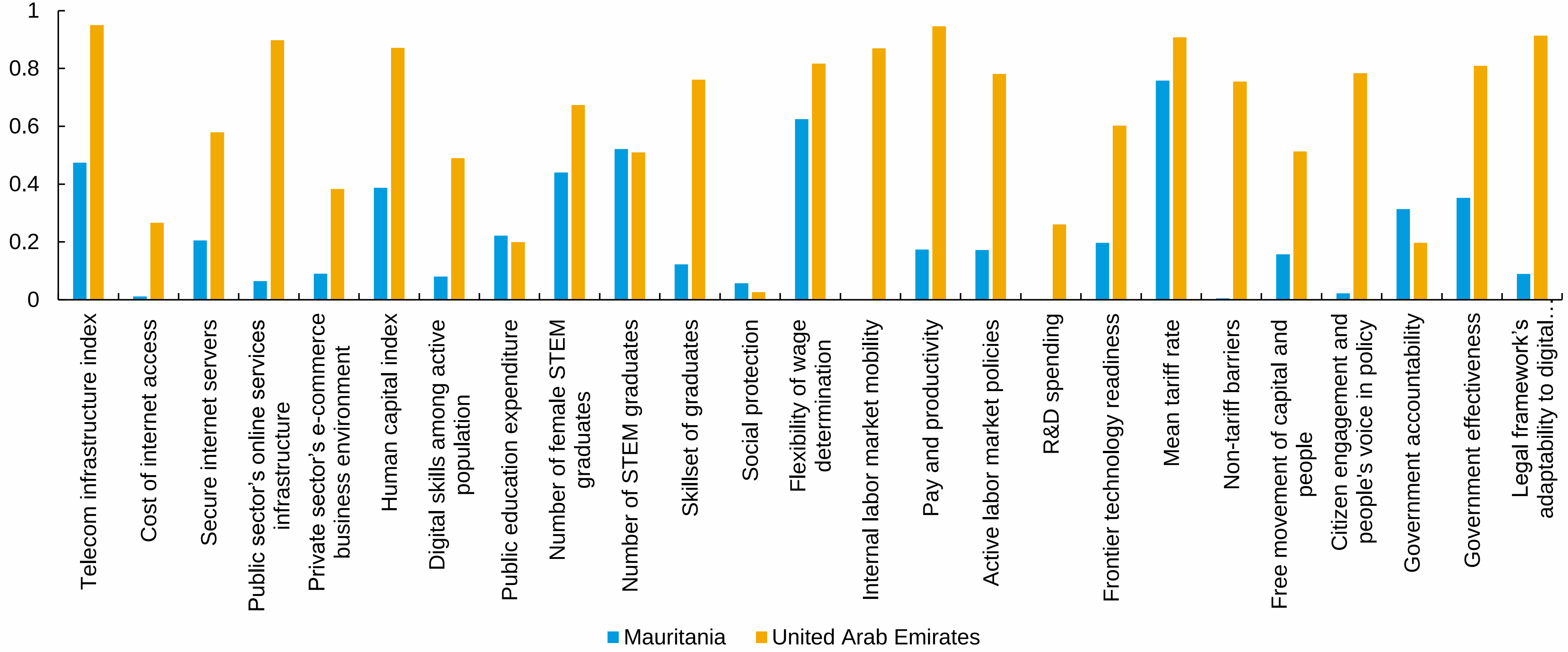
2. AI Preparedness Index
(Index value)



Sources: International Labour Organization (ILO); and IMF staff calculations.
Note: In plot 1, eight countries (Egypt, Iraq, Jordan, Lebanon, Somalia, Tunisia, United Arab Emirates, and Yemen) are considered in the Arab League due to data availability. In plot 2, All countries in the Arab League are included except Palestine. AEs = advanced economics; EMs = emerging markets

Heterogeneity in AI Preparedness: Mauritania vs UAE

AI Preparedness Index Components
(Index value)



Sources: International Labour Organization (ILO); and IMF staff calculations.
Note: 25 subindicators used for computing AIPI are shown in this plot. Mauritania has the lowest score in AIPI while UAE has the highest among Arab League countries.

Conclusions

Conclusions

AI adoption may generate labor market shifts with significant cross-country differences

- AI offers potential for productivity gains but also poses risks of job displacements.
- AI may lead to a large increase in inequality within and across countries.

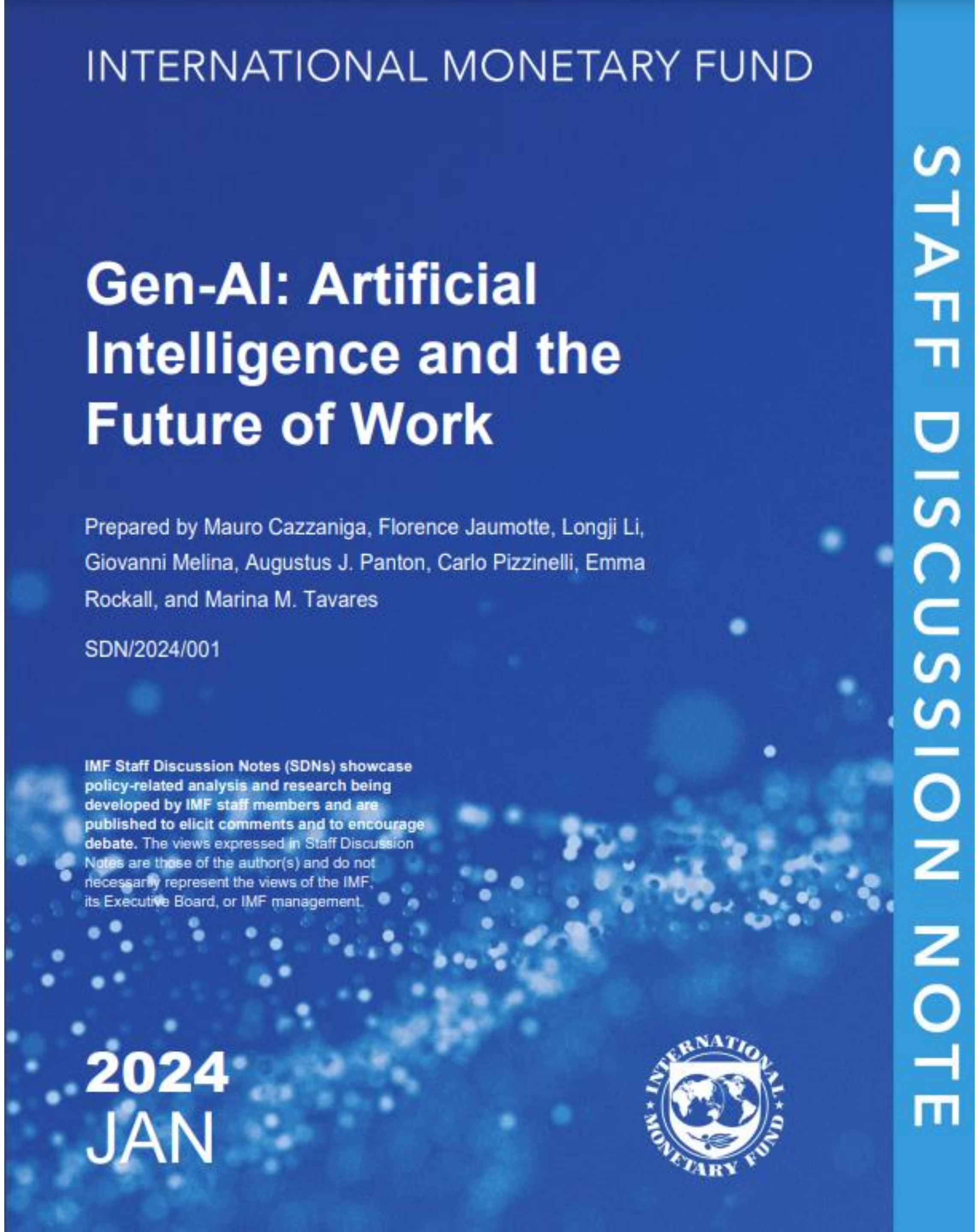
Harnessing the advantages of AI will depend on countries' preparedness

- AEs and some EMs are better prepared (than the Arab League) to harness AI's benefits while mitigating risks.
- Less prepared countries, including in the Arab League, should prioritize digital infrastructure and human capital investments.
- AEs and some EMs should invest in AI innovation while advancing regulatory frameworks.

The potential implications of AI demand a proactive approach from policymakers.

- AI-induced labor market disruptions have the potential to create social unrest.
- Policies should promote:
  - equitable and ethical integration of AI
  - train the next generation of workers
  - protect and help retrain workers currently at risk from disruptions.
- AI's cross-border nature creates ethical and data security challenges and calls for international cooperation.

Merci!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STAFF DISCUSSION NOTE

Gen-AI: Artificial Intelligence and the Future of Work

Prepared by Mauro Cazzaniga, Florence Jaumotte, Longji Li, Giovanni Melina, Augustus J. Panton, Carlo Pizzinelli, Emma Rockall, and Marina M. Tavares

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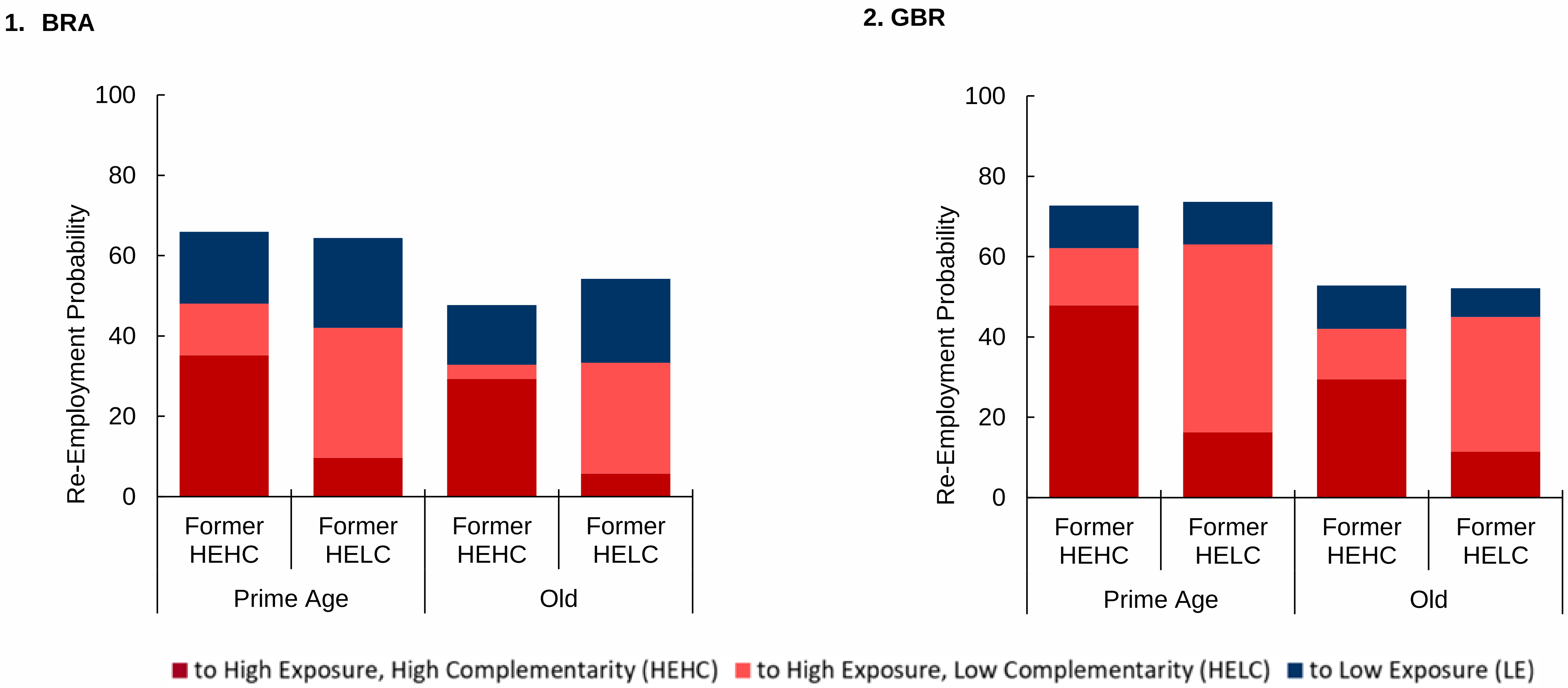
JAN

Older workers may be less adaptable and face additional barriers to mobility, as reflected in their lower likelihood to be re-employed after termination

1-Year Re-Employment Probability of Separated Workers



Sources: Pesquisa Nacional por Amostra de Domicílios Contínua (PNADC); UK Labour Force Survey (LFS); and IMF staff calculations.
Note: The bars report the re-employment probability of workers who have recently (within the last quarter) transitioned from employment to unemployment, which is defined as the share of these workers who are again employed one year later. "From" indicates the exposure category of the occupation the individual had before being unemployed, while "to" indicates the exposure category of the occupation the worker transitioned to. "Prime Age" refers to workers over 35 and under 55, while "old" refers to workers 55 and older. Country names use International Organization for Standardization (ISO) country codes.

Model Details: Households

- **Epstein-Zin preferences:**

$$v_0 = \mathbb{E}_0 \int_0^\infty f(c_t, v_t)\, dt \quad \text{with } f(c, v) = \frac{\rho(1-\gamma)v}{1-\sigma}\left(\left(\frac{c}{((1-\gamma)v)^{1/(1-\gamma)}}\right)^{1-\sigma} - 1\right)$$

$$da_{z,t} + db_{z,t} = (r_K a_{z,t} + r_B b_{z,t} + w_z + T - c_{z,t})\, dt + a_{z,t} \nu\, dW_t$$

- **Where:**
  - $\rho = \varrho + p$: discount rate = impatience + probability of dissipation shock
  - γ: risk aversion, σ: inverse IES
  - r_K: return on capital, r_B: return on bonds
  - Only a fraction χ of households can invest in capital

- **Key assumption:**
  - ‘Perpetual youth’ households with imperfect dynasties
  - With some probability households hit with a dissipation shock and lose all their wealth
  - Obviously unrealistic but tractable stand-in for other churn
  - Delivers non-degenerate wealth distribution and long-run capital supply elasticity<∞

Model Details: Technology

- **Final and intermediate good production:**

$$Y = A\prod_z Y_z^{\eta_z} \qquad\qquad Y_z = \left(K\frac{\eta_z}{\alpha}\right)^{\alpha_z}\left(\frac{\psi_z L_z}{1-\alpha_z}\right)^{1-\alpha_z}.$$

- **Where:**
  - z: occupation index – will ultimately proxy for this with income percentile
  - α_z: share of tasks for a given occupation done by capital (i.e. automated/using AI)
  - η_z : importance in value-added of tasks performed by workers
  - ψ_z: cost-savings from adopting automation/AI in a given occupation

- **Key assumption:**
  - Task-based model (following Acemoglu-Restrepo)
  - Output a combination of tasks, of which different workers perform different sets
  - Worker skills fixed (workers cannot switch occupations)
  - Automation/AI substitutes for tasks, not jobs

Displacement in the Baseline Model

- **Key equation:**

Exposure to task displacement by income percentile

$$\boxed{\frac{1}{1-\alpha_{z,2014}} - \frac{1}{1-\alpha_{z,1980}}} = \boxed{\omega_z^R} \boxed{\left(\frac{1}{1-\alpha_{2014}} - \frac{1}{1-\alpha_{1980}}\right)}, \quad (18)$$

Estimated displacement by income percentile

Change in aggregate capital share

- **Task displacement:**
  - Baseline scenario of automation, estimating α_z^R using routine exposure ω_z^R
  - Then re-estimate the model to obtain α_z^{AI} to get task displacement for AI
    - Use AIOE measure of Felten et al. ω_z^{AIOE}
    - → Need values for aggregate displacement → use the same displacement as automation as the baseline, then consider high and low scenarios

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)