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WORKERS' EXPOSURE TO AI ACROSS DEVELOPMENT STAGES

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Since data on AI use are scarce, most research has focused on exposures, but ignored cross-country differences in occupational tasks

- AI exposure measures based on tasks (Webb, 2020; Gmyrek et al.,2023) and abilities (Felten et al., 2021; Felten et al., 2018) focus on occupations;
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- Most studies use O*NET – US database on occupational demands, abilities, and tasks – implicitly assuming occupations are identical worldwide
- Task content of occupations differs across development levels, depending on technology use, skill supply, and position in global value chain (Lewandowski et al., 2022, Caunedo et al., 2023)
- Workers' exposures to AI likely differ across development too

Starting point: Felten et al. (2021) AI exposure shows what proportion of occupational abilities are susceptible to AI

Language modeling

Image recognition

Speech recognition

10 AI dimensions

Abilities exposed to AI (O*NET)

All abilities required for occupation (O*NET)

=

Occupational exposure

Felten et al. (2021)

Three steps to create country-specific AI exposure measures that reflect international differences in occupational tasks

- Replicate Felten et al. (2021) for the US using PIAAC survey questions on job tasks instead of O*NET abilities to map AI functions into occupations

- Use PIAAC (2011-2018, 2022-2023), STEP, CULS (2016, 2023) survey data to calculate worker-level AI exposure measures for 53 countries

- Predict occupational AI exposures for 55 countries lacking relevant survey data, conditional on technology stock, skill supply, globalisation, and development factors

We approximate the distribution of abilities across occupations using US PIAAC work-related questions, connecting workers' tasks to specific AI dimensions

Abilities	PIAAC questions
Perceptual speed	• How often are you confronted with **more complex problems** that take at least 30 minutes to find a good solution? • In your job, how often do you usually **calculate prices, costs or budgets?**
Mathematical reasoning	• In your job, how often do you usually **read articles in professional journals** or scholarly publications? • In your job, how often do you usually use or **calculate fractions, decimals or percentages?**

Replicating Felten et al. (2021) for the US with PIAAC questions on job tasks

For each O*NET ability, we identify a set of PIAAC questions that provides the best approximation of that ability across 2-digit occupations in the US

O*NET ability j in occupation o

$$Y_{j,o} = \sum_n^N \beta_{jn} Q_{i,o}^n + \epsilon_{i,o}$$

answers to PIAAC question n of worker i in occupation o

survey-based AI exposure of worker i in occupation o

$$AIE_{i,o} = \frac{1}{Y_O} \sum_1^J A_j \left(\sum_n^N \widehat{\beta_{jn}} Q_{i,o}^n \right)$$

ability j exposure to AI

PIAAC questions selected to map AI functions used by Felten et al. (2021) onto worker-level tasks

Q1	Do you manage or supervise other employees?
Q2	The next few questions are about the amount of flexibility you have in deciding how you do your job: To what extent can you choose or change the sequence of your tasks?
Q3	In your job, what proportion of your time do you usually spend cooperating or collaborating with co-workers?
Q4	How often does your job usually involve making speeches or giving presentations in front of five or more people?
Q5	How often does your job usually involve planning your own activities?
Q6	How often does your job usually involve organising your own time?
Q7	And how often are you usually confronted with more complex problems that take at least 30 minutes to find a good solution? The 30 minutes only refers to the time needed to THINK of a solution, not the time needed to carry it out.
Q8	How often does your job usually involve working physically for a long period?
Q9	In your job, how often do you usually read articles in newspapers, magazines or newsletters?
Q10	In your job, how often do you usually read articles in professional journals or scholarly publications?
Q11	In your job, how often do you usually read manuals or reference materials?
Q12	In your job, how often do you usually read bills, invoices, bank statements or other financial statements?
Q13	In your job, how often do you usually fill in forms?
Q14	In your job, how often do you usually calculate prices, costs or budgets?
Q15	In your job, how often do you usually use more advanced math or statistics such as calculus, complex algebra, trigonometry or use of regression techniques?
Q16	In your job, how often do you usually use email?
Q17	In your job, how often do you usually use spreadsheet software, for example Excel?
Q18	In your job, how often do you usually use a programming language to program or write computer code?

For the US, our method replicates Felten et al. (2021) very well. Cross-country differences will reflect cross-country differences in tasks

Regression-based variance decomposition to examine drivers of cross-country variation in AI exposure

We estimate the following regression:

$$AIE_{ijsc} = \beta_0 + \beta_1 T_{sc} + \beta_2 H_{ijsc} + \tau_o + \beta_3 F_{sc} + \beta_4 D_c + \delta_c^{2022} + \varepsilon_{ijsc}$$

- AIE_{ijsc} - AI exposure of worker i in occupation j in sector s in country c;
- T_{sc} - ICT intensity in sector s in country c;
- H_{ijsc} - worker-level human capital;
- τ_o - occupation fixed effects;
- F_{sc} - firm characteristics in sector s in country c (including sector FE);
- D_c - development indicator at the country level (interacted with sectors FE)
- δ_c^{2022} - a fixed effect for countries in the 2022-2023 surveys

Data sources and measurement

- ICT intensity: measured as the share of workers using computers at the country-sector level, including a squared term to capture non-linear effects (PIAAC, STEP)
- Human capital: includes worker-level variables such as educational attainment, test-based literacy proficiency (four levels), gender and age groups (PIAAC, STEP)
- Firm characteristics: foreign direct investment, both forward and backward participation in global value chains, measured at the country-sector level of International Standard Industrial Classification (1-digit ISIC Rev.4), sector fixed effects (WDI, EORA)
- Occupational structure: 2-digit ISCO fixed effects (PIAAC, STEP)
- Development level: Log of GDP per capita (PPP) as a proxy for development level (WDI)

Predicting occupational AI exposures for 55 countries without survey data, conditional on available country-level technological and socioeconomic indicators

$$AIE_{poc} = \beta_{o0} + \beta_{o1} GDP_c + \beta_{o2} \delta_c + \beta_{o3} T_c + \beta_{o4} H_c + \beta_{o5} G_c + \beta_{o6} I_c + \delta_c^{2022} + \gamma_{po} + \varepsilon_{poc}$$

AIE_{poc} - AI exposure of occupation p, a 2-digit ISCO subcategory in 1-digit group o

T_c - access to technology (use of internet, digital readiness index, ICT development index) in country $\mathbf{c}$

H_c - human capital and socio-economic factors (school enrolment, compulsory years of schooling, learning adjusted years of scholling, harmonized test scores, 15-60 survival rate, urbanisation, average hours worked, share of 16-64 population) in country $\mathbf{c}$

X_c - participation in global economy (GVC, exports, FDI) in country $\mathbf{c}$

I_c - infrastructure (electricity, urbanisation) in country $\mathbf{c}$

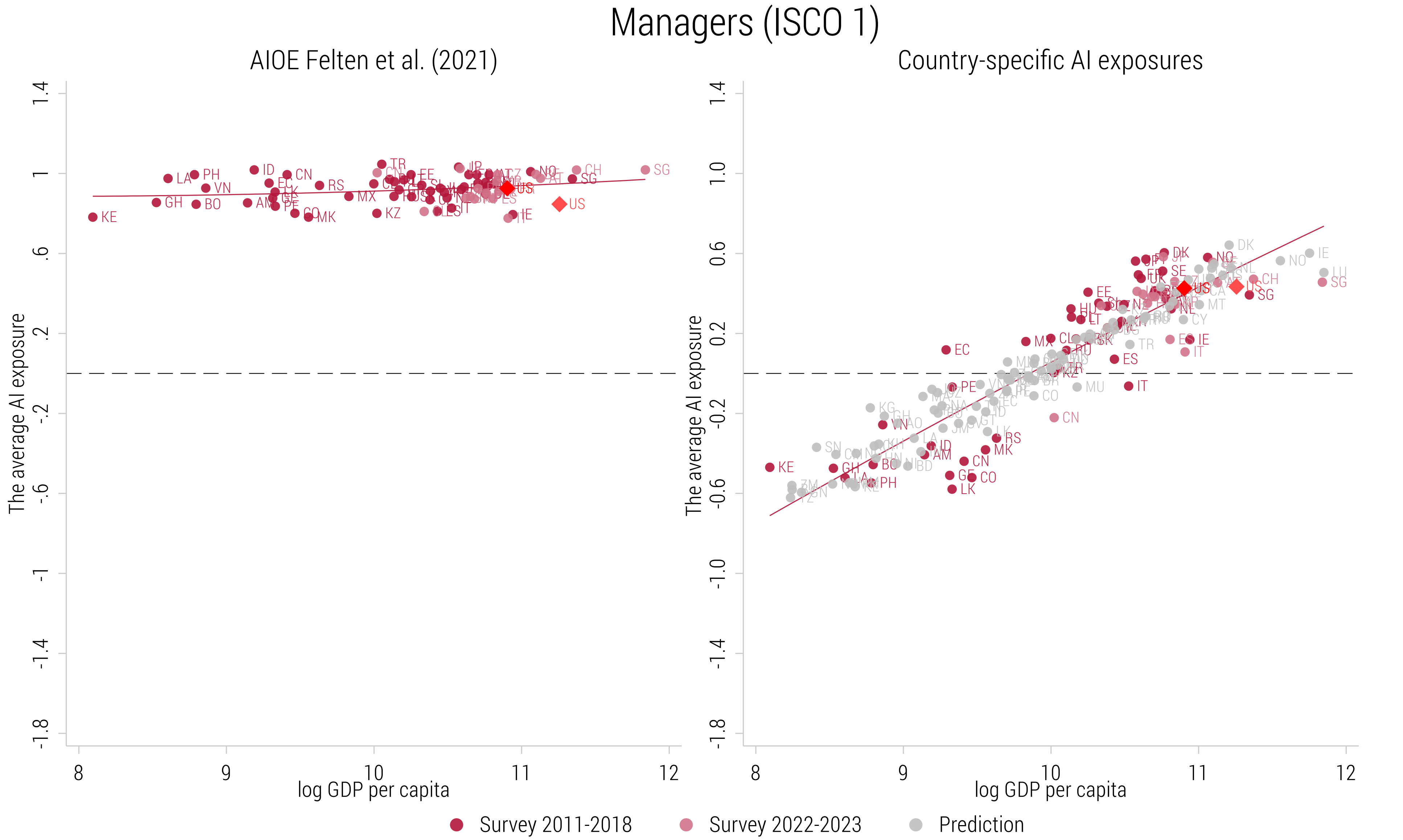
GDP_{sc} - log GDP per capita in country $\mathbf{c}$,

δ_c^{2022} - fixed effects for 2022-2023 surveys

γ_{po} - fixed effects for 2-digit occupations p within a given 1-digit group, o

Data sources: WDI, EORA, International Telecommunication Union (ITU), and CISCO databases.

Adjusting for workers' tasks reveals substantial cross-country heterogeneity within occupations, especially among high-skilled workers

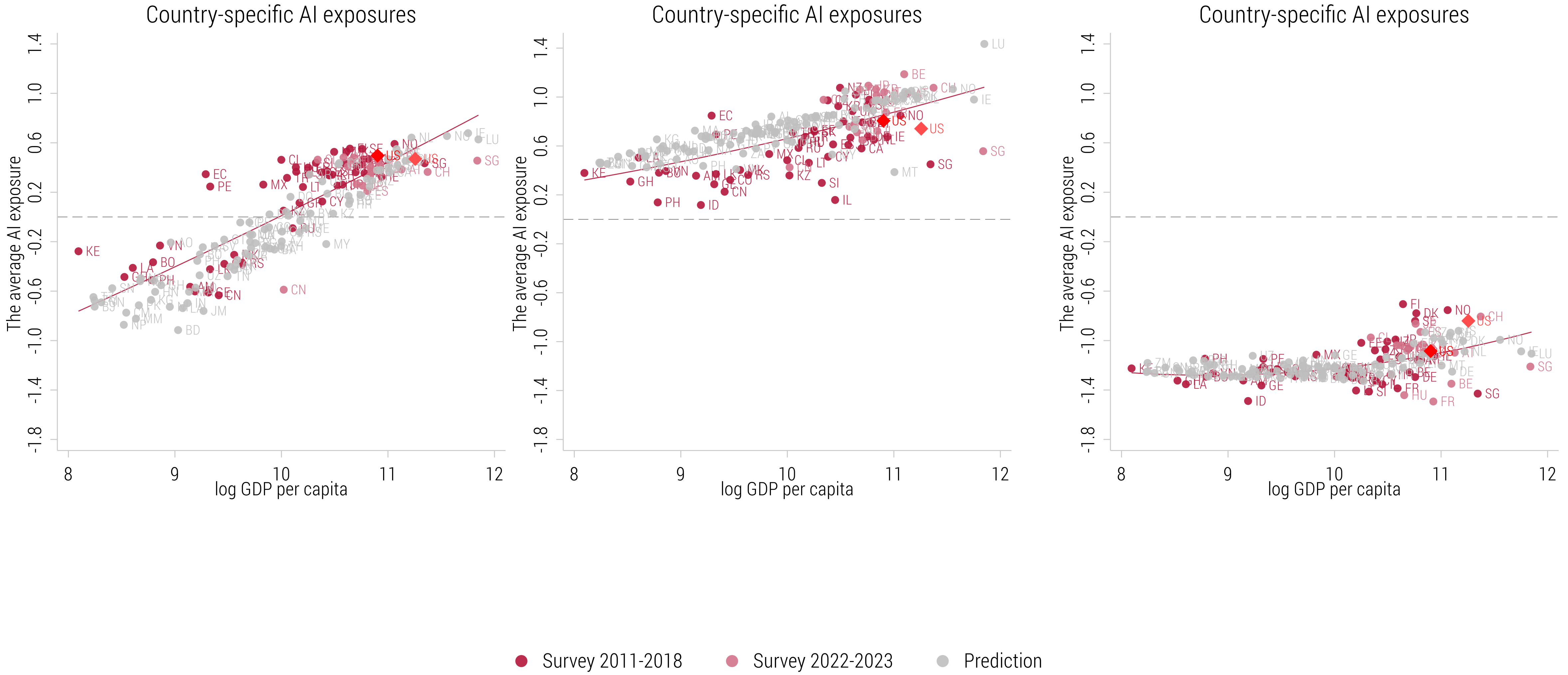


Adjusting for workers’ tasks reveals substantial cross-country heterogeneity within occupations, especially among high-skilled workers

Professionals (ISCO 2)

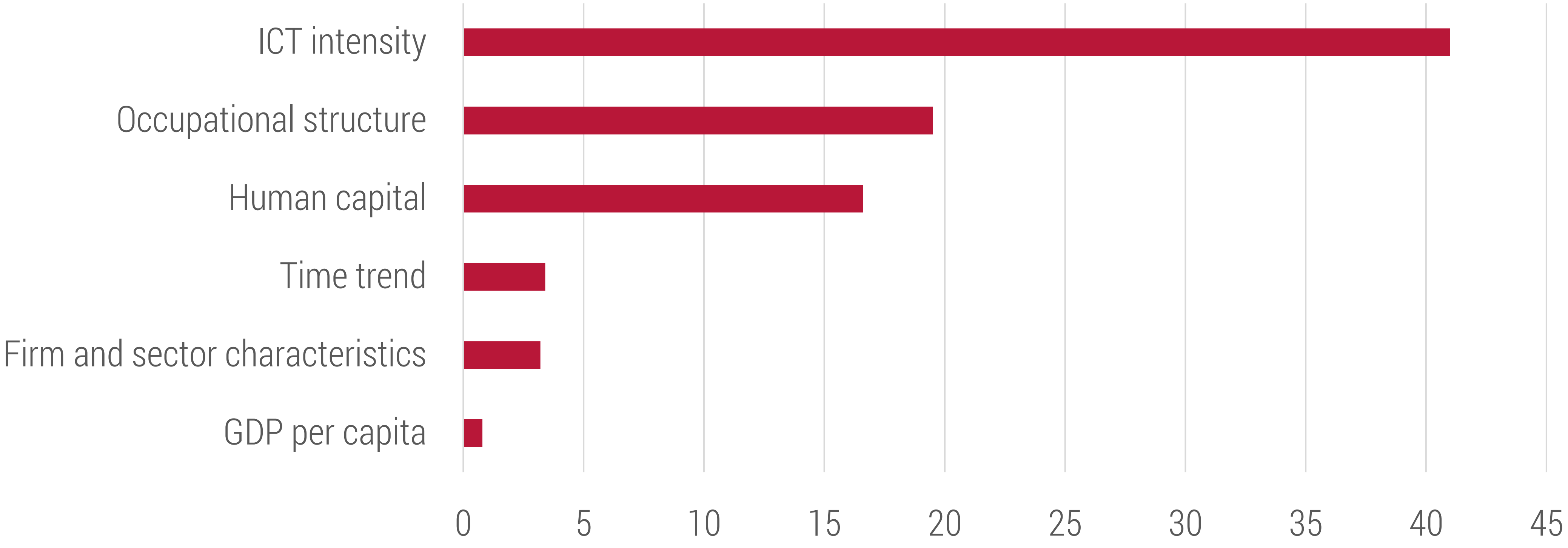
Clerical workers (ISCO 4)

Plant and machine operators, and assemblers (ISCO 8)



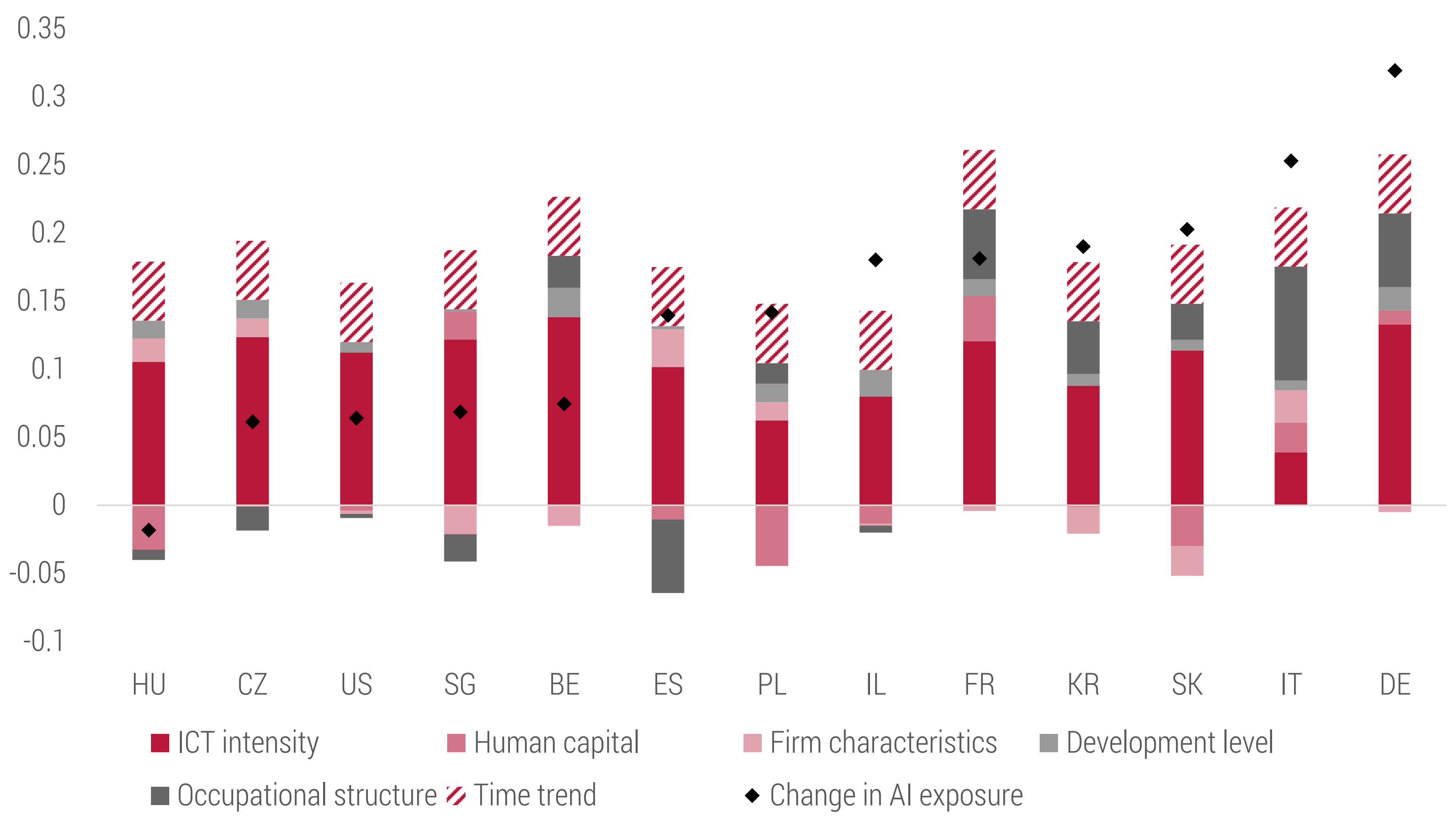
ICT intensity contributes the most to the cross-country variance, followed by human capital and occupational structure

Regression-based decomposition of cross-country variance in workers' AI exposure (in % of variance)



The contribution of a variable group, k, to the variance of AIE_c: $\sigma_k = \frac{cov(\beta_k \bar{X}_c^k, \overline{AIE}_c)}{var(\overline{AIE}_c)}$

Rising ICT intensity also explains most of the AI exposure increase over time, followed by a secular trend – change in task composition across the board



Workers who are the most exposed to AI cluster in High Income Countries, workers the least exposed cluster in Low- and Middle Income Countries

- Least exposed jobs – bottom 25% of the global AI exposure distribution
- Most exposed jobs – top 25%

Global distribution of the most/least AI-exposed workers, by country groups
(in % of employment in a given category)

	Low or lower-middle income	Upper-middle income	Lower-tier high-income	Upper-tier high-income
Most exposed (top 25% globally)	16.7	24.2	16.9	42.2
Least exposed (bottom 25% globally)	61.8	26.2	7.1	4.8
Total employment	40.2	34.0	8.4	17.5

AI exposure – what have we learned

- Accounting for worker tasks crucial in assesing individual and country-specific AI exposures
- Substantial heterogeneity between countries at different development stages, most pronounced among workers in high-skilled occupations
- ICT intensity explains most cross-country differences in AI exposure and most changes over time in countries with two waves of survey data
- AI exposures for 108 countries, covering 89% of global employment, show highly exposed workers cluster in High Income Countries

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Thanks for listening

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