Buffer or Bottleneck? Jobs' Exposure to Generative AI and the Digital Divide in Latin America

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What do we do? (1)

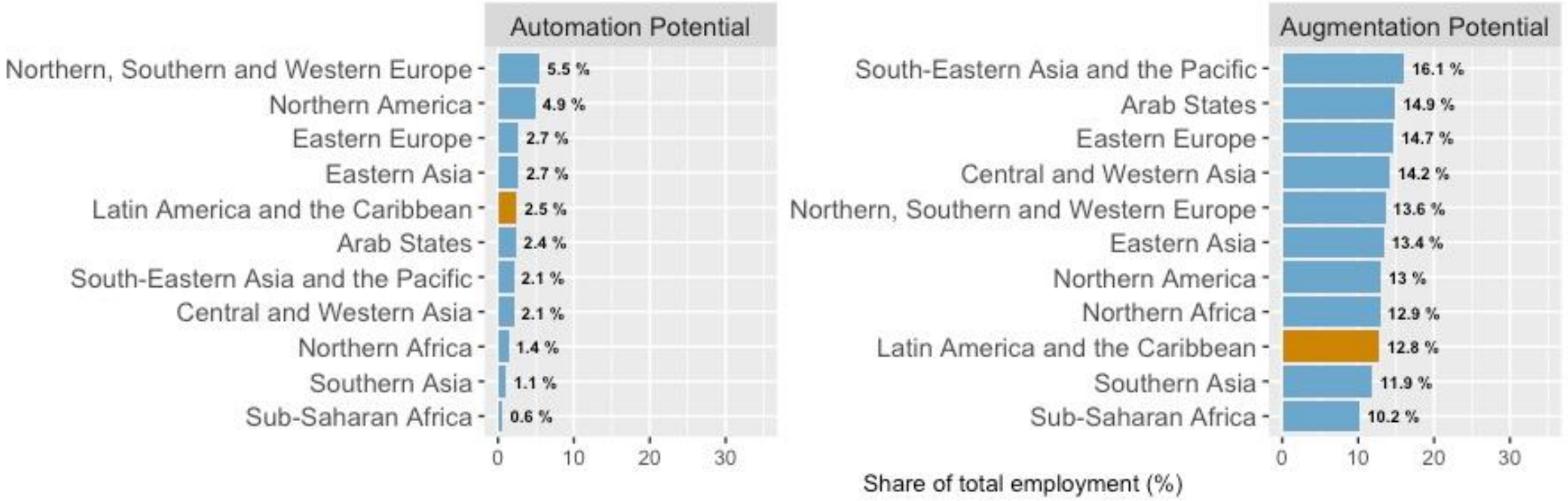
- We measure labor markets' exposure to GenAI by imputing the exposure scores from Gmyrek, Berg and Bescond 2023 ("GBB" from now on) to 22 household and labor market surveys from Latin America and the Caribbean (LAC).
- We estimate three exposures types:
  - **Automation**: Occupations where most tasks can be replaced by GenAI.
  - **Augmentation**: Occupations where some tasks could be automated but where human role remains crucial for the majority of tasks.
  - **Big Unknown**: Occupations that could fall closer to automation or augmentation depending on the progress of the technology.
- We compute measures of exposure across several socio-economic characteristics, to provide insights about the potential distributional impacts of GenAI.

What do we do? (2)

- We build on GBB methods by providing an additional adjustment: the role of access to digital technologies.
- In particular, we use the likelihood of using a computer at work to split each GenAI exposure into two categories:
  - Occupation exposed to GenAI and worker uses a computer at work
  - Occupation exposed to GenAI and worker does not use a computer at work
- To our knowledge, this is the first attempt at adapting measures of GenAI exposure to developing countries.

Motivation (1)

- While there is some variation in terms of GenAI labor market exposure across income levels, the gaps are not that wide.
- But aggregate estimates hide important within-country differences, which are critical to assess distributional implications of GenAI exposure (e.g. are rich workers more or less exposed than middle-class ones?)

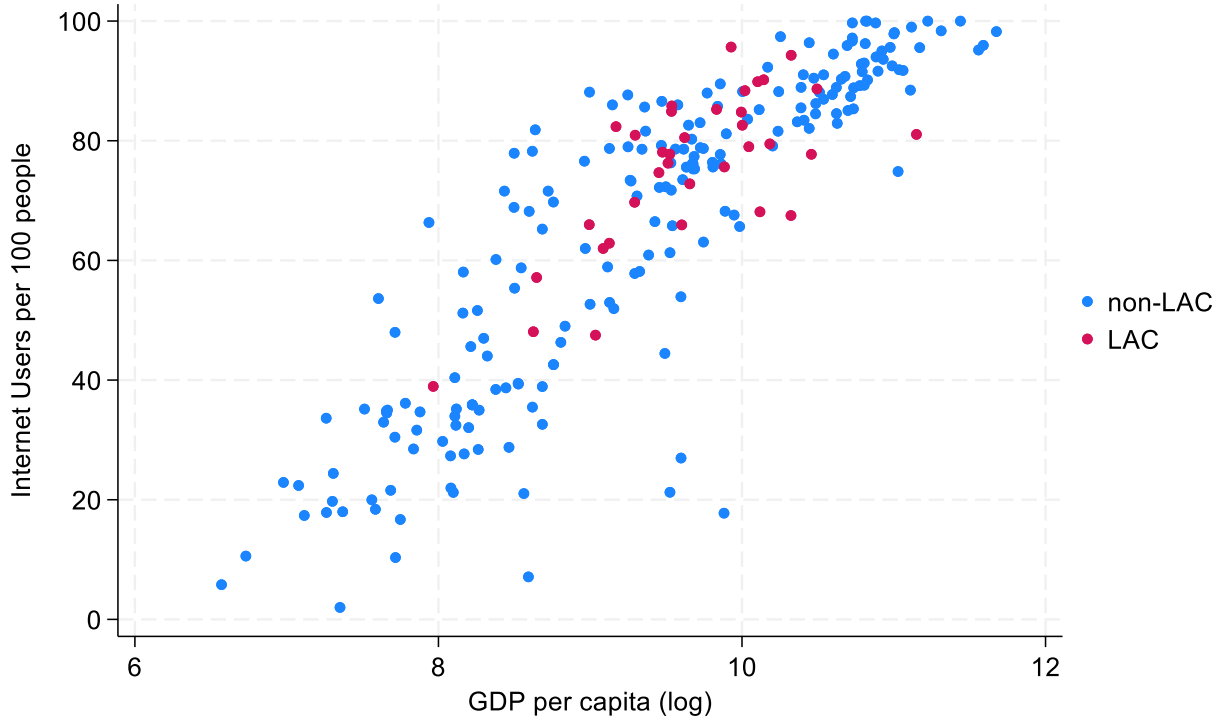


Source: GBB

Motivation (2)

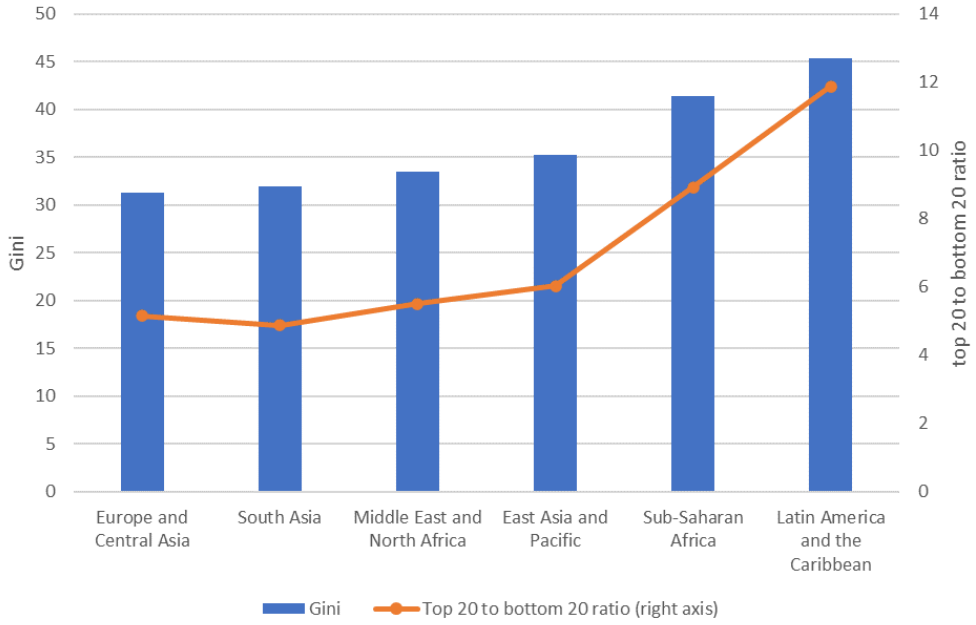
- While GenAI could bring significant productivity gains, developing countries can miss such opportunities if, for example, workers lack foundational skills or access to digital technologies.

- In addition, existing methods consider rich and poor countries in the similar way, and thereby any differences in GenAI exposure are driven solely by differences in the occupational structure.



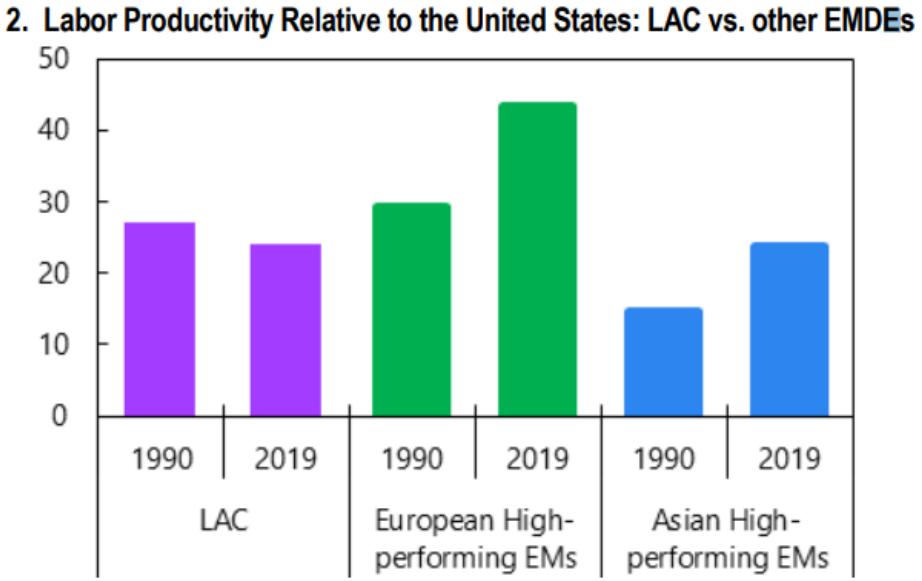
Why Latin America? Two important features of the region

High inequality



Source: own elaboration based on latest data from https://pip.worldbank.org/

Low labor productivity



Source: IMF, 2022. Productivity in Latin America and the Caribbean: Recent Trends and the COVID-19 Shock.

Preview of results

- **Overall Exposure:**
  - 30-40% of LAC employment exposed to GenAI
  - Notable inter-country variation influenced by income levels

- **Who are more exposed?**
  - Workers in urban areas, with higher education levels, higher income, and who are formal have more exposure
  - Automation exposure is highest among women, young people, and salaried employees
  - Augmentation potential more equally distributed across genders, and higher among high-income, urban, formal jobs (salaried and self-employed)
  - Gender: Women have higher exposure to both automation and "the big unknown"
  - Age: Younger demographics more exposed overall

- **Sector profile:**
  - Banking, finance, insurance, public administration: High automation exposure
  - Education, health, personal services: More augmentation potential
  - Retail, wholesale trade, restaurant, hotels: Higher exposure to "the big unknown"

- **Digital Infrastructure and Augmentation:**
  - Digital access limitations hinder the potential for augmentation transformation
  - Approximately half of jobs with augmentation potential unable to benefit due to digital gaps
    - These gaps correspond to 6.2% of female employment and 5.9% of male employment
    - They add up to 17 million jobs: Some 7 million such jobs are held by women and nearly 10 million are held by men
  - Jobs exposed to automation have high levels of digitalization
  - Large digital gaps across socio-economic groups

Methods

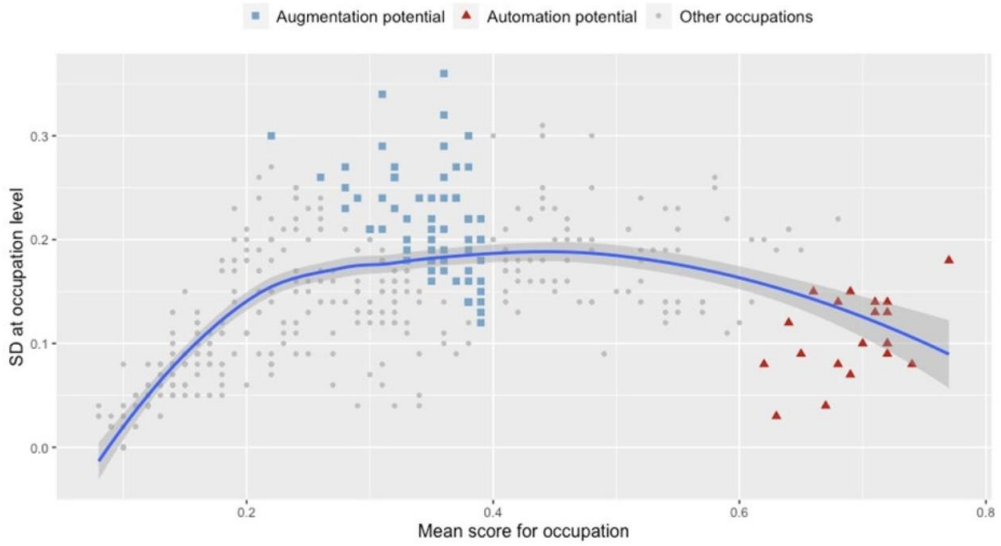
Overview of GBB (2023) scores (1))

- Gmyrek, Berg and Bescond (2023) estimate scores of exposure to GenAI for each ISCO08 4-digit occupation.
- Each ISCO category has a set of tasks attached to it
- They ask ChatGPT to provide a score (and a justification) about the extent to which each task could be potentially automated with GPT technology.

Overview of GBB (2023) scores (2)

- Considering an occupation as a collection of tasks with different levels of exposure to GenAI, they focus on two parameters: (i) the mean score for a given occupation, and (ii) its standard deviation (SD).
- Based on these parameters, they classify occupations in four groups (table 5)

▶ Figure 4. Augmentation vs automation potential at occupational level



▶ Table 5: Grouping of occupations based on task-level scores

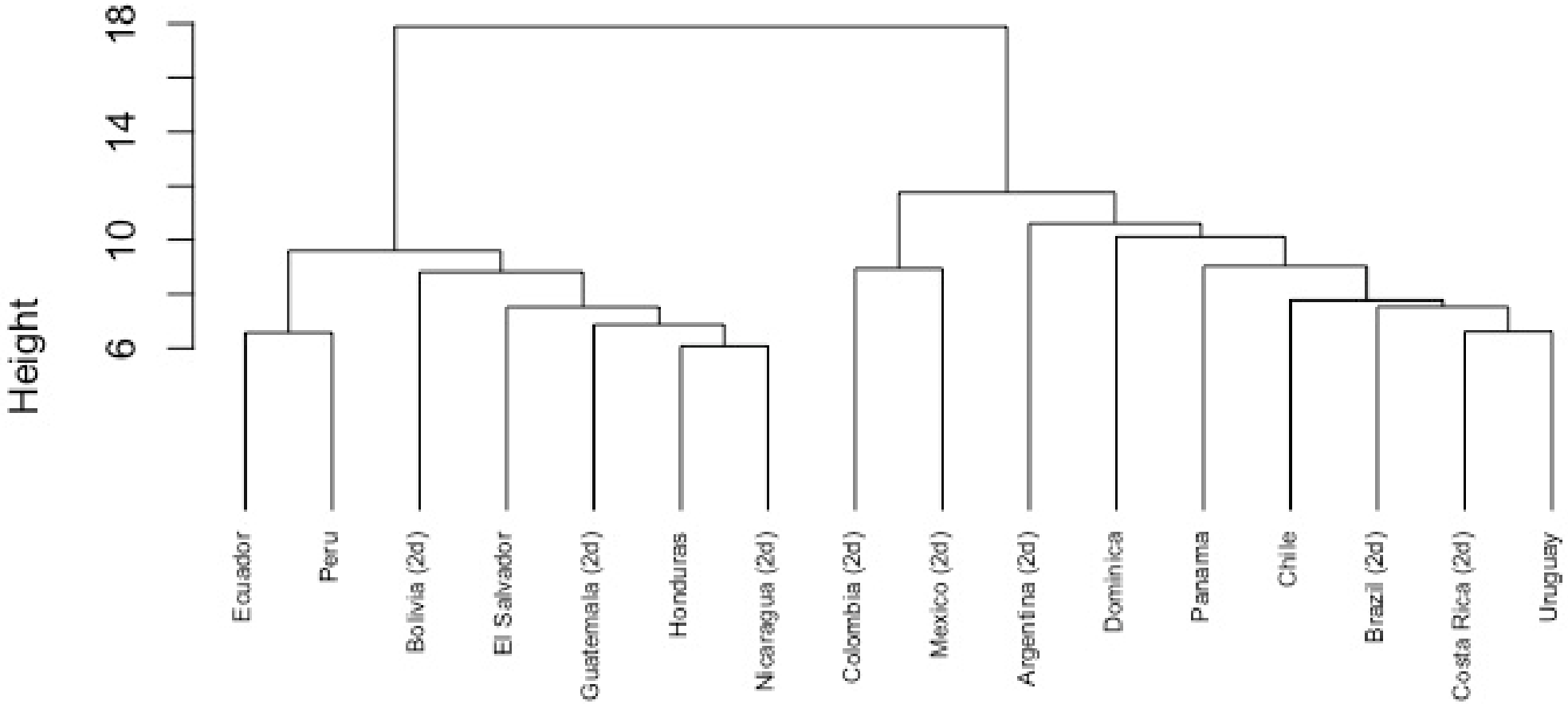
	Low Mean	High Mean
High SD	Augmentation potential	The big unknown
Low SD	Not affected	Automation potential

Our paper

- GenAI ISCO08 4-digit exposure Scores from GBB
- 16 countries with individual response level microdata from SEDLAC
- 22 countries for overall exposure (SEDLAC + ILO data)
- Imputation at the 4-digit level is simple
- But SEDLAC has ISCO08 4-digit for 8 countries, and 2-digit for the remaining 8 countries.
- It is not straightforward to apply GBB's 4-digit scores to 2-digit data.
- For countries with 2-digit level data we have two cases:
  - If the country has 4-digit level data in ILO, we calculate the exposure measures at the 2-digit level and impute those to SEDLAC. This is the case for Brazil, Colombia, Costa Rica and Mexico.
  - If the country does not have 4-digit level in ILO, we impute to SEDLAC the 2-digit level exposure from a "similar" country using a clustering algorithm. This is the case for Argentina, Bolivia, Guatemala and Nicaragua

Imputation of GenAI scores (4)

Hierarchical clustering based on ISCO 2-digit shares, GDP(PPP) and total population



Computer use at work (1)

- Lack of digitalization will likely be an important barrier to GenAI adoption in developing countries.
- Information about use of digital technologies at work is not typically collected in HH surveys.
- The PIAAC surveys include a variable on whether workers use a computer at work.
- We use it to split each GenAI exposure measure between those who are exposed and use a computer at work, and those who are exposed but do not use a computer at work.

Computer use at work (2)

- Since there are only 4 Latin American countries in PIAAC, we need to impute this information to countries in SEDLAC.
- First, we pooled the microdata of the 35 countries in PIAAC and estimate the following Logit model for the probability of using a computer at work:

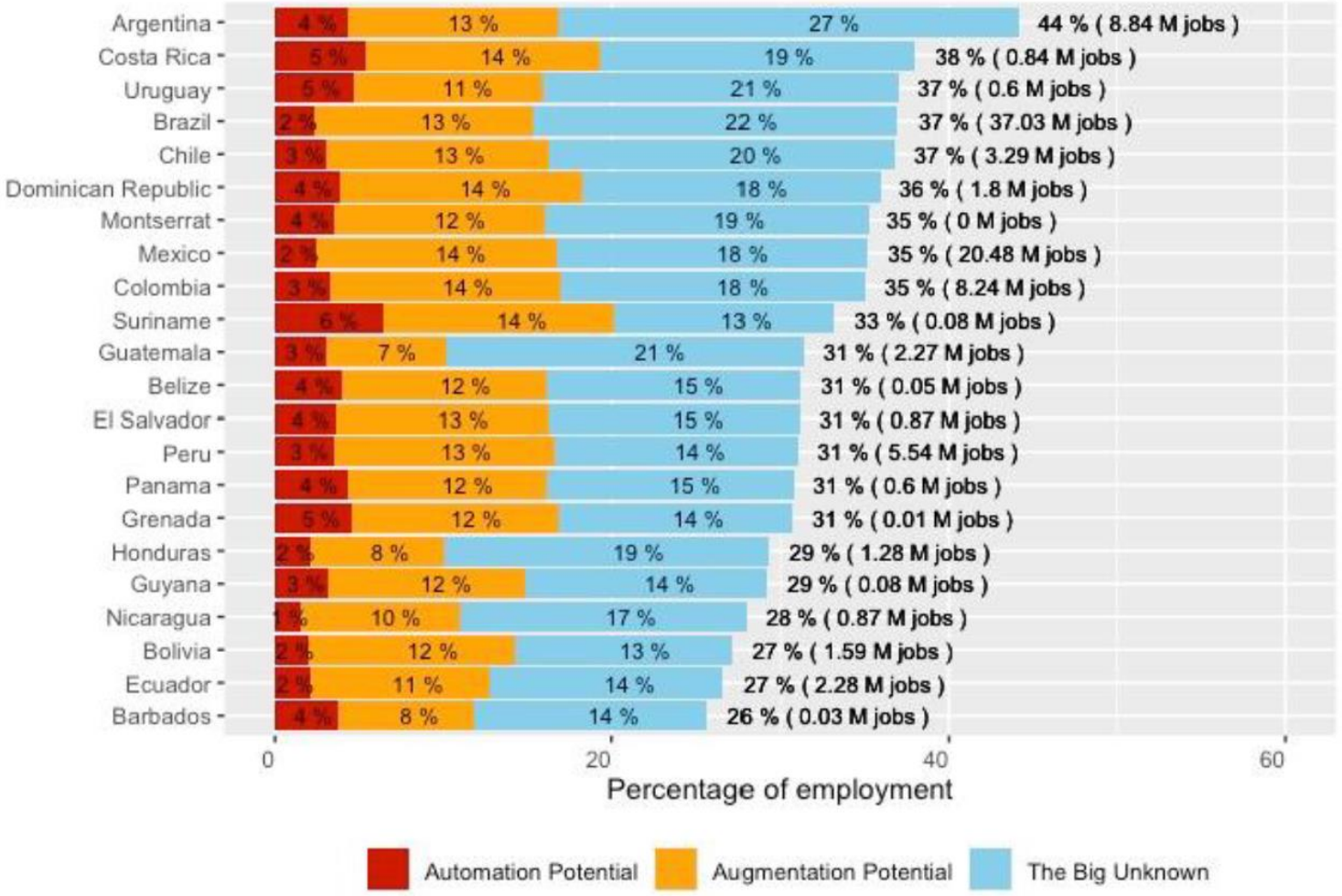
$$\Pr\left(computer_{c,i}=1\right)=f\left(ISCO^{o}_{c,i}, age^{a}_{c,i}, female_{c,i}, edu_{c,i}, \mathrm{GDP}_{c}, internet_{c}, broadband_{c}\right)$$

- Second, we use the estimated equation to predict the probability of computer use at work at the individual level in SEDLAC. The explanatory variables are the same in PIAAC and SEDLAC.
- The probability of not using a computer at work is imply 1-P(computer=1).
- Each GenAI augmentation measure can be split in two by multiplying it by P(computer=1) and 1-P(computer=1).
- We carry out some robustness check using data on computer ownership and internet subscription at home in SEDLAC

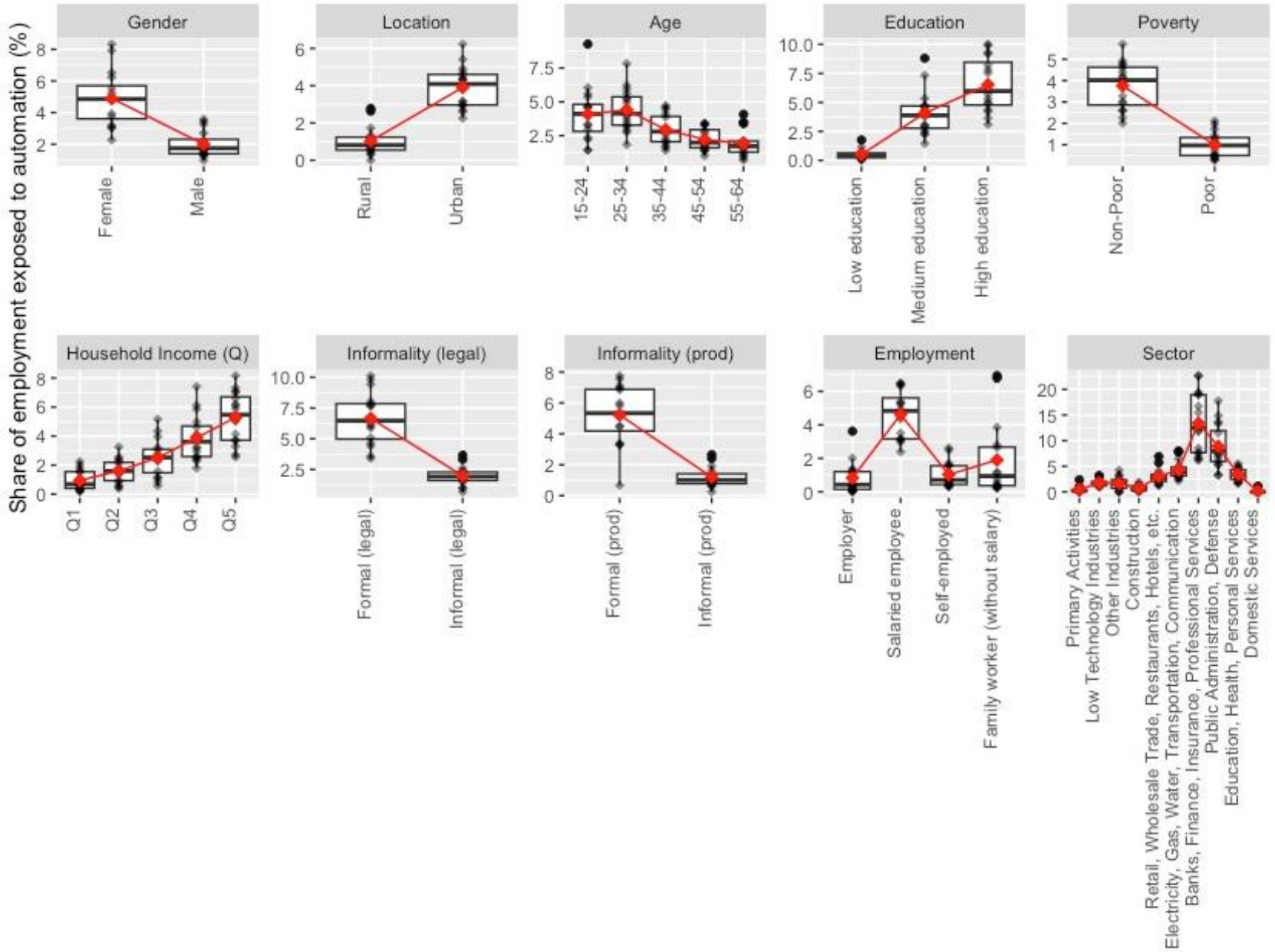
Results

Total exposure to GenAI by country

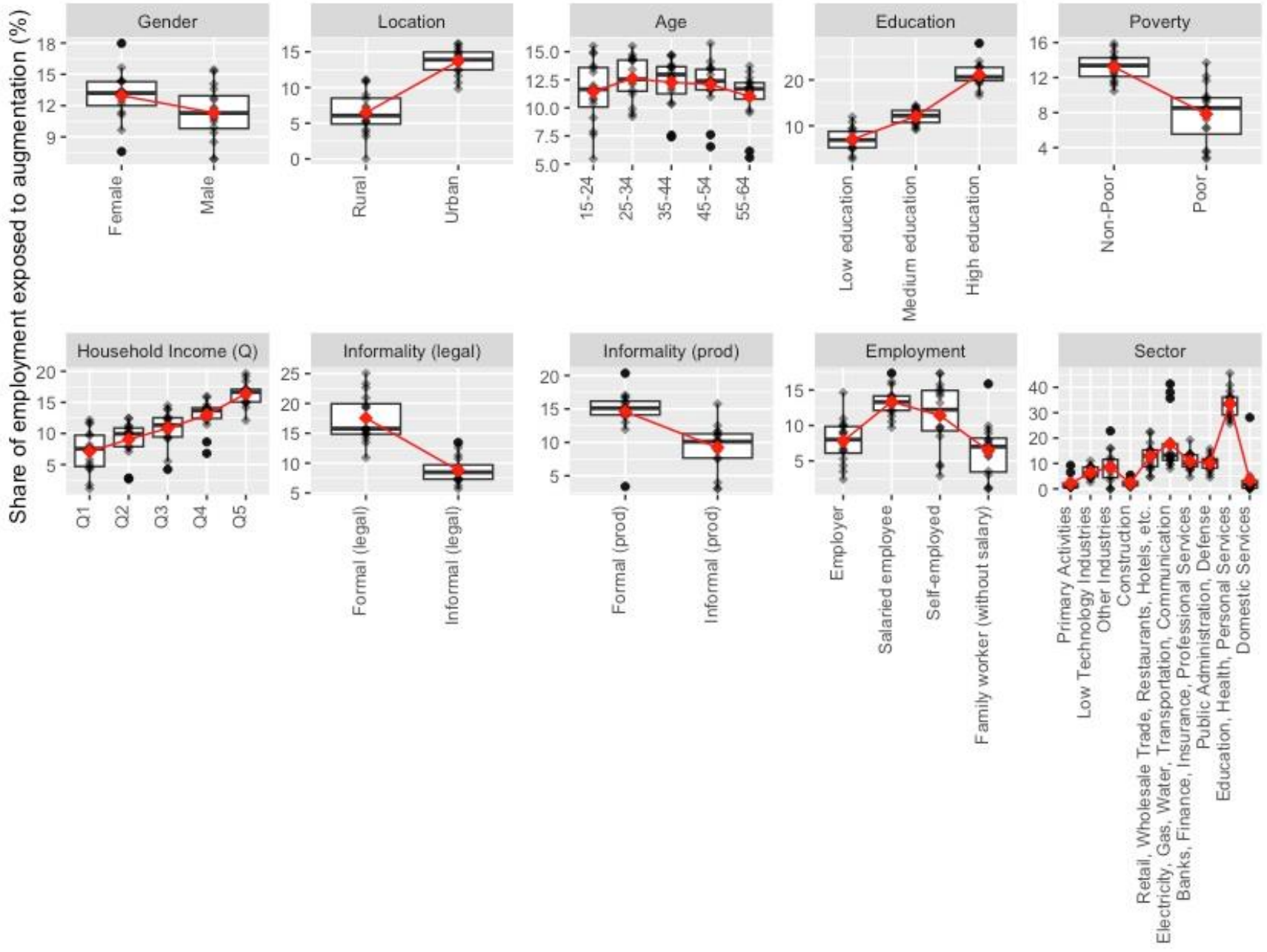
Figure 7. Total exposure to GenAI by country[23]



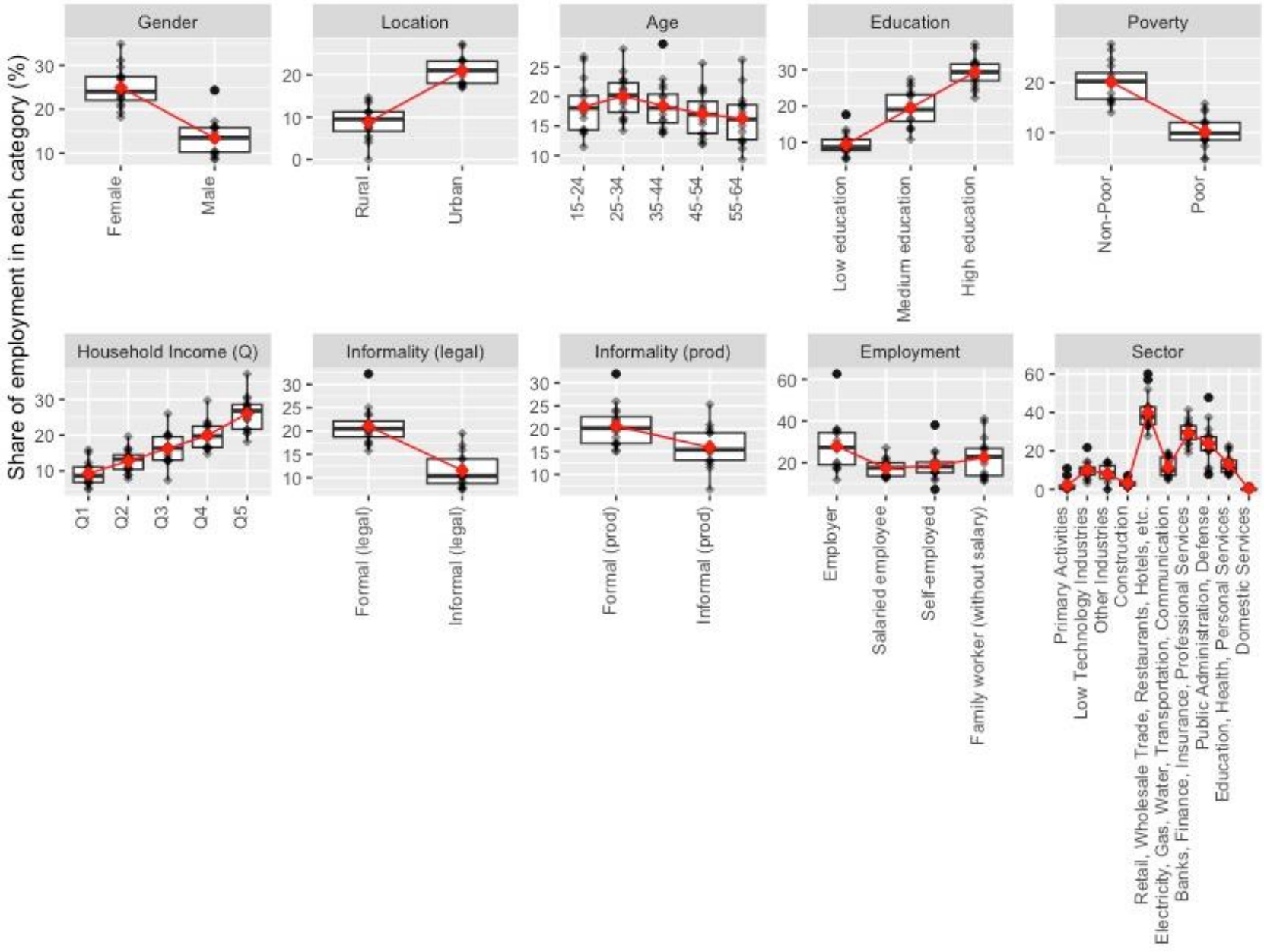
Cross-country findings: automation



Cross-country findings: augmentation



Cross-country findings: the big unknown



Adjusting for the digital divide

The impact of access to digital infrastructure

Figure 10. Jobs with augmentation potential and access to computer at work, based on PIAAC data

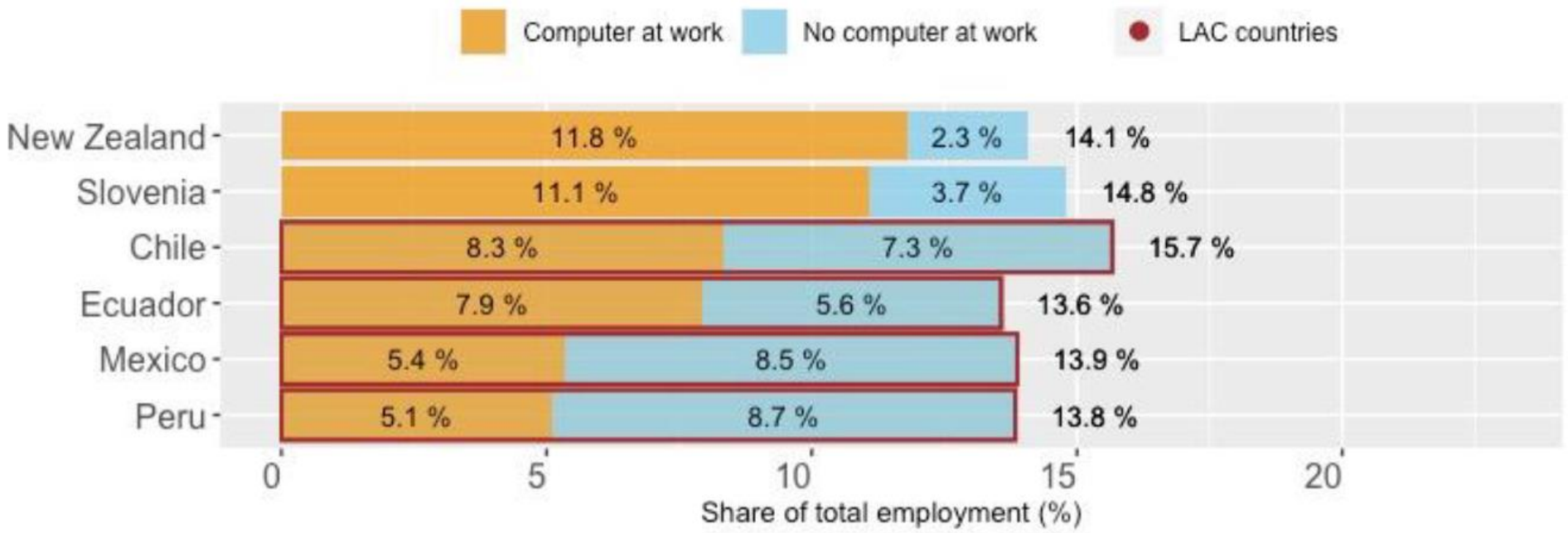


Figure 12. Exposure by country, exposure type and access to digital infrastructure

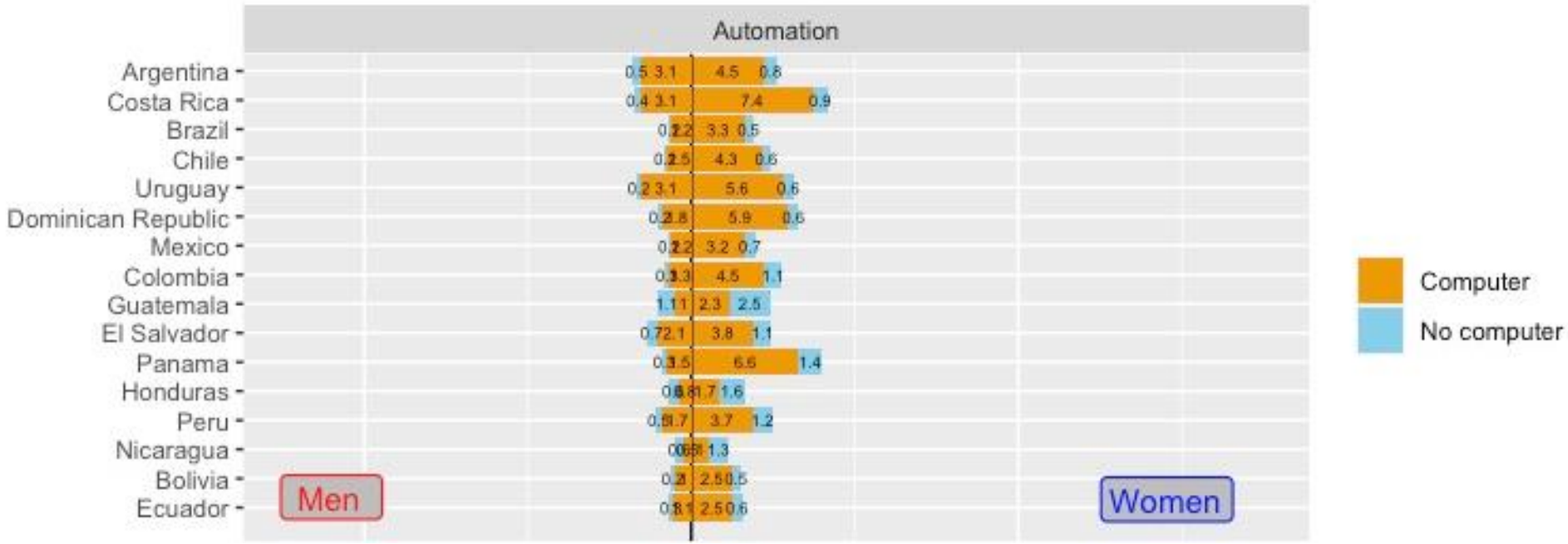


Figure 12. Exposure by country, exposure type and access to digital infrastructure

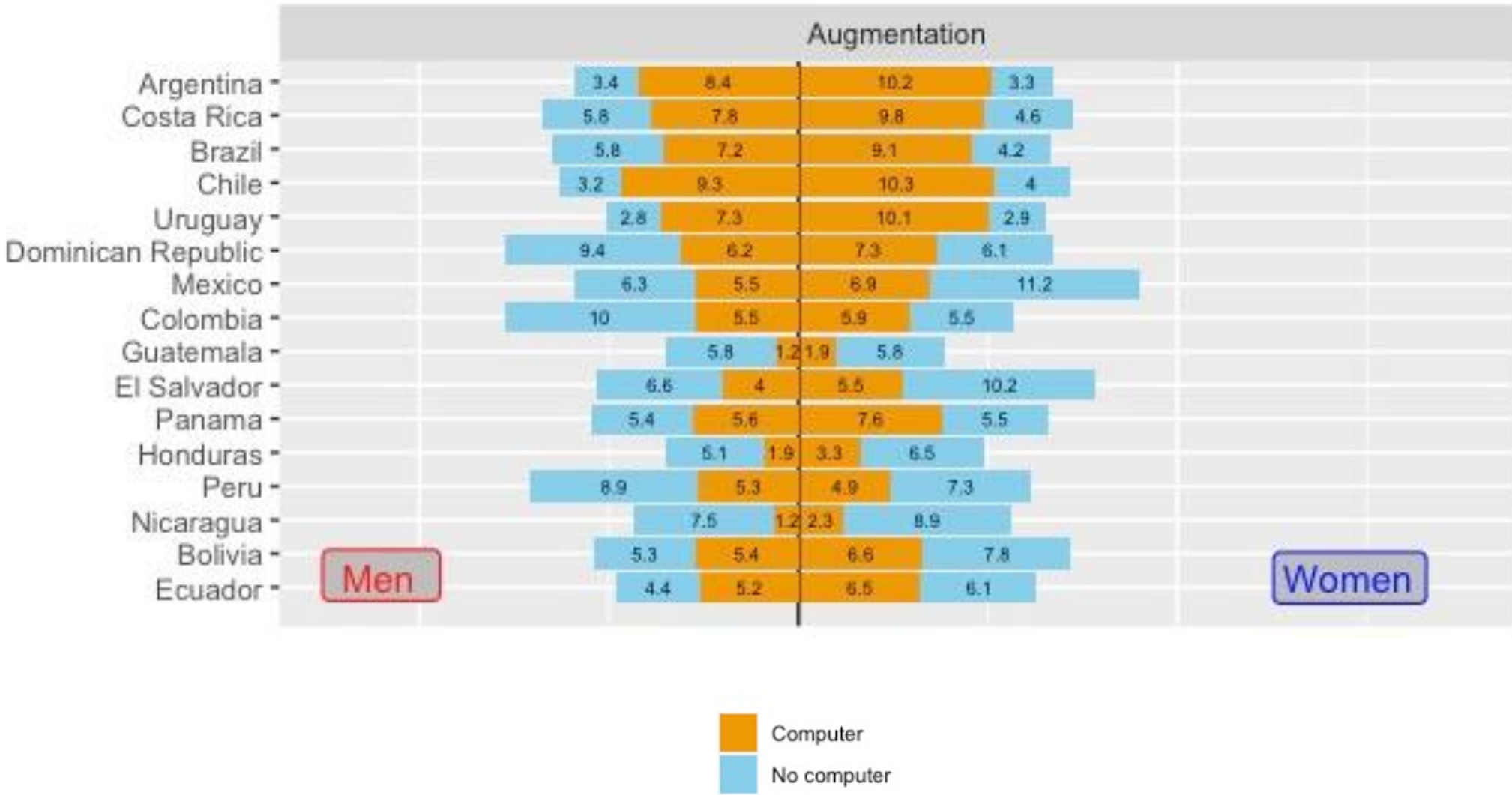


Figure 12. Exposure by country, exposure type and access to digital infrastructure

Exposure across earnings levels

- Most of the exposed categories concern jobs around what could be defined as middle- and upper-middle income jobs, with hardly any occupations showing significant exposure among the low-income jobs.

- In other words, the first order effects of GenAI are more likely to benefit people who already have high incomes and who are in jobs requiring relatively higher skills levels, while the jobs of the poor are quite likely to remain outside the immediate effects of this technological transition.

Figure 14. Earnings of occupations exposed to GenAI, by employment status (exposure above 25%)

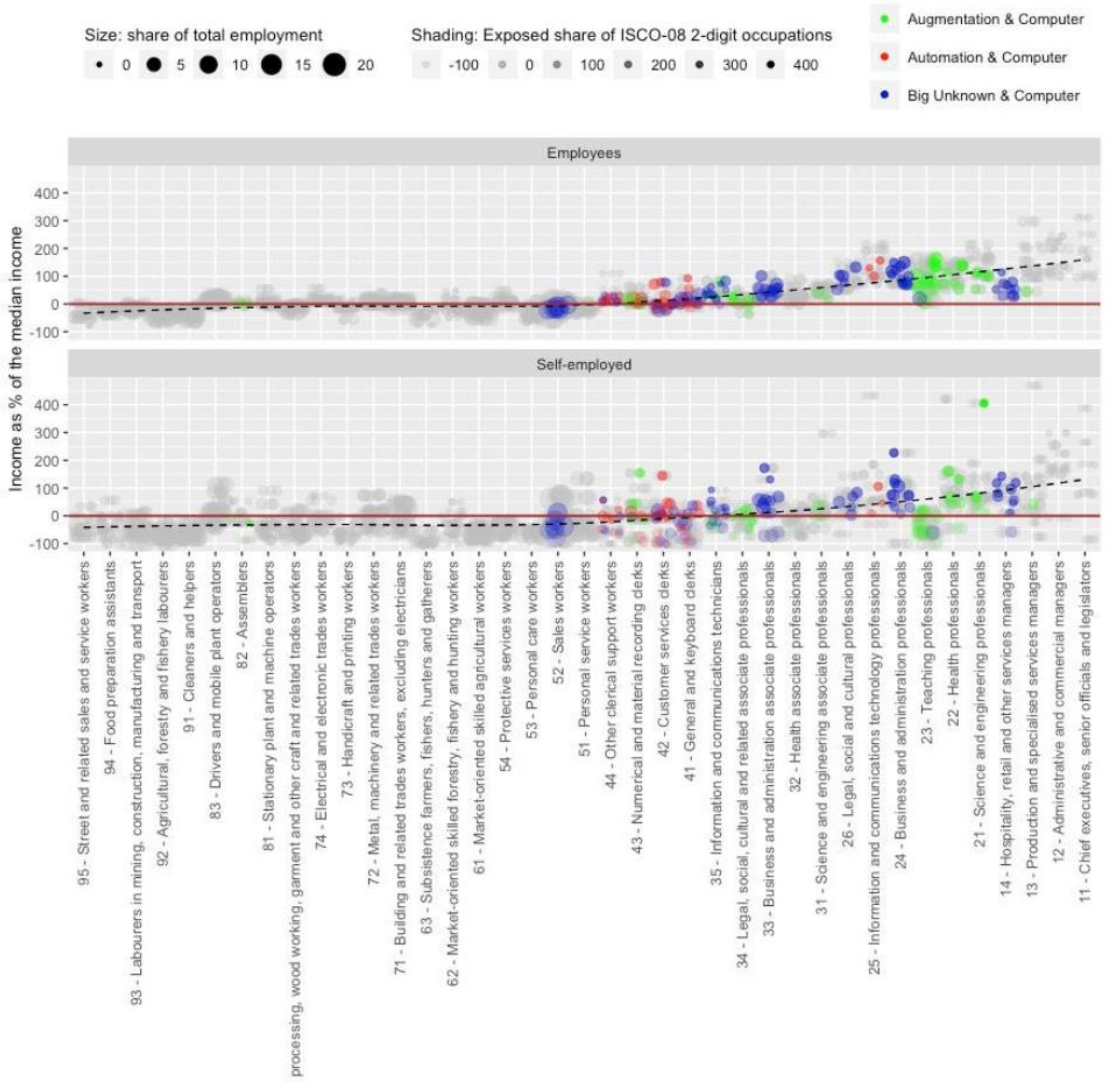
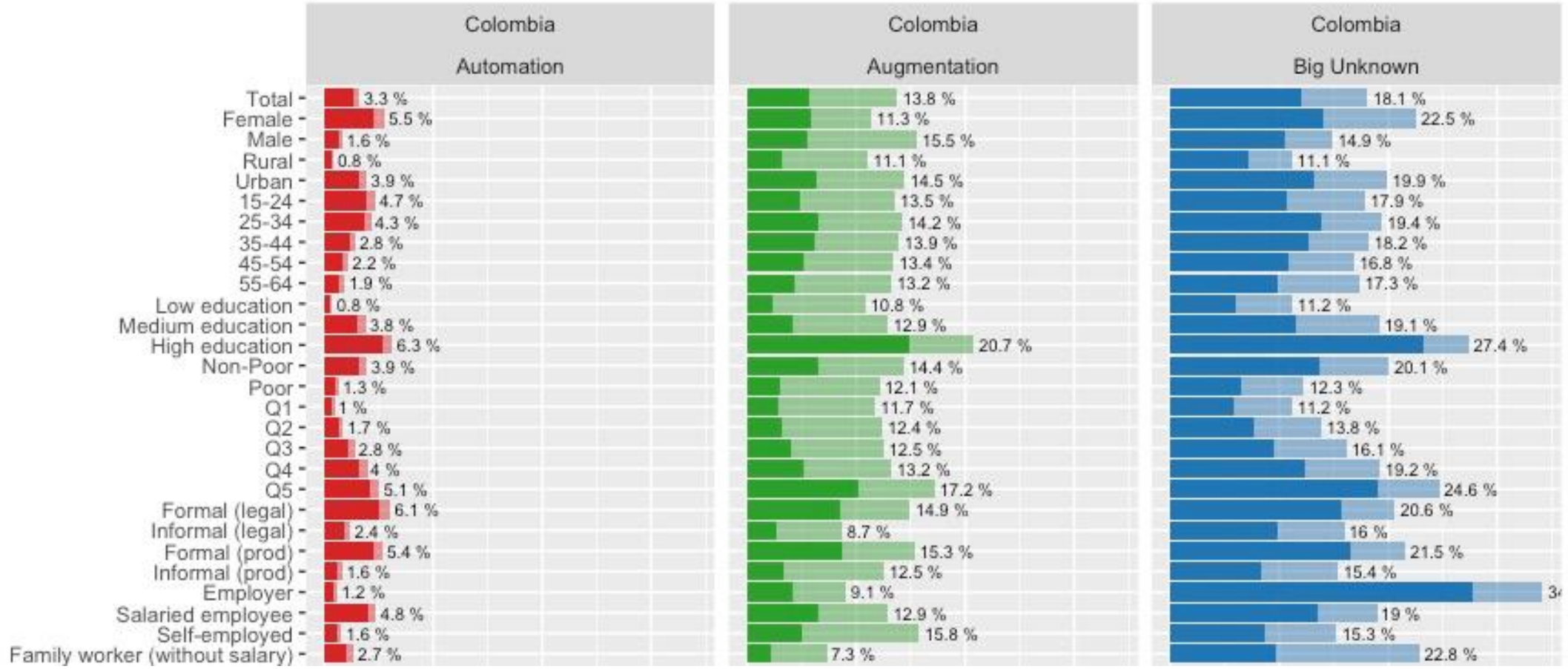


Figure 13: Exposure by country, type and detailed country-level characteristics

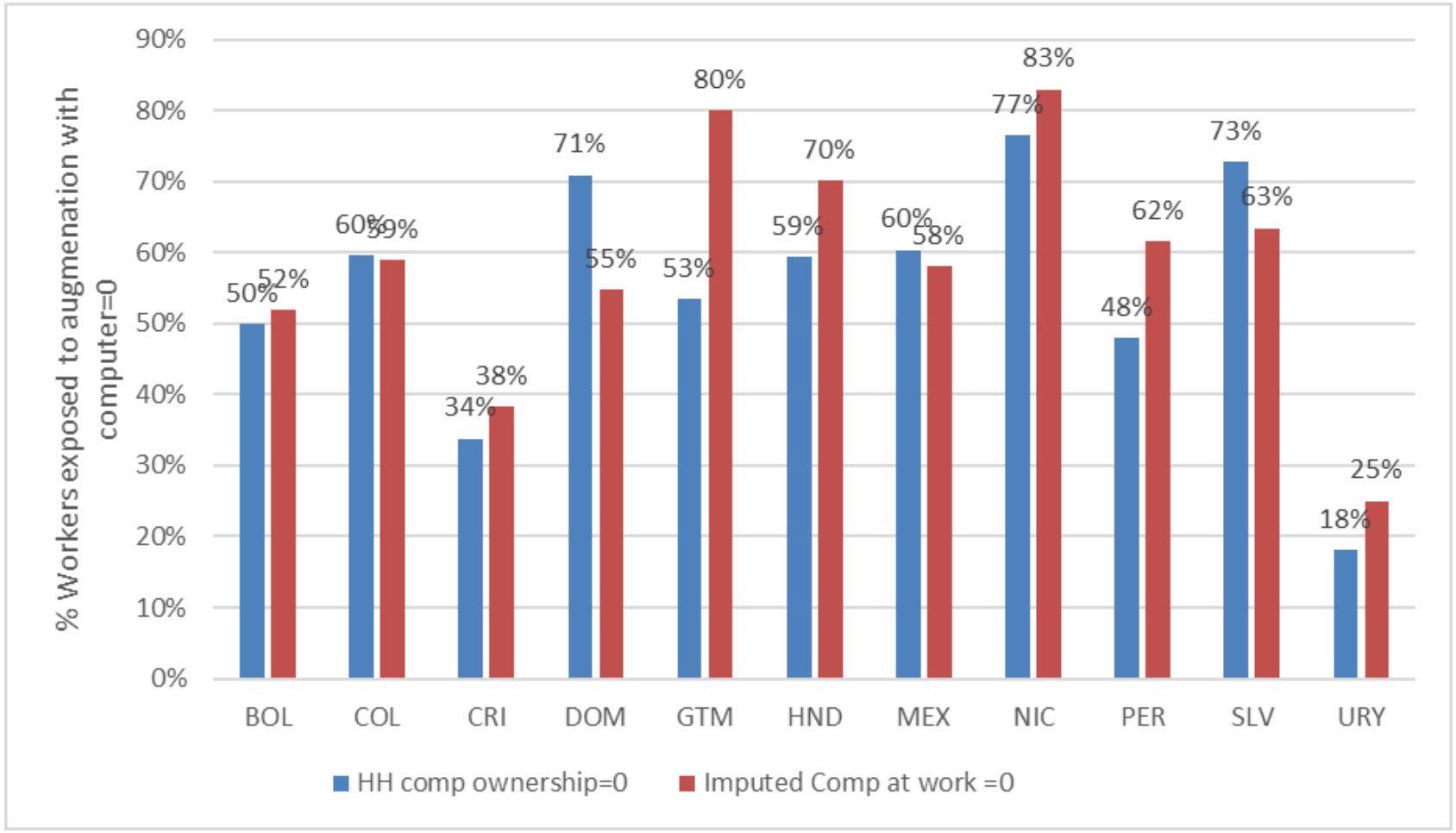


Detailed visuals:

https://pgmyrek.shinyapps.io/App_LATAM/

Robustness check: Imputed Computer Use at Work vs Household Computer Ownership (SEDLAC)

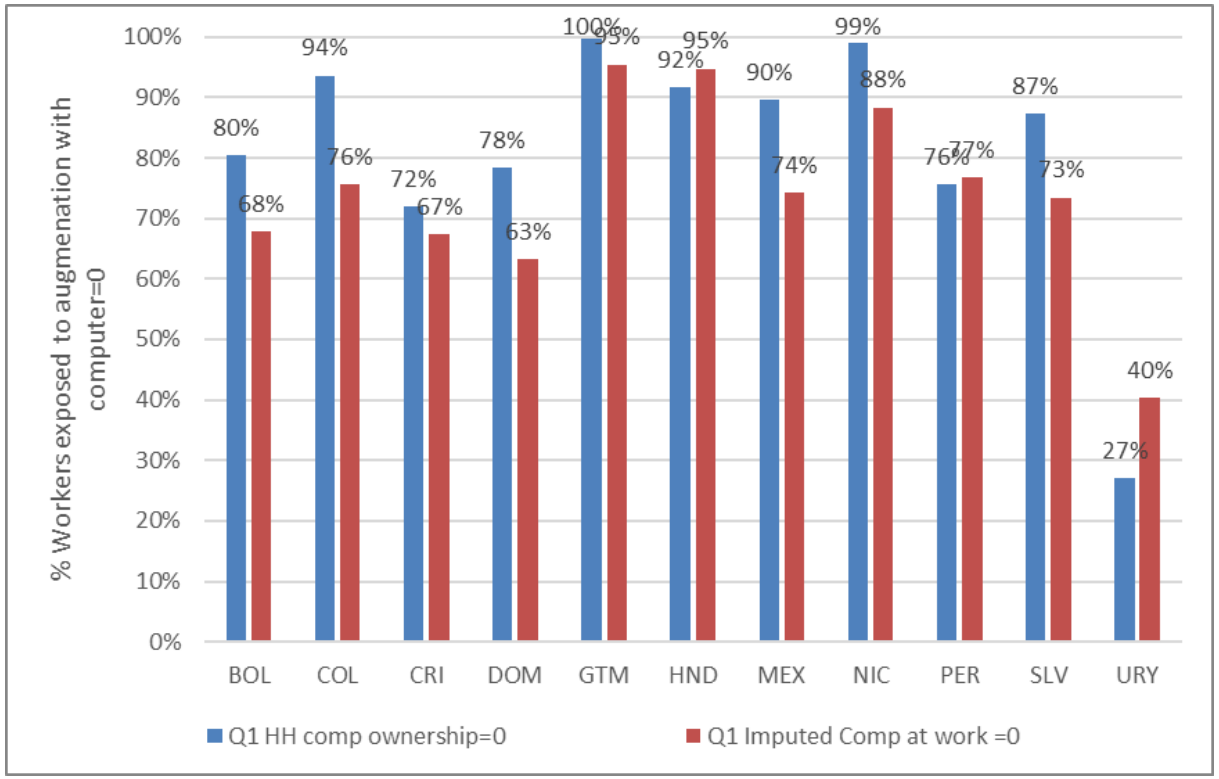
Share of workers without computer access
(among workers exposed to GenAI augmentation)



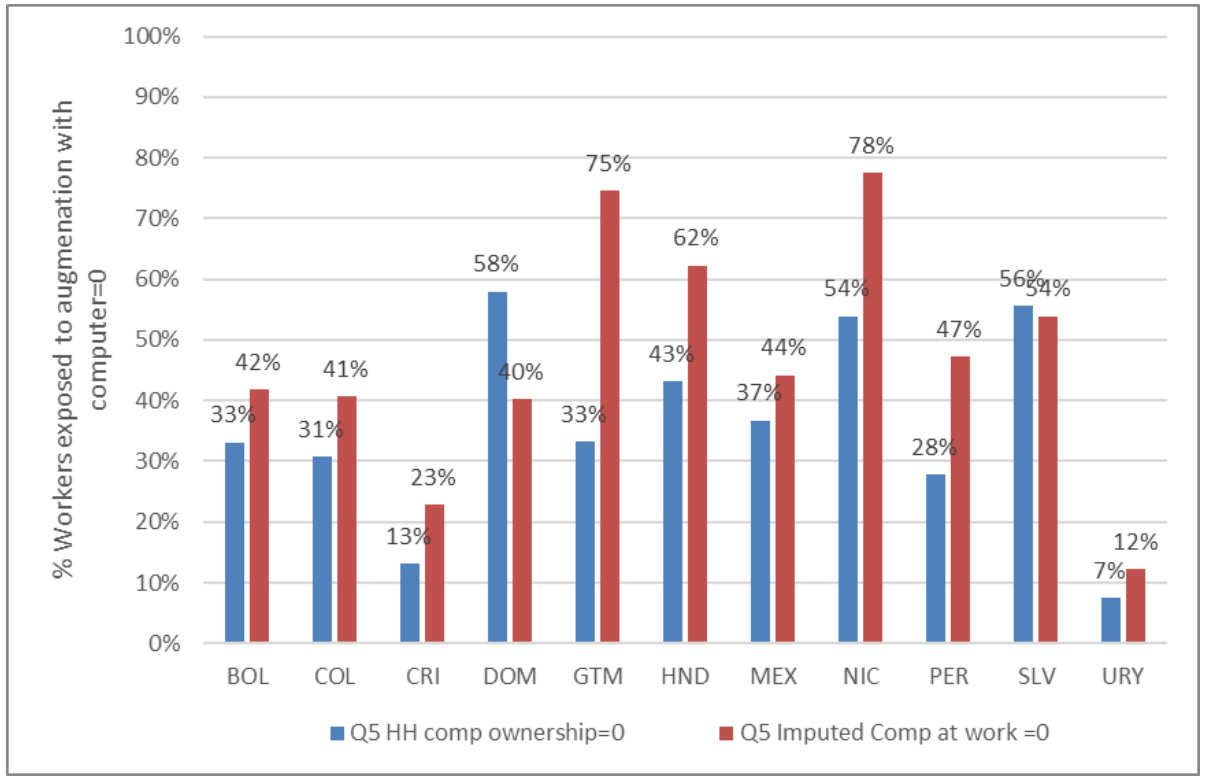
Robustness check: Imputed Computer Use at Work vs Household Computer Ownership (SEDLAC)

Share of workers without computer access
(among workers exposed to GenAI augmentation)

Poorest HH Income Quintile



Richest HH Income Quintile



Final Remarks

Final Remarks

- Studies of labor market exposure to GenAI are largely focused on rich countries, and thereby their methods should be applied with caution to developing countries.
- In LAC:
  - Nearly half of the jobs that could potentially benefit from GenAI augmentation are hampered by digital shortcomings that will prevent them from realizing that potential.
  - There are 17 million jobs that could, in theory, experience additional productivity from the technological transformation with GenAI, but which will not be in position to do so due to the lack of digital infrastructure.
  - Some 7 million such jobs are held by women and nearly 10 million are held by men.

Final Remarks

- Data requirements to apply the methodology of the paper:
  - Survey with ISCO 08 data, ideally at the 4-digit level. If only available at a more aggregated level, it is important to calculate the exposure scores at such level of aggregation using a survey from a similar country.
  - Imputation of digitalization can be done using the PIAAC data, or using self-reported information on access to digital technologies in the same survey.

- When assessing the impacts of GenAI in countries at lower levels of development than LAC (e.g. economies of Sub-Saharan Africa), a different focus is probably more useful:
  - Likely, a negligible share of jobs will be exposed to GenAI
  - However, the missing opportunities could be very large if GenAI has the potential to increase access and lower the cost of key services such as healthcare and education.

Resources

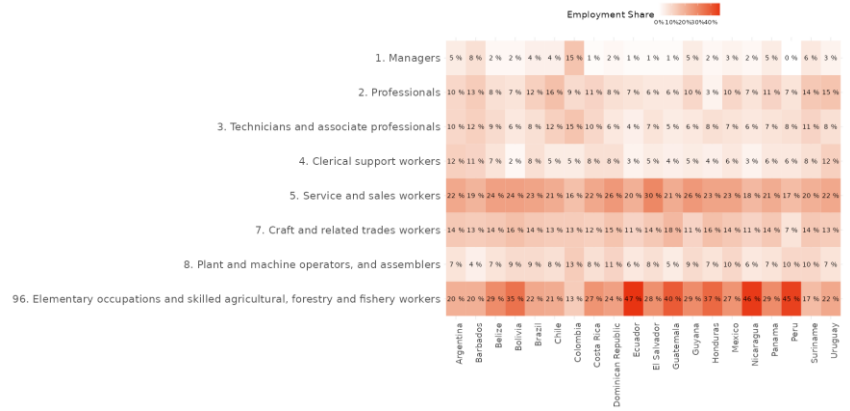
Link to article


Generative AI and Jobs in Latin America and the Caribbean: Is the Digital Divide a Buffer or Bottleneck?

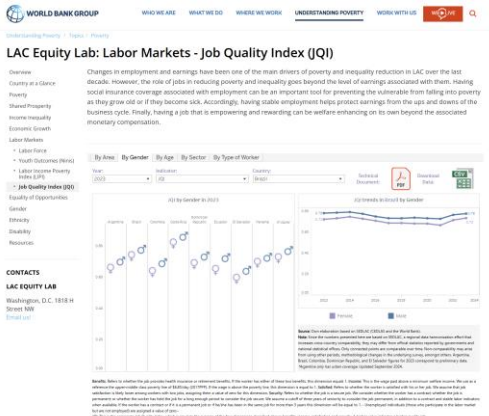
AT A GLANCE

- Overall, a total of 26-38% of jobs in Latin America and the Caribbean could be exposed to Generative AI.
- Generative AI could result in a productivity-enhancing transformation of 8-14% of jobs, with a higher likelihood in urban, educated, and formal sectors, and among higher-income earners.
- About 2-5% of jobs are at risk of full automation due to the current capabilities of GenAI.
- Up to half of the jobs that could improve productivity with GenAI – about 17 million jobs – are hindered by gaps in digital access and infrastructure.
- Governments should implement policies to protect jobs, enhance productivity, and maximize the transformative potential of GenAI to promote more inclusive growth and sustainable development.

GenAI interactive dashboard



LAC Equity Lab


LAC Equity Lab: Labor Markets - Job Quality Index (JQI)

Green Jobs Article, Replication Package and database

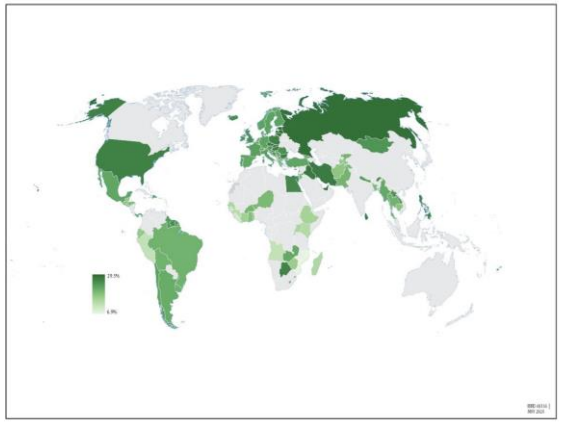


Figure 2 – Green occupations (all types) across the world

Note: share of green occupations as percentage with respect to total employment

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Thank you!

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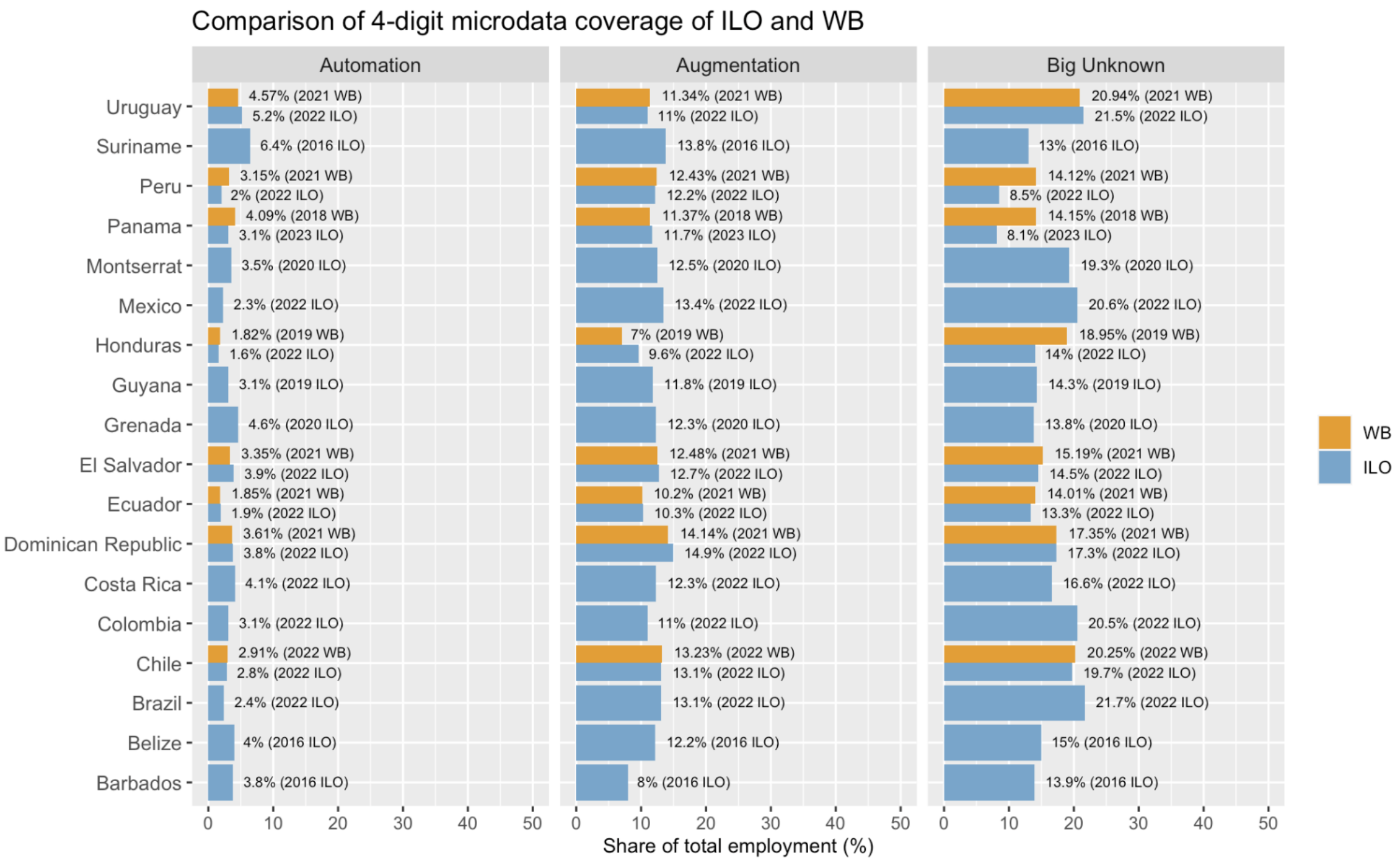
Annex


Comparison of 4-digit microdata coverage of ILO and WB
Automation
Augmentation
Big Unknown
Uruguay
Suriname
Peru
Panama
Montserrat
Mexico
Honduras
Guyana
Grenada
El Salvador
Ecuador
Dominican Republic
Costa Rica
Colombia
Chile
Brazil
Belize
Barbados
4.57% (2021 WB)
5.2% (2022 ILO)
6.4% (2016 ILO)
3.15% (2021 WB)
2% (2022 ILO)
4.09% (2018 WB)
3.1% (2023 ILO)
3.5% (2020 ILO)
2.3% (2022 ILO)
1.82% (2019 WB)
1.6% (2022 ILO)
3.1% (2019 ILO)
4.6% (2020 ILO)
3.35% (2021 WB)
3.9% (2022 ILO)
1.85% (2021 WB)
1.9% (2022 ILO)
3.61% (2021 WB)
3.8% (2022 ILO)
4.1% (2022 ILO)
3.1% (2022 ILO)
2.91% (2022 WB)
2.8% (2022 ILO)
2.4% (2022 ILO)
4% (2016 ILO)
3.8% (2016 ILO)
11.34% (2021 WB)
11% (2022 ILO)
13.8% (2016 ILO)
12.43% (2021 WB)
12.2% (2022 ILO)
11.37% (2018 WB)
11.7% (2023 ILO)
12.5% (2020 ILO)
13.4% (2022 ILO)
7% (2019 WB)
9.6% (2022 ILO)
11.8% (2019 ILO)
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12.48% (2021 WB)
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11% (2022 ILO)
13.23% (2022 WB)
13.1% (2022 ILO)
13.1% (2022 ILO)
12.2% (2016 ILO)
8% (2016 ILO)
20.94% (2021 WB)
21.5% (2022 ILO)
13% (2016 ILO)
14.12% (2021 WB)
8.5% (2022 ILO)
14.15% (2018 WB)
8.1% (2023 ILO)
19.3% (2020 ILO)
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18.95% (2019 WB)
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14.01% (2021 WB)
13.3% (2022 ILO)
17.35% (2021 WB)
17.3% (2022 ILO)
16.6% (2022 ILO)
20.5% (2022 ILO)
20.25% (2022 WB)
19.7% (2022 ILO)
21.7% (2022 ILO)
15% (2016 ILO)
13.9% (2016 ILO)
0
10
20
30
40
50
Share of total employment (%)
WB
ILO