DOCUMENTOS DE TRABAJO

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Matias Ciaschi, Guillermo Falcone, Santiago Garganta, Leonardo Gasparini, Octavio Bertín y Lucía Ramirez-Leira

Documento de Trabajo Nro. 361
Diciembre, 2025
ISSN 1853-0168
www.cedlas.econo.unlp.edu.ar

Cita sugerida: Ciaschi, M., G. Falcone, S. Garganta, L. Gasparini, O. Bertín y L. Ramirez-Leira (2025). The Potential Distributive Impact of AI-driven Labor Changes in Latin America. Documentos de Trabajo del CEDLAS Nº 361, Diciembre, 2025, CEDLAS-Universidad Nacional de La Plata.

The Potential Distributive Impact of AI-driven Labor Changes in Latin America*

Matias Ciaschi
Guillermo Falcone
Santiago Garganta
Leonardo Gasparini
Octavio Bertín
Lucía Ramirez-Leira †

November 18, 2025

Abstract

This paper investigates the potential distributional consequences of artificial intelligence (AI) adoption in Latin American labor markets. Using harmonized household survey data from 14 countries, we combine four recently developed AI occupational exposure indices—the AI Occupational Exposure Index (AIOE), the Complementarity-Adjusted AIOE (C-AIOE), the Generative AI Exposure Index (GBB), and the AI-Generated Occupational Exposure Index (GENOE)—to analyze patterns across countries and worker groups. We validate these measures by comparing task profiles between Latin America and high-income economies using PIAAC data, and develop a contextual adjustment that incorporates informality, wage structures, and union coverage. Finally, we simulate first-order impacts of AI-induced displacement on earnings, poverty, and inequality. The results show substantial heterogeneity, with higher levels of AI-related risk among women, younger, more educated, and formal workers. Indices that account for task complementarities show flatter gradients across the income and education distribution. Simulations suggest that displacement effects may lead to only moderate increases in inequality and poverty in the absence of mitigating policies.

JEL Codes: O33, J21, D31.
Keywords: Artificial Intelligence (AI), Labor Market, Income Distribution, Latin America.

 The work was financed with the support of the Latin America and the Caribbean Research Network of the Inter-American Development Bank. The opinions expressed in this publication are those of the authors and do not necessarily reflect the views of the Inter-American Development Bank, its Board of Directors, or the countries they represent. The authors are very grateful to the IDB for its financial support. They also sincerely appreciate Daron Acemoglu, Juan Pablo Chauvin, and participants at seminars at the IDB and UNLP for their valuable comments and suggestions, and Francisco Diéguez, Ana McNally and Pablo Gallo for excellent research assitance.

†All authors are affiliated with CEDLAS (IIE-FCE, Universidad Nacional de La Plata). Ciaschi, Falcone and Gasparini are also affiliated with CONICET.

1 Introduction

The rapid advancement of Artificial Intelligence (AI) is poised to reshape how we learn, work, and produce globally—and Latin America is no exception. While AI technologies hold the promise of significant productivity gains, they also raise important distributional concerns. In regions characterized by high inequality and labor market segmentation, such as Latin America, understanding who is most exposed to AI and what the implications are for poverty and inequality is a critical research and policy priority.

These concerns echo long-standing debates about the labor market effects of technological change. A vast literature has studied how previous waves of automation—such as the diffusion of computer-based technologies and the rise of industrial robots —reshaped employment patterns, often displacing routine tasks while complementing cognitive and analytical skills. In high-income economies, this has contributed to job polarization (Autor et al., 2003; Spitz-Oener, 2006; Goos and Manning, 2007; Goos et al., 2014; Michaels et al., 2014). More recently, attention has shifted to AI and machine learning, which may affect a broader set of occupations, including non-routine cognitive work (Calvino and Fontanelli, 2023; Czarnitzki et al., 2023; Nucci et al., 2023; Acemoglu, 2024; Venturini et al., 2024; Acemoglu and Restrepo, 2018; Agrawal et al., 2019; and Korinek and Suh, 2024). However, most of this evidence pertains to the United States and Europe, where labor markets and institutional settings differ markedly from those in Latin America. Whether AI adoption will follow similar patterns in developing economies—where informality, limited digital infrastructure, and labor market segmentation are pervasive—remains an open empirical question.

This paper analyzes the potential distributive consequences of AI adoption in Latin American labor markets. We quantify which groups of workers are most exposed to AI technologies and simulate how these exposure patterns could affect earnings, poverty, and inequality. To do this, we combine SEDLAC harmonized household survey microdata from 14 Latin American countries with four recently developed AI exposure indices: the AI Occupational Exposure Index (AIOE), the Complementarity-Adjusted AIOE (C-AIOE), the Generative AI Exposure Index (GBB), and the AI-Generated Occupational Exposure Index (GENOE). We assess differences in exposure across countries and population subgroups (gender, age, education, income), explore key institutional and structural features (such as informality and unionization), and conduct microsimulations to estimate first-order effects on the income distribution. To validate the relevance of these exposure indices in the Latin American context, we also draw on internationally comparable data from the PIAAC survey to examine differences in task profiles between Latin America and high-income countries.

Our main findings can be summarized as follows. We document substantial heterogeneity in occupational exposure to AI technologies across Latin America, with higher exposure levels in countries where professional, clerical, and service occupations represent a larger share of the workforce. Within countries, exposure is systematically higher among women, younger individuals, and workers with higher education and earnings. These patterns, however, vary depending on the exposure index considered. While the AIOE and GBB indices tend to reflect greater exposure among high-skilled workers, the GENOE and C-AIOE indices, which incorporate potential complementarities between AI and human labor, reveal flatter or even declining gradients at the upper end of the income and education distribution. Exposure is also consistently higher among formal workers compared to their informal counterparts, a pattern that holds across alternative definitions of informality. Finally, our counterfactual simulations suggest that AI-driven displacement could lead to modest increases in poverty and inequality in the absence of complementary labor market policies, though the magnitude of these effects varies across countries depending on their occupational structures and institutional contexts.

Building on these findings, our paper makes four main contributions. First, we harmonize and apply four recently developed AI exposure indices—the AIOE, C-AIOE, GENOE, and GBB—to nationally representative household microdata for 14 Latin American countries. This is the first effort to systematically implement and compare these measures in a Global South context. Second, we document heterogeneity in exposure across countries and worker characteristics—particularly gender, education, and income—and identify which groups are most at risk under plausible AI diffusion scenarios. Third, we conduct a set of microsimulations to quantify the potential effects of AI-driven displacement on income, poverty, and inequality across the region. Fourth, we develop a contextual adjustment for AI exposure indices that incorporates institutional features of Latin American labor markets—such as informality, wages, and union coverage—to approximate the effective risk of displacement. In addition, we validate the relevance of these indices using task-level data from the PIAAC survey, which allows us to compare occupational content and potential exposure between Latin America and advanced economies. These contributions together provide a regionally grounded, policy-relevant perspective on the potential distributive implications of AI in developing countries.

This paper is most closely related to the recent literature that seeks to quantify occupational exposure to artificial intelligence. Measuring exposure to AI is challenging given its intangible and rapidly evolving nature (Haskel and Westlake, 2017). A growing number of studies have developed innovative indices based on task-level descriptions or expert assessments. Felten, Raj and Seamans (2021) propose the AI Occupational Exposure index (AIOE), which combines O*NET task descriptors with expert surveys on AI capabilities. Pizzinelli et al. (2023) extend this measure by adjusting for task complementarity through the Complementarity-Adjusted AIOE (C-AIOE), showing that accounting for complementarities meaningfully alters exposure rankings. Other indices such as those by Briggs and Kodnani (2023) and Eloundou et al. (2024) offer alternative task-based exposure scores, highlighting important differences across methods. Benítez-Rueda and Parrado (2024) introduce the GENOE index, which uses AI-generated surveys to assess the likelihood that occupational tasks will be automated, providing projections at one-, five-, and ten-year horizons. Gmyrek, Berg and Bescond (2023) develop the GBB index, based on ISCO-08 classifications and GPT-4 evaluations of 436 occupational groups. Their framework incorporates the potential for augmentation and automation, and is particularly suited for application in developing countries. While these indices provide a useful mapping of AI exposure, they remain largely untested in developing-country contexts, and few studies assess their implications for income distribution or labor market inequality. Our paper builds on this literature by applying multiple indices to harmonized household survey micro data across Latin America, and by proposing a contextual adjustment that incorporates country-specific labor market features such as informality, wages, and union coverage.

Our work is also related to a growing body of research examining how automation and robotics affect labor markets in Latin America. Brambilla et al. (2022, 2023a, 2023b) document heterogeneous employment impacts of automation exposure in Argentina and Brazil, emphasizing demographic disparities and the role of informality as a buffer. These studies focus primarily on routinization and traditional forms of capital-labor substitution. In contrast, this paper considers a broader set of occupational tasks and focuses on the emerging class of AI technologies.

Finally, our paper contributes more broadly to the literature on the labor market consequences of technological change. Seminal work has shown that technological progress often raises the relative demand for skilled workers, contributing to job polarization and earnings inequality (e.g., Katz and Murphy, 1992; Bound and Johnson, 1992; Card and Lemieux, 2001). More recent studies emphasize the task content of jobs and the potential for substitution or complementarity with technology (Autor, Levy and Murnane, 2003; Acemoglu and Autor, 2011; Goos and Manning, 2007; Goos, Manning and Salomons, 2014; Michaels, Natraj and Van Reenen, 2014). A subsequent strand of research has focused on automation and industrial robots, documenting their effects on productivity, employment, and wage distribution in high-income countries (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Autor and Salomons, 2018). However, most of this evidence is concentrated in developed economies, leaving open questions about how these dynamics play out in more segmented, institutionally distinct labor markets such as those in Latin America.

The rest of the paper is organized as follows. Section 2 reviews the main occupational AI exposure indices recently proposed in the literature. Although these measures were developed primarily for high-income countries, they provide a natural starting point for understanding potential exposure in Latin America. Section 3 describes the SEDLAC harmonized household surveys and outlines how we match occupational data to AI exposure indices across 14 countries in the region.

In Section 4, we present a first-pass analysis of potential displacement risks under the assumption that AI technologies diffuse to Latin America in ways similar to developed countries. The results in Section 4 differ, however, from those observed in the developed world, as the structure of occupations and other sociodemographic characteristics of the working population in Latin America are different.

Section 5 turns to a cross-country comparison of occupational content using data from the PIAAC survey. We construct an index of labor resilience to AI adoption and examine differences between Latin American and industrialized countries, both in levels and recent trends. This analysis enables us to assess whether, based on actual tasks and occupational characteristics, jobs in Latin America face similar displacement risks as their counterparts in more developed economies.

Section 6 examines additional country-specific institutional and structural characteristics that may influence the adoption and impact of AI. We focus on three key dimensions: informality, relative wages, and unionization.

In Section 7, we present a highly conjectural yet potentially insightful microsimulation exercise. Drawing on the findings from earlier sections regarding displacement effects, we simulate potential changes in incomes, poverty, and inequality that may arise from AI adoption. This exercise is intentionally simple and, among other assumptions, considers AI as being solely associated with displacement effects.

Finally, section 8 closes with a summary and some concluding comments.

2 Indices

Assessing the exposure of occupations to artificial intelligence (AI) is inherently challenging due to the complex and intangible nature of these technologies (Haskel & Westlake, 2017). Recent advances in research, however, have yielded innovative methodologies to quantify this exposure. In this paper, we combine harmonized household survey data from SEDLAC—introduced in detail in Section 3—with four advanced AI occupational exposure indices: the AI Occupational Exposure Index (AIOE) introduced by Felten et al. (2021), the Complementarity-Adjusted AIOE (C-AIOE) proposed by Pizzinelli et al. (2023), the Generated Index of Occupational Exposure (GENOE) developed by Benítez-Rueda and Parrado (2024), and the GBB index presented by Gmyrek et al. (2023). This integration enables a detailed examination of the extent to which different occupations in Latin America are exposed to AI and provides a foundation for evaluating its potential effects on employment patterns, wages, informality, and income distribution.

The AIOE index (Felten et al., 2021) measures the degree to which AI applications align with occupational tasks, utilizing data from the Occupational Information Network (O*NET). By focusing on the connections between AI capabilities and task requirements, the index identifies occupations at risk of replacement or enhancement by AI technologies. Pizzinelli et al. (2023) build on this work by introducing the C-AIOE, which adjusts for the complementarity between AI and human labor. This adjustment accounts for scenarios where AI augments productivity and improves worker outcomes, as opposed to simply replacing them. Their findings emphasize disparities across countries and demographics, with certain groups, such as women and highly educated workers, showing greater exposure to both the risks and benefits of AI-driven transformations. The GENOE index, developed by Benítez-Rueda and Parrado (2024), employs a groundbreaking approach using synthetic AI surveys powered by large language models (LLMs). This methodology estimates exposure at the task level, providing both a snapshot of current dynamics and forecasts for one-, five-, and ten-year periods. By considering factors like productivity improvements, short-term labor market disruptions, and the reallocation of workers across industries, the GENOE index enables comprehensive simulations of both immediate and long-term impacts of AI.

The GBB index, introduced by Gmyrek et al. (2023), provides a distinct approach by directly using the ISCO-08 occupational classification system. This index evaluates the exposure of tasks to Generative AI (GenAI) across 436 detailed ISCO-08 occupational groups, considering tasks that could be automated, augmented, or remain uncertain based on evolving AI capabilities. Using the Application Programming Interface (API) of GPT-4, the authors designed a sequential call that loops over 3,123 tasks, requesting the model to assess the technical feasibility of performing each task with GPT-4 or LLM technology of similar capabilities. This approach offers a closer alignment with Latin American labor realities, providing a comprehensive analysis of AI's potential labor market impacts, particularly in a context where formal and informal work dynamics coexist.

By combining these innovative measures, our study highlights the nuances of AI exposure in the region. While the GBB index provides critical insights into the immediate impacts of Generative AI (GenAI), particularly in terms of automation and task augmentation, the GENOE index stands out for its forward-looking approach, emphasizing the dynamic nature of AI's influence over time. The AIOE and C-AIOE indices contribute by offering a more immediate, task-based view of AI's integration into occupations, considering both risks and potential benefits, such as productivity gains and labor reallocation. Together, these indices enrich our understanding of the efficiency-equity trade-offs associated with AI adoption in Latin America, shedding light on the disruptions and opportunities that AI may bring in the short and long term, with implications for economic growth, employment dynamics and income distribution.

Most AI exposure indices used in this study (specifically the AIOE, C-AIOE, and GENOE) are originally constructed using the U.S. Standard Occupational Classification (SOC) system. To ensure consistency with Latin American occupational data, we harmonize these indices to the ISCO-08 classification system used in our household surveys. Table 1 presents the average scores for each of the four AI exposure indices across 2-digit ISCO-08 occupational categories, offering a broad overview of the occupational distribution of AI-related risks. Although all four indices aim to measure occupational exposure to AI technologies—albeit through different conceptual and methodological approaches—they differ in construction and scale, and are therefore not strictly comparable in magnitude. For instance, the AIOE index, developed by Felten et al. (2021), quantifies exposure by linking 10 widely used AI applications (e.g., language modeling, image recognition, translation) to 52 occupational abilities defined in the O*NET database. For each ability, an exposure score between 0 and 1 is computed based on its relatedness to each AI application. These scores are then summed across applications, yielding an ability-level exposure that can range theoretically from 0 (no exposure) to 10 (maximum exposure, if the ability is fully related to all applications). At the occupational level, the AIOE aggregates these ability exposures using weights based on the importance and frequency of each ability within an occupation, and normalizes by the total weighted ability set. This ensures that the final score reflects the degree to which an occupation's most critical abilities are exposed to current AI capabilities. In practice, AIOE values fall within a narrower range (approximately between 5 and 7) reflecting variation in the alignment between occupational ability profiles and the current frontier of AI applications.

Importantly, only the C-AIOE is directly comparable to the AIOE, as it is constructed by adjusting the latter to account for the potential complementarity between AI technologies and human occupational tasks. This adjustment, proposed by Pizzinelli et al. (2023), introduces a downward correction based on an index of potential complementarity, which incorporates a range of contextual factors from the O*NET database—such as responsibility, communication requirements, physical proximity, and training intensity—reflecting the likelihood that tasks are performed jointly with, rather than replaced by, AI. As a result, the C-AIOE is always less than or equal to the AIOE. Conceptually, the AIOE can be interpreted as capturing both the potential displacement and complementarity effects of AI, insofar as it reflects the overall relatedness between occupational abilities and AI applications. In contrast, the C-AIOE aims to provide a more refined measure of displacement risk by adjusting the AIOE downward to account for task-level characteristics that are likely to foster human-AI complementarities.

The GBB index, developed by Gmyrek et al. (2023), maps ISCO-08 occupations to a set of tasks and scores each task on a 0–1 scale based on its likelihood of being automated by current generative AI tools, particularly large language models. Task-level scores are averaged to obtain occupation-level exposure. The index thus captures the technical feasibility of automation and serves as an upper-bound estimate of AI-induced displacement. Although values range from 0 to 1, they tend to concentrate around mid-range levels, depending on the intensity of language- and information-based tasks. The GENOE index (Benítez-Rueda and Parrado, 2024), quantifies the likelihood that occupations will be displaced by AI using synthetic surveys conducted with large language models (LLMs). Unlike other indices that rely on predefined mappings between technologies and tasks, GENOE leverages the generative capabilities of LLMs to simulate expert assessments across a comprehensive set of occupational tasks, incorporating not only technical feasibility but also contextual factors such as social acceptability, ethical constraints, and regulatory barriers. Exposure scores range from 0 to 1, where higher values indicate a greater perceived risk of AI-driven occupational replacement. Depending on the time horizon considered, the distribution of scores varies, but typically reflects moderate and heterogeneous exposure across occupations.

Although the GBB and GENOE indices share a similar 0–1 scale and both aim to capture the displacement potential of AI technologies, they differ in scope and construction. The GBB focuses on the technical feasibility of automating tasks via large language models, and is conceptually closer to the AIOE in that it reflects an overall relatedness between occupational content and AI capabilities. In contrast, GENOE incorporates a broader range of contextual dimensions—social, ethical, and regulatory—mirroring in some ways the conceptual adjustment made in the C-AIOE to account for complementarities. Thus, while AIOE and GBB are more aligned with measures of task-level technical exposure or automation feasibility, C-AIOE and GENOE both attempt, through different methodologies, to net out those aspects of exposure that are less likely to translate into actual displacement.

Table 1: Indices of AI-exposure by occupation, 2-digit ISCO-08

Occupation	ISCO	AIOE	C-AIOE	GENOE	GBB
Chief Executives, Senior Officials and Legislators	11	6.46	4.08	0.17	0.30
Administrative and Commercial Managers	12	6.57	4.63	0.23	0.28
Production and Specialized Services Managers	13	6.40	4.18	0.19	0.33
Hospitality, Retail and Other Services Managers	14	6.28	4.18	0.23	0.40
Science and Engineering Professionals	21	6.48	4.64	0.22	0.35
Health Professionals	22	6.25	3.85	0.14	0.25
Teaching Professionals	23	6.43	4.44	0.17	0.38
Business and Administration Professionals	24	6.60	4.93	0.33	0.48
Information and Communications Technology Professionals	25	6.53	5.22	0.28	0.41
Legal, Social and Cultural Professionals	26	6.37	4.59	0.22	0.39
Science and Engineering Associate Professionals	31	6.03	4.20	0.27	0.32
Health Associate Professionals	32	5.99	4.31	0.20	0.25
Business and Administration Associate Professionals	33	6.44	4.82	0.36	0.49
Legal, Social, Cultural and Related Associate Professionals	34	6.03	4.33	0.21	0.33
Information and Communications Technicians	35	6.25	4.85	0.29	0.43
General and Keyboard Clerks	41	6.40	5.55	0.68	0.70
Customer Services Clerks	42	6.44	5.29	0.52	0.64
Numerical and Material Recording Clerks	43	6.41	5.20	0.63	0.58
Other Clerical Support Workers	44	6.21	5.11	0.54	0.59
Personal Services Workers	51	5.86	4.35	0.20	0.27
Sales Workers	52	6.11	4.94	0.41	0.38
Personal Care Workers	53	5.97	4.30	0.15	0.22
Protective Services Workers	54	5.80	3.76	0.19	0.17
Market-oriented Skilled Agricultural Workers	61	5.66	4.15	0.23	0.21
Market-oriented Skilled Forestry, Fishery and Hunting Workers	62	5.62	4.07	0.18	0.19
Subsistence Farmers, Fishers, Hunters and Gatherers	63	5.42	4.36	0.19	0.12
Building and Related Trades Workers (excluding Electricians)	71	5.48	3.94	0.16	0.12
Metal, Machinery and Related Trades Workers	72	5.60	4.21	0.30	0.15
Handicraft and Printing Workers	73	5.75	4.77	0.31	0.18
Electrical and Electronic Trades Workers	74	5.74	3.95	0.17	0.17
Food Processing, Woodworking, Garment and Other Craft and Related	75	5.67	4.52	0.39	0.17
Stationary Plant and Machine Operators	81	5.60	4.60	0.53	0.20
Assemblers	82	5.69	4.65	0.36	0.34
Drivers and Mobile Plant Operators	83	5.71	4.13	0.30	0.20
Cleaners and Helpers	91	5.33	4.50	0.27	0.11
Agricultural, Forestry and Fishery Labourers	92	5.44	4.28	0.20	0.11
Labourers in Mining, Construction, Manufacturing and Transport	93	5.48	4.11	0.33	0.13
Food Preparation Assistants	94	5.53	4.62	0.33	0.10
Street and Related Sales and Services Workers	95	6.16	4.90	0.41	0.22
Refuse Workers and Other Elementary Workers	96	5.55	4.24	0.33	0.20
Unweighted mean		5.99	4.49	0.30	0.30

Source: Authors' own calculations based on AI exposure indices.

These conceptual differences and similarities are consistent with the empirical correlations observed between the indices in Table 2.[1] In particular, the AIOE and the GBB index show a high degree of correlation, suggesting they capture similar relative exposure across occupations. Conversely, the C-AIOE and the GENOE are more closely correlated with each other than with the AIOE or GBB, possibly reflecting different methodological approaches and task domains they emphasize, and potentially the fact that both indices, in different ways, account for potential complementarities between AI technologies and tasks.

Table 2: Pearson correlation between AI exposure indices

	AIOE	C-AIOE	GENOE	GBB
AIOE	1			
C-AIOE	0.4417*	1		
GENOE	0.0335	0.6366*	1	
GBB	0.7119*	0.5515*	0.3619*	1

Source: Authors' own calculations based on data on AI exposure indices.

3 Data

To explore the labor market and distributional implications of the increasing adoption of artificial intelligence in Latin America, we rely on microdata from national household surveys conducted in several countries across the region. We include all LAC economies for which their main surveys enable the identification of workers' occupations using ISCO-08 codes, at least at the 2-digit level, or for which national occupational classifications can be matched to ISCO-08 through official or alternative validated crosswalks. Specifically, we use microdata from 14 countries (see Table 3), including the following surveys: *Encuesta Permanente de Hogares (EPH)* in Argentina, *Encuesta de Hogares (EH)* in Bolivia, *Pesquisa Nacional por Amostra de Domicilios Contínua (PNAD)* in Brazil, *Encuesta de Caracterización Socioeconómica Nacional (CASEN)* in Chile, *Gran Encuesta Integrada de Hogares (GEIH)* in Colombia, *Encuesta Nacional de Hogares (ENAHO)* in Costa Rica, *Encuesta de*

[1] Table 2 shows Pearson correlations between AI indices. Similar results are obtained using Spearman's rank correlation coefficient.

Empleo, Desempleo y Subempleo (ENEMDU) in Ecuador, *Encuesta de Hogares de Propósitos Múltiples (EHPM)* in El Salvador, *Encuesta Permanente de Hogares de Propósitos Múltiples (EPHPM)* in Honduras, *Encuesta Nacional de Ingresos y Gastos de los Hogares (ENIGH)* in Mexico, *Encuesta de Hogares (EH)* in Panama, *Encuesta Nacional de Hogares (ENAHO)* in Peru, *Encuesta Nacional Continua de Fuerza de Trabajo (ECNFT)* in Dominican Republic, and *Encuesta Continua de Hogares (ECH)* in Uruguay. It is worth noting that the Argentinean survey (EPH) only covers urban areas, which may introduce some bias in the estimated occupational structure and the resulting exposure measures. However, given that over 93% of Argentina's population resides in urban areas, the potential bias is likely to be limited.

Table 3: National household surveys of Latin America used in the analysis

Country	Survey	Acronym	Year
Argentina	Encuesta Permanente de Hogares – Continua	EPH-C	2023
Bolivia	Encuesta de Hogares	EH	2022
Brazil	Pesquisa Nacional por Amostra de Domicílios – Continua	PNADC	2023
Chile	Encuesta de Caracterización Socioeconómica Nacional	CASEN	2022
Colombia	Gran Encuesta Integrada de Hogares	GEIH	2019
Costa Rica	Encuesta Nacional de Hogares	ENAHO	2019
Ecuador	Encuesta de Empleo, Desempleo y Subempleo	ENEMDU	2023
El Salvador	Encuesta de Hogares de Propósitos Múltiples	EHPM	2023
Honduras	Encuesta Permanente de Hogares de Propósitos Múltiples	EPHPM	2023
Mexico	Encuesta Nacional de Ingresos y Gastos de los Hogares	ENIGH	2018
Panama	Encuesta de Hogares	EH	2018
Peru	Encuesta Nacional de Hogares	ENAHO	2023
Dominican Republic	Encuesta Nacional Continua de Fuerza de Trabajo	ECNFT	2023
Uruguay	Encuesta Continua de Hogares	ECH	2023

Source: Authors' own calculations.

These surveys are harmonized following the protocol of the Socioeconomic Database for Latin America and the Caribbean (SEDLAC), a joint initiative of CEDLAS at *Universidad Nacional de La Plata* and the World Bank. Given that household surveys in Latin America differ in structure, questionnaire design, and methodological approaches (not only across countries but sometimes also over time within the same country), ensuring comparability is a key challenge. SEDLAC addresses this issue by applying a standardized and common methodology across countries in the region, enabling the construction of consistent and comparable labor, distributional, and other socioeconomic variables. In line with this approach, we apply uniform definitions and data processing procedures to enhance cross-country comparability in the indicators used throughout our analysis (SEDLAC, 2024).

We conduct the analysis using the most recent national household surveys available in each country of our sample for which the identification of workers' occupations using ISCO-08 codes is feasible. As discussed above, the dataset covers 14 Latin American countries, including the region's largest economies. As such, the resulting sample provides broad coverage of the Latin American labor force and offers high statistical power for analyzing heterogeneity in AI exposure across countries and worker groups.

A key challenge in conducting cross-country occupational analysis in the region is the lack of a unified occupational coding system. Countries in Latin America rely on different versions of the ISCO classification, or use national classifications that do not always align directly with international standards. To ensure comparability, we harmonize all occupation codes to the International Standard Classification of Occupations 2008 (ISCO-08) using official or validated crosswalks. Table 4 provides methodological details on this harmonization procedure for the six largest economies of the region.

Table 4: Harmonization of occupational classifications ISCO-08

Country	Occupational classification	ISCO-08 harmonization process
Argentina	Clasificador Nacional de Ocupaciones	Official crosswalk provided by INDEC
Brazil	Classificação de Ocupações para Pesquisas Domiciliares	Own ad-hoc crosswalk
Chile	International Standard Classification of Occupations	Own ad-hoc crosswalk based on ILO official crosswalk
Colombia	Clasificación Nacional de Ocupaciones	Own ad-hoc crosswalk based on DANE crosswalk and individual's educational attainment
Mexico	Sistema Nacional de Clasificación de Ocupaciones	Own ad-hoc crosswalk
Peru	Código de Ocupaciones	Own ad-hoc crosswalk based on INEI crosswalk

Source: Authors' own calculations.

This harmonization is particularly important for integrating the occupational AI exposure indices described in Section 2 with the SEDLAC microdata. While the GBB index is natively defined using ISCO-08 codes, the AIOE, C-AIOE, and GENOE indices are originally based on the Standard Occupational Classification (SOC) system used in the United States.

Establishing a correspondence between the SOC 2018 and ISCO-08 systems is therefore a necessary step for assigning exposure scores to workers in the region. Once this mapping is completed, the harmonized dataset enables a consistent comparative analysis of AI exposure across occupations and countries.

An additional constraint is that the granularity of the occupational information varies across LAC surveys. Specifically, the surveys of Chile, Ecuador, El Salvador, Honduras, Peru, the Dominican Republic, and Uruguay allow for the identification of occupations at the 4-digit level of ISCO-08. In contrast, for the remaining countries (including the largest economies in the region) only 2-digit occupational codes are available. Since the AI exposure indices are originally defined at the 4-digit level (after adapting most of them to ISCO-08 from their original SOC-based classification), this poses a challenge for ensuring consistency across countries.

To address this limitation, we aggregate the indices to the 2-digit level, which allows us to maximize country coverage while maintaining sufficient occupational detail. The aggregation is conducted in two stages. First, for each of the seven countries with 4-digit information, we compute the exposure of each 2-digit ISCO-08 code as a weighted average of the corresponding 4-digit codes, using country-specific occupational structures as weights. Then, for each 2-digit code, we take the unweighted average of the values obtained across those seven countries. This procedure yields harmonized AI exposure scores at the 2-digit level for all four indices—AIOE, C-AIOE, GENOE, and GBB—which we use to assign exposure values to workers in all 14 countries in our sample.[2]

The final dataset merges the SEDLAC microdata with the four occupational exposure indices (GBB, GENOE, AIOE, and C-AIOE) allowing us to identify the degree of AI exposure at the individual worker level across Latin America. This enriched dataset serves as the basis for the empirical analysis that follows, enabling an examination of how AI exposure varies with worker characteristics such as gender, age, education, and skill level. Building on this, we explore the potential implications of AI for key labor market outcomes, including wages,

[2] We find that the results obtained using the 2-digit indices closely mirror those based on the original 4-digit versions, suggesting that the aggregation procedure does not significantly alter the underlying patterns of AI exposure.

employment, and informality, and assess how these impacts may differ across demographic and socioeconomic groups. This approach provides a comprehensive perspective on the potential distributive consequences of AI adoption in the Latin American context, which we examine in the following sections.

4 Labor market exposure to AI in Latin America

In this section, we characterize the exposure of Latin American labor markets to the expansion of AI technologies by applying the set of indices of AI exposure discussed in Section 2 to the harmonized microdata from national household surveys presented in Section 3. This analysis provides an overview of AI exposure in the region and its implications for various groups. We focus on the potential displacement effects of AI under the assumption that new technologies will be adopted in Latin America in a manner similar to richer countries. While this is clearly a simplification, we believe it serves as a natural benchmark to initiate the analysis. In the following sections, we extend the discussion to account for differences in actual tasks and occupational characteristics between Latin America and the US, as well as other factors that may influence the adoption of new technologies, such as wage structures, and the incidence of self-employment and informality.

Table 5 presents a key input for our cross-country results: the structure of occupations at the 2-digit ISCO level, by country. Since, by construction, the AI indices are the same across all countries, differences in exposure to AI stem from variations in the occupational structure. Although our calculations use information at the 2-digit level (and at the 4-digit level in some cases), for illustration purposes Table 6 presents the simpler occupational structure at the 1-digit level. The table reveals significant differences across countries. For instance, the share of managers ranges from 5.4% in Panama to just 0.3% in Peru. The share of professionals varies from 18.7% in Chile to just 5.3% in Honduras, while the share of clerical support workers ranges from 11.9% in Argentina to 2.6% in Ecuador. These differences suggest significant variations in exposure to AI. For instance, Uruguay has a relatively large share of professionals and clerical support workers, two occupations that are more exposed to AI. In contrast, Ecuador has a lower share of these occupations and a higher concentration of Skilled Agricultural, Forestry, and Fishery Workers, as well as Elementary Occupations, which suggests a lower risk from AI, at least in the short run.

Table 5: Structure of occupations, ISCO 2-digits, by country

Occupation	**ISCO**	**LATAM**	**ARG**	**BOL**	**BRA**	**CHL**	**COL**	**CRI**	**ECU**	**SLV**	**HND**	**MEX**	**PAN**	**PER**	**DOM**	**URY**
Chief Executives, Senior Officials and Legislators	11	0,31	0,03	0,15	0,25	0,16	0,40	0,20	0,22	0,19	0,57	0,17	0,68	0,08	0,22	1,02
Administrative and Commercial Managers	12	0,46	-	0,50	1,12	0,44	0,07	0,29	0,12	0,39	0,46	1,06	1,25	0,02	0,23	0,45
Production and Specialized Services Managers	13	1,11	2,44	0,78	1,08	1,80	1,75	0,72	0,41	0,76	0,56	1,68	1,80	0,15	0,66	0,97
Hospitality, Retail and Other Services Managers	14	0,84	2,36	0,87	0,96	1,66	0,19	0,04	0,26	0,49	0,52	0,87	1,70	0,03	1,31	0,48
Science and Engineering Professionals	21	1,24	0,71	1,31	1,29	3,94	1,00	1,64	0,86	0,54	0,38	0,80	1,46	1,01	0,80	1,63
Health Professionals	22	1,58	2,15	1,96	2,22	3,22	1,82	1,55	1,17	1,13	0,25	1,13	1,36	0,75	1,28	2,09
Teaching Professionals	23	3,63	5,18	3,50	4,24	4,40	2,97	4,36	3,13	2,14	3,01	3,30	3,75	2,78	3,34	4,75
Business and Administration Professionals	24	1,58	0,85	1,08	1,93	2,85	3,40	2,23	0,74	1,22	1,02	1,71	1,67	0,66	1,19	1,58
Information and Communications Technology Professionals	25	0,56	0,38	0,31	0,76	1,42	0,95	1,03	0,19	0,33	0,14	0,43	0,48	0,19	0,21	0,97
Legal, Social and Cultural Professionals	26	1,48	0,52	1,64	2,44	2,89	0,57	1,77	1,14	1,26	0,56	1,58	1,73	0,77	1,67	2,19
Science and Engineering Associate Professionals	31	1,43	2,05	1,58	1,56	2,11	1,87	1,41	1,11	0,89	1,19	1,94	0,80	1,44	1,09	1,03
Health Associate Professionals	32	1,38	2,39	0,78	2,41	2,13	1,39	1,03	0,60	1,86	0,62	0,86	1,16	0,98	1,20	1,96
Business and Administration Associate Professionals	33	2,94	3,53	1,84	2,74	4,79	3,32	4,41	2,01	1,76	1,54	3,21	4,43	3,02	2,12	2,50
Legal, Social, Cultural and Related Associate Professionals	34	1,09	0,80	1,35	1,21	0,97	2,26	1,47	0,53	0,58	0,88	1,04	1,00	0,55	1,27	1,30
Information and Communications Technicians	35	0,58	1,67	0,45	0,83	0,64	0,26	0,80	0,29	0,32	0,34	0,38	0,49	0,38	0,56	0,75
General and Keyboard Clerks	41	2,30	7,65	0,71	4,50	1,20	1,63	3,53	0,25	0,96	0,48	2,16	1,82	0,48	1,74	5,07
Customer Services Clerks	42	1,85	0,28	1,24	2,12	1,35	1,83	3,05	0,78	2,14	1,71	2,18	1,61	0,90	5,15	1,52
Numerical and Material Recording Clerks	43	1,81	3,33	0,65	1,60	2,13	1,52	2,36	1,29	1,48	1,35	1,00	1,69	1,90	1,73	3,36
Other Clerical Support Workers	44	0,51	0,67	0,41	0,20	0,57	0,37	0,34	0,25	0,66	0,14	0,16	1,23	1,42	0,21	0,44
Personal Services Workers	51	5,31	5,71	5,60	6,16	4,76	5,10	5,23	5,30	6,48	5,70	3,43	3,78	4,70	7,51	4,90
Sales Workers	52	13,21	14,24	14,97	12,18	11,33	11,22	10,11	12,41	19,27	17,55	12,81	10,92	13,32	14,08	10,55
Personal Care Workers	53	1,58	2,67	0,63	2,29	1,82	1,91	2,12	0,60	0,66	1,07	0,73	2,32	0,57	1,26	3,49
Protective Services Workers	54	2,44	2,98	1,02	1,73	2,66	2,72	3,68	2,07	3,28	2,51	2,26	2,57	0,91	3,12	2,73
Market-oriented Skilled Agricultural Workers	61	7,27	0,23	22,79	4,73	2,26	8,80	2,88	15,85	6,73	8,52	5,81	2,00	13,33	4,04	3,80
Market-oriented Skilled Forestry, Fishery and Hunting Workers	62	0,46	0,01	0,60	0,43	0,50	0,38	0,21	1,00	0,36	0,51	0,33	0,89	0,39	0,27	0,52
Subsistence Farmers, Fishers, Hunters and Gatherers	63	0,91	-	-	-	0,05	0,44	0,01	2,83	0,15	-	2,31	6,96	0,02	-	-
Building and Related Trades Workers (excluding Electricians)	71	4,25	6,93	6,29	4,82	4,98	0,56	2,33	2,99	3,90	4,57	3,01	5,57	2,30	6,31	4,92
Metal, Machinery and Related Trades Workers	72	3,08	3,57	3,24	3,29	3,51	5,54	2,44	2,13	3,17	2,85	2,23	2,86	1,59	3,78	2,84
Handicraft and Printing Workers	73	0,87	0,34	0,72	0,72	0,79	1,30	0,85	0,61	1,38	0,63	0,80	1,31	1,35	0,56	0,87
Electrical and Electronic Trades Workers	74	1,17	0,27	0,27	1,27	1,52	2,53	1,22	1,27	1,03	0,81	0,85	1,59	0,68	1,57	1,59
Food Processing, Woodworking, Garment and Other Craft and Related Trades Workers	75	3,83	2,63	6,15	3,33	3,08	3,72	3,22	3,53	4,75	4,99	4,77	3,03	3,63	3,28	3,48
Stationary Plant and Machine Operators	81	1,74	2,26	1,36	2,25	1,98	2,76	0,90	0,94	2,89	2,47	2,43	0,56	0,67	1,19	1,65
Assemblers	82	0,26	0,14	-	0,34	0,05	0,23	0,38	0,00	0,07	0,63	1,27	0,03	0,00	0,43	0,04
Drivers and Mobile Plant Operators	83	5,94	5,45	7,94	6,43	6,95	5,16	5,80	5,55	4,05	3,64	5,27	6,99	6,52	7,73	5,64
Cleaners and Helpers	91	5,99	8,74	3,19	7,59	5,68	5,32	8,76	4,20	6,15	5,19	2,50	6,01	4,22	8,00	8,27
Agricultural, Forestry and Fishery Labourers	92	5,75	1,13	0,75	2,35	3,42	1,07	7,43	11,10	7,59	14,65	6,14	3,97	13,89	3,22	3,80
Labourers in Mining, Construction, Manufacturing and Transport	93	4,96	3,44	1,78	4,49	3,30	6,77	6,59	5,97	5,52	5,49	8,51	4,90	4,56	3,43	4,74
Food Preparation Assistants	94	1,39	1,59	0,69	0,87	1,03	2,44	0,99	2,53	0,36	0,80	1,29	0,85	2,67	2,61	0,71
Street and Related Sales and Services Workers	95	1,13	0,43	0,00	0,37	0,66	1,71	0,90	2,51	1,48	0,45	2,34	1,52	2,53	0,76	0,22
Refuse Workers and Other Elementary Workers	96	1,78	0,25	0,91	0,91	1,01	2,75	1,71	1,25	1,61	1,29	5,26	1,28	4,66	0,89	1,18
Total		100,00	100,00	100,00	100,00	100,00	100,00	100,00	100,00	100,00	100,00	100,00	100,00	100,00	100,00	100,00

Source: Authors' calculations based on microdata from national household surveys.

Table 6: Structure of occupations, ISCO 1-digit, by country

Occupation	**ISCO**	**LATAM**	**ARG**	**BOL**	**BRA**	**CHL**	**COL**	**CRI**	**ECU**	**SLV**	**HND**	**MEX**	**PAN**	**PER**	**DOM**	**URY**
Managers	1	2,7	4,8	2,3	3,4	4,1	2,4	1,3	1,0	1,8	2,1	3,8	5,4	0,3	2,4	2,9
Professionals	2	10,1	9,8	9,8	12,9	18,7	10,7	12,6	7,2	6,6	5,3	9,0	10,4	6,2	8,5	13,2
Technicians and Associate Professionals	3	7,4	10,4	6,0	8,8	10,6	9,1	9,1	4,5	5,4	4,6	7,4	7,9	6,4	6,2	7,5
Clerical Support Workers	4	6,5	11,9	3,0	8,4	5,2	5,4	9,3	2,6	5,2	3,7	5,5	6,4	4,7	8,8	10,4
Service and Sales Workers	5	22,5	25,6	22,2	22,4	20,6	20,9	21,1	20,4	29,7	26,8	19,2	19,6	19,5	26,0	21,7
Skilled Agricultural, Forestry, and Fishery Workers	6	8,6	0,2	23,4	5,2	2,8	9,6	3,1	19,7	7,2	9,0	8,4	9,9	13,7	4,3	4,3
Craft and Related Trades Workers	7	13,2	13,7	16,7	13,4	13,9	13,6	10,1	10,5	14,2	13,8	11,7	14,4	9,5	15,5	13,7
Plant and Machine Operators and Assemblers	8	7,9	7,8	9,3	9,0	9,0	8,2	7,1	6,5	7,0	6,7	9,0	7,6	7,2	9,3	7,3
Elementary Occupations	9	21,0	15,6	7,3	16,6	15,1	20,1	26,4	27,6	22,7	27,9	26,0	18,5	32,5	18,9	18,9
Total		100,0	100,0	100,0	100,0	100,0	100,0	100,0	100,0	100,0	100,0	100,0	100,0	100,0	100,0	100,0

Source: Authors' calculations based on microdata from national household surveys.

Table 7 presents the mean values of the four AI-exposure indices by country. We first focus on our preferred index: the AIOE. The mean value of the AIOE for Latin America is 5.89 which is a bit lower than those computed for more developed economies.

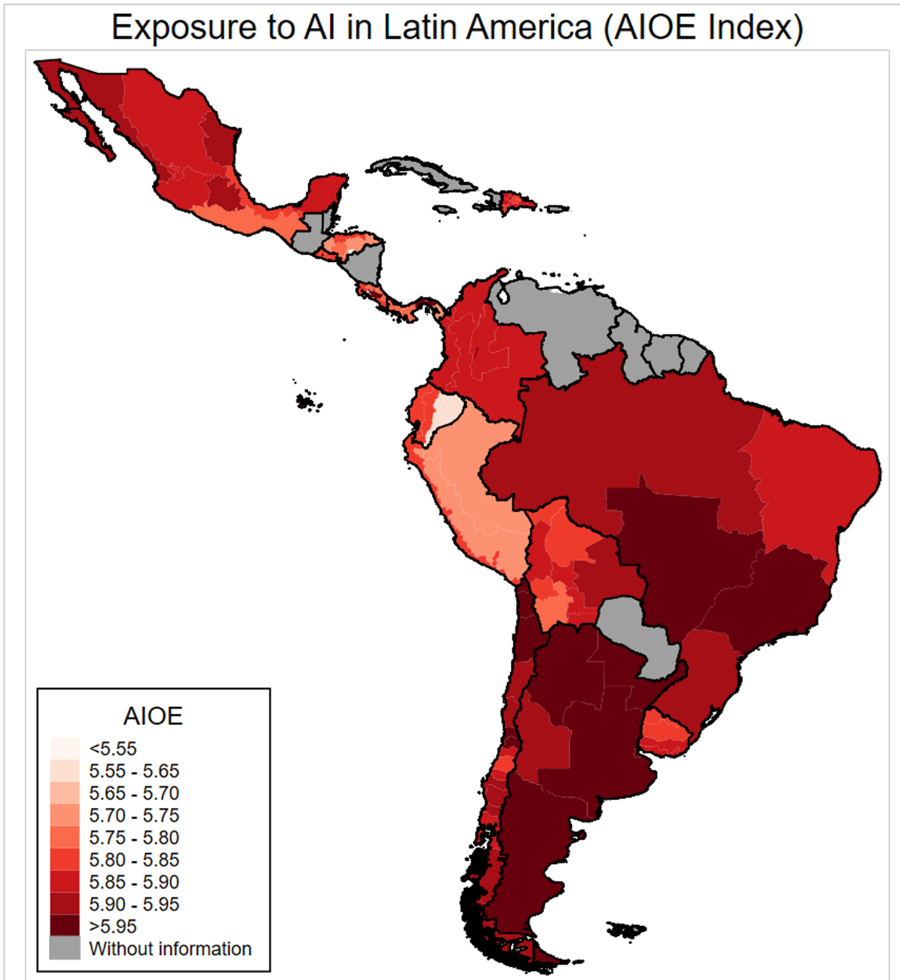
Table 7: Indices of AI exposure, by country

	Values				Rankings			
Country	**AIOE**	**GBB**	**C-AIOE**	**GENOE**	**AIOE**	**GBB**	**C-AIOE**	**GENOE**
Argentina	5.97	0.310	4.54	0.291	2	1	1	1
Bolivia	5.88	0.264	4.39	0.268	10	11	14	14
Brazil	5.94	0.291	4.51	0.280	3	2	4	9
Chile	5.98	0.291	4.47	0.272	1	3	10	11
Colombia	5.91	0.272	4.48	0.287	7	8	7	4
Costa Rica	5.92	0.284	4.53	0.287	5	5	2	5
Ecuador	5.80	0.233	4.42	0.269	14	14	13	13
El Salvador	5.87	0.270	4.49	0.289	11	10	6	2
Honduras	5.81	0.250	4.46	0.278	13	12	12	10
Mexico	5.89	0.270	4.48	0.289	9	9	8	3
Panama	5.91	0.273	4.47	0.272	6	7	9	12
Peru	5.81	0.247	4.47	0.283	12	13	11	7
Dominican Rep.	5.90	0.283	4.50	0.285	8	6	5	6
Uruguay	5.93	0.287	4.51	0.280	4	4	3	8
Latin America	5.89	0.273	4.48	0.281				

Source: Authors' calculations based on microdata from national household surveys.

There are significant differences across countries. According to the AIOE, Ecuador, Honduras, and Peru face the lowest threat of displacement effects from AI in Latin America. In contrast, Uruguay, Brazil, Argentina, and Chile have labor markets that are more exposed to AI. The results are similar when considering the GBB index. In fact, the correlations between these two indices are very high: Pearson 0.9473 and Spearman 0.9648. The correlations weaken somewhat when compared with the C-AIOE (Spearman 0.6571) and become much weaker with the GENOE (0.1868). Naturally, differences are even larger across subnational regions. The AIOE ranges from 5.58 in Ecuador's Amazonia region to more than 6.05 in the Metropolitan Region of Santiago de Chile (Figure 1).

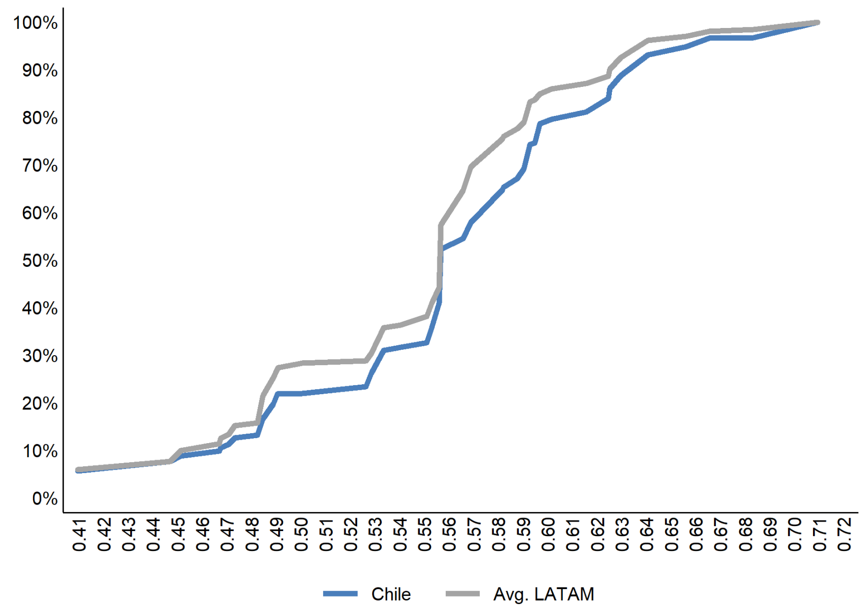
Figure 1: Map of exposure to AI by region



Source: Authors' calculations based on microdata from national household surveys.

Chile is an example of the differences in rankings when using different indices. Chile ranks relatively high in terms of AI exposure according to the AIOE and GBB indexes, and it shifts toward the middle of the distribution when using the C-AIOE and GENOE. In the case of the C-AIOE, this shift reflects the structure of Chile's labor market. The adjustment from AIOE to C-AIOE depends on each occupation's complementarity parameter (theta). Compared to the Latin American average, Chile has a larger share of employment in occupations with higher theta values. Figure 2 illustrates this difference by comparing the cumulative distribution of workers by occupational complementarity levels in Chile and the rest of the region.

Figure 2: Cumulative distribution of workers by occupational complementarity theta



Source: Authors' calculations based on microdata from national household surveys.

Chile's occupational distribution is relatively skewed toward jobs that exhibit greater complementarity with artificial intelligence. Among the five occupations with the highest complementarity scores (theta) at the 2-digit level, Chile has a higher employment share than the Latin American average in four of them, with differences ranging from 0.7 to 1.6 percentage points. This composition contributes to Chile's lower relative exposure to AI when adjusting for how technologies complement, rather than substitute, specific types of work.

A similar analysis can help explain the difference between Chile's position in the GBB and GENOE rankings, as the country shows a higher concentration of occupations with relatively high GBB-to-GENOE ratios. However, this interpretation should be taken with caution, since the GBB and GENOE indexes are conceptually less aligned than the AIOE and C-AIOE. While the latter are directly connected through the complementarity adjustment, the former capture different dimensions of AI exposure and are not constructed to be directly comparable.

Table 8 replicates the analysis using 4-digit information for the subgroup of seven countries where this is available. The results remain robust, both in terms of values and rankings.

Table 8: Indices of AI exposure (4-digit ISCO), by country

	Values				**Rankings**			
	AIOE	**GBB**	**C-AIOE**	**GENOE**	**AIOE**	**GBB**	**C-AIOE**	**GENOE**
Chile	5.97	0.29	4.47	0.28	1	2	4	4
Ecuador	5.79	0.23	4.45	0.27	7	7	6	6
El Salvador	5.86	0.26	4.55	0.29	4	5	1	2
Honduras	5.81	0.25	4.43	0.27	6	6	7	7
Perú	5.84	0.26	4.47	0.28	5	4	5	5
Dominican R.	5.89	0.27	4.50	0.29	3	3	3	3
Uruguay	5.93	0.29	4.53	0.29	2	1	2	1
Latin America	5.87	0.26	4.49	0.28	–	–	–	–

Source: Authors' calculations based on microdata from national household surveys.

The following tables present unweighted mean values of AI-exposure indicators for Latin America, based on the sample of 14 countries with 2-digit ISCO information.

Table 9 reports the mean AI exposure by sector. Given the capabilities of new AI technologies, the risk of displacement is expected to be higher in public administration, banking, finance, education, and health. However, there is significant variability within industries, as production in each sector relies on a diverse set of occupations.

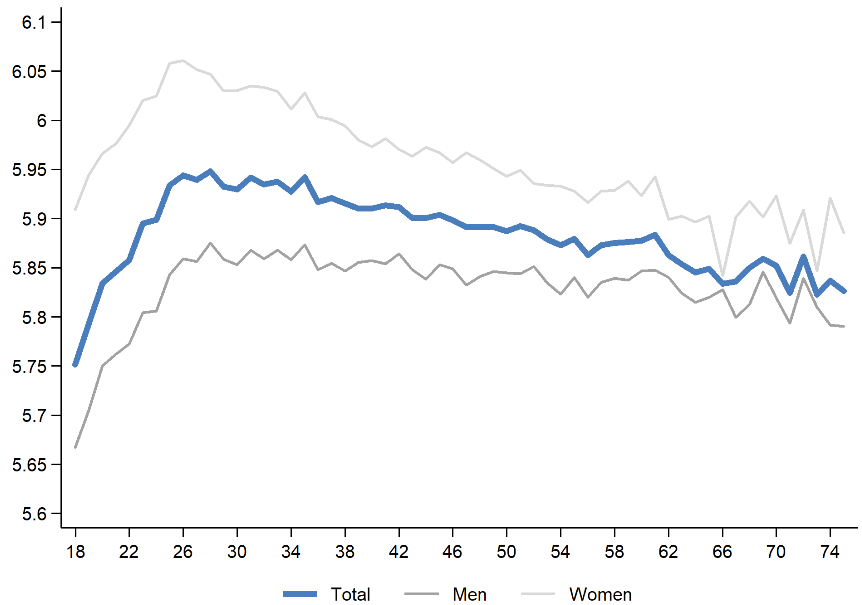
Table 9: Indices of AI exposure, by sector. Latin America

	Values				Rankings			
	AIOE	**GBB**	**C-AIOE**	**GENOE**	**AIOE**	**GBB**	**C-AIOE**	**GENOE**
Primary Act.	5.59	0.167	4.32	0.243	8	8	9	7
Low tech. Industries	5.77	0.215	4.58	0.333	7	7	4	1
Other industries	5.79	0.230	4.47	0.304	6	6	6	5
Construction	5.58	0.163	4.05	0.212	9	9	10	10
Retail, wholesale trade, restaurants, hotels, etc.	6.03	0.349	4.62	0.327	4	3	3	3
Elect., gas, water, transp., communication	5.90	0.286	4.38	0.299	5	5	8	6
Banks, finance, insurance, professional ss.	6.14	0.362	4.69	0.327	2	1	1	2
Public Adm., defense	6.15	0.353	4.58	0.316	1	2	5	4
Education, Health, personal services	6.13	0.305	4.43	0.214	3	4	7	9
Domestic ss.	5.49	0.152	4.65	0.229	10	10	2	8
Total	5.86	0.258	4.48	0.280	–	–	–	–

Source: Authors' calculations based on microdata from national household surveys.

According to the AIOE index, the risk of AI-driven displacement is higher for young workers, peaking in their late 20s and early 30s (Figure 3). However, the relationship between AI exposure and age is not linear. Very young workers tend to have lower exposure, as they often enter the labor market in unskilled occupations. AI exposure rises rapidly, reaching its highest value at age 27 for both women and men. Beyond this point, the AIOE index declines gradually and steadily with age. This non-linear pattern remains similar when using alternative indices of AI exposure (Figure 4).

Figure 3: Index AIOE, by gender and age



Source: Authors' calculations based on microdata from national household surveys.

Figure 4: Indices by age

Source: Authors' calculations based on microdata from national household surveys. Note: values in the vertical axis refer to the standarized values of each index at the level of occupations.

According to the AIOE index, AI exposure is significantly higher for women than for men throughout the entire life cycle (Figure 3). The gender gap is particularly pronounced among younger workers. The greater exposure of women remains consistent when considering alternative AI-exposure indices (Table 10).

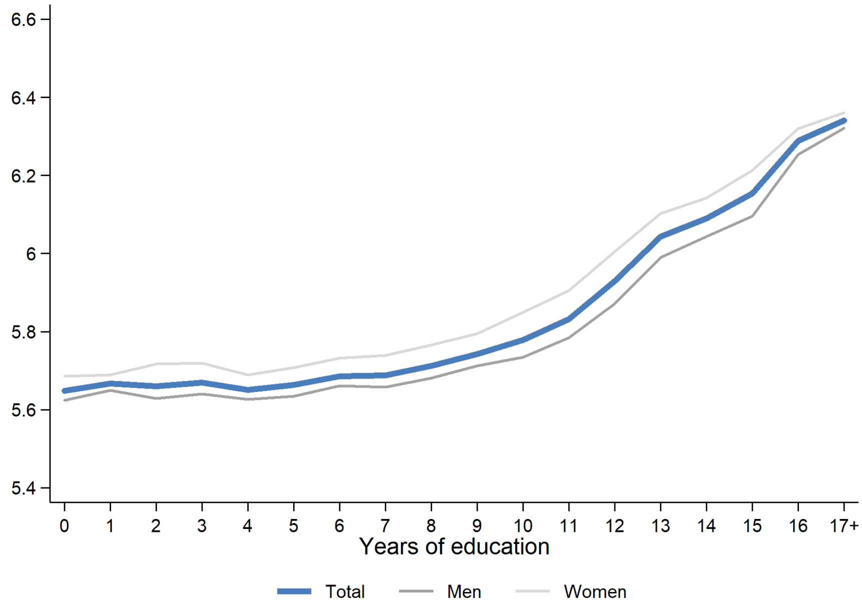
Table 10: Indices of AI exposure, by gender. Latin America.

	AIOE	**GBB**	**C-AIOE**	**GENOE**
Females	5.98	0.310	4.62	0.291
Males	5.83	0.246	4.38	0.273
Total	5.90	0.278	4.50	0.282

Source: Authors' calculations based on microdata from national household surveys.

Figure 5 suggests that, according to the AIOE index, skilled workers are the group most affected by AI adoption. The index increases monotonically with workers' years of education. Also, it is always higher for women than for men along the education distrbution. The increasing pattern in AI-exposure aligns with findings in the literature, as AI development tends to automate complex and abstract tasks that are more concentrated among highly skilled workers.

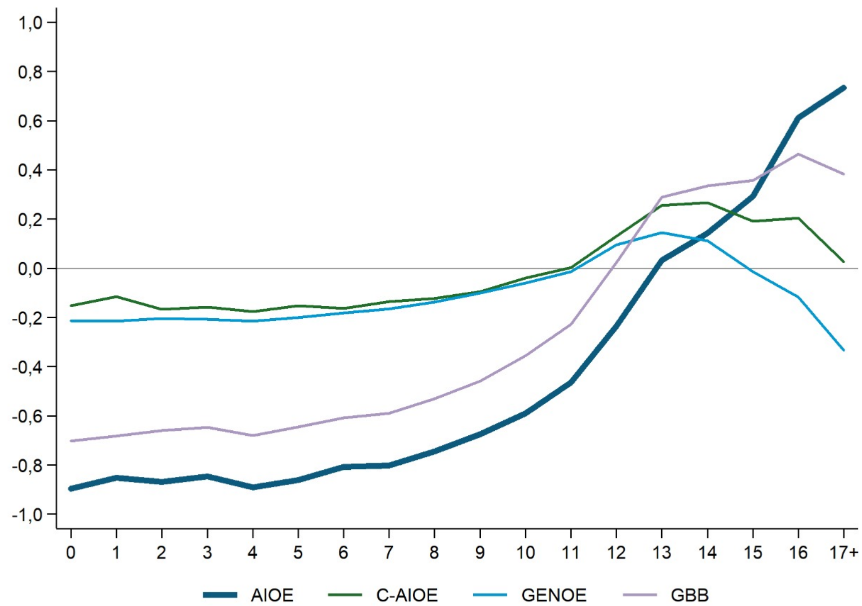
Figure 5: Index AIOE by years of education



Source: Authors' calculations based on microdata from national household surveys.

When considering other indices, the picture becomes more nuanced (Figure 6). There are some similarities in principle. The GBB index follows a pattern very similar to that of the AIOE. In fact, all indices exhibit similar trends up to around 13 years of education, roughly corresponding to the completion of secondary school. Hoewever, beyond this point, while the AIOE and GBB indices continue to rise, the C-AIOE and especially the GENOE begin to decline. The GENOE focuses on the probability of entire occupations (rather than tasks) being displaced in the short run, while also accounting for institutional factors. Given these considerations, the GENOE suggests that the displacement of skilled workers by AI technologies is highly unlikely.

Figure 6: Indices by years of education



Source: Authors' calculations based on microdata from national household surveys.Note: values in the vertical axis refer to the standarized values of each index at the level of occupations.

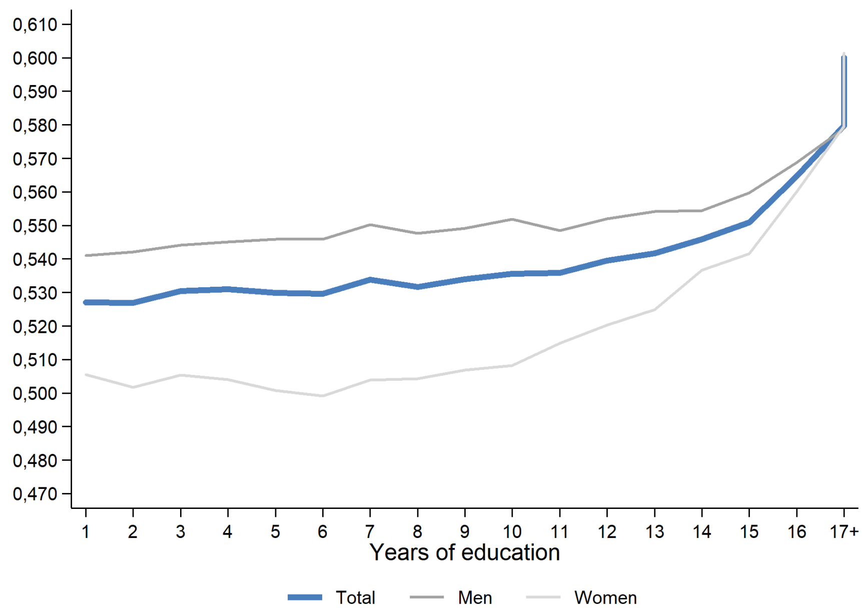
For the C-AIOE, this result aligns with its consideration of AI technologies' potential to complement, rather than replace, skilled workers. More precisely, the difference between the AIOE and C-AIOE indexes can be attributed purely to each occupation's complementarity to AI.

To analyze these different trends further we treat each occupation's complementarity level used to construct the C-AIOE index, theta, as another index and compute the average complementarity coefficient for each level of educational attainment [3] across Latin America. Figure 7 shows how complementarity to artificial intelligence rises with years of education for everyone, although more sharply for women. The higher potential for complementarity

[3] We first take the complementarity theta for each occupation in the ISCO 4-digits classification from Pizzinelli et al. (2023) and merge that data with microdata from the Socioeconomic Database for Latin America and the Caribbean (SEDLAC) for all countries where household surveys report occupation classification codes at the 4-digit level (Chile, Ecuador, El Salvador, Honduras, Peru, Dominican Republic and Uruguay). For each of those countries we then compute the complementarity theta for all occupations in the ISCO 2-digit classification using weighted averages. Finally, we construct a new complementarity theta index for all occupations in the ISCO 2-digit classification by computing the unweighted mean from all aforementioned countries and use that index for all 14 countries considered in the study. Nota: esta explicación es medio redundante si ya detallamos la metodología en la sección 3, pero queda acá por las dudas.

with artificial intelligence shown by skilled workers illustrates why the strongly positive relation between exposure measured by the AIOE and educational attainment flattens when considering the C-AIOE instead: the relation between skills and complementarity is just as strong.

Figure 7: Complementarity theta by years of education



Source: Authors' calculations based on microdata from national household surveys.

In Table 11 we divide Latin American workers by employment relationship and informality status. The threat of AI-driven displacement is higher for employers and salaried employees than for the self-employed. Accordingly, AI exposure is greater for formal workers, regardless of how informality is defined or which AI index is used. This pattern likely reflects the over-representation of informal workers in low-skill, manual occupations and in low-technology self-employment activities—such as subsistence farming, street vending, or other informal microenterprises—that involve limited use of digital tools and remain relatively shielded from current AI capabilities. While this may suggest that countries with high informality could experience less AI-induced labor market disruption in the short term, the implications are nuanced. Lower exposure may come at the cost of slower technology adoption and limited productivity gains, potentially widening gaps in growth and modernization across sectors.

Moreover, it may reflect an unequal diffusion of AI technologies, which could reinforce existing labor market dualities and exacerbate long-run inequality. Understanding whether informality acts as a protective buffer or as a barrier to inclusive technological progress remains a key question for future research.

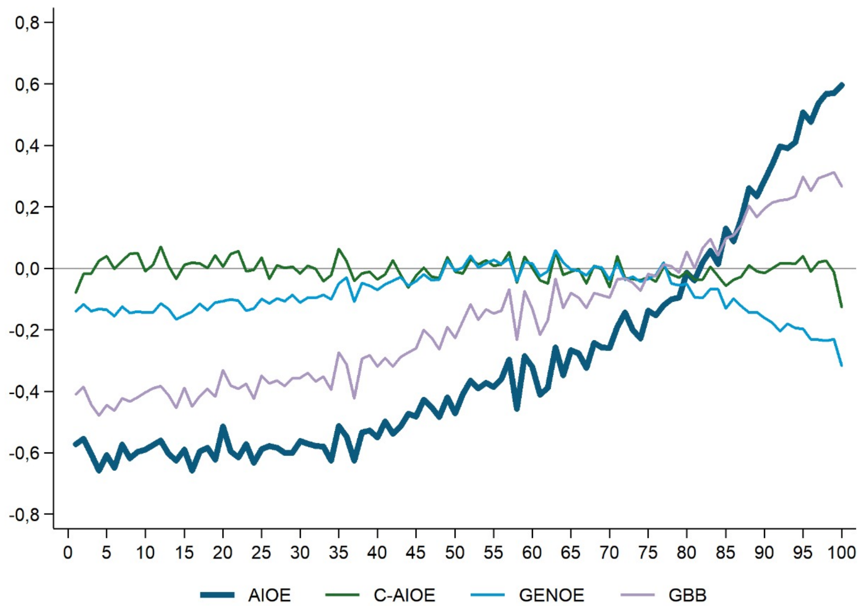
Table 11: Indices of AI-exposure, by labor relationship and informality

	AIOE	**GBB**	**C-AIOE**	**GENOE**
Labor relationship				
Employer	6,00	0,301	4,38	0,261
Salaried employee	5,92	0,283	4,50	0,285
Self-employed	5,86	0,257	4,45	0,274
Family worker	5,80	0,264	4,52	0,292
Informality (productive def.)				
Formal	6,02	0,309	4,50	0,288
Informal	5,77	0,238	4,46	0,272
Informality (legal def.)				
Formal	6,03	0,317	4,53	0,294
Informal	5,78	0,237	4,44	0,269
Total	5,90	0,276	4,47	0,279

Source: Authors' calculations based on microdata from national household surveys.

Given the strong relationship between earnings and education, the patterns of AI exposure across earnings percentiles are unsurprising (Figure 8). Both the AIOE and GBB indices increase gradually along the earnings distribution. In contrast, when using the C-AIOE index, AI exposure is rather constant along the earnings distribution, while the GENOE index suggests a fall in exposure for the high-earnings workers.

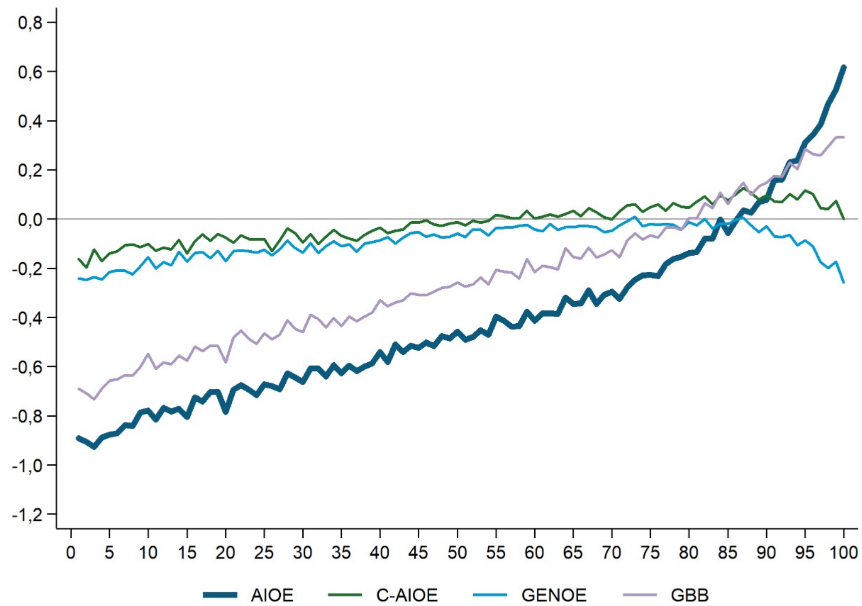
Figure 8: Indices by earnings percentiles



Source: Authors' calculations based on microdata from national household surveys. Note: values in the vertical axis refer to the standardized values of each index at the level of occupations.

The patterns of AI exposure by household income closely resemble those observed for workers' earnings (Figure 9). According to the AIOE and GBB indices, the risk of AI-driven displacement increases roughly monotonically with income. In contrast, the C-AIOE index shows that exposure levels off around the 80th percentile. The GENOE index suggests a decline in displacement risk in the upper part of the income distribution.

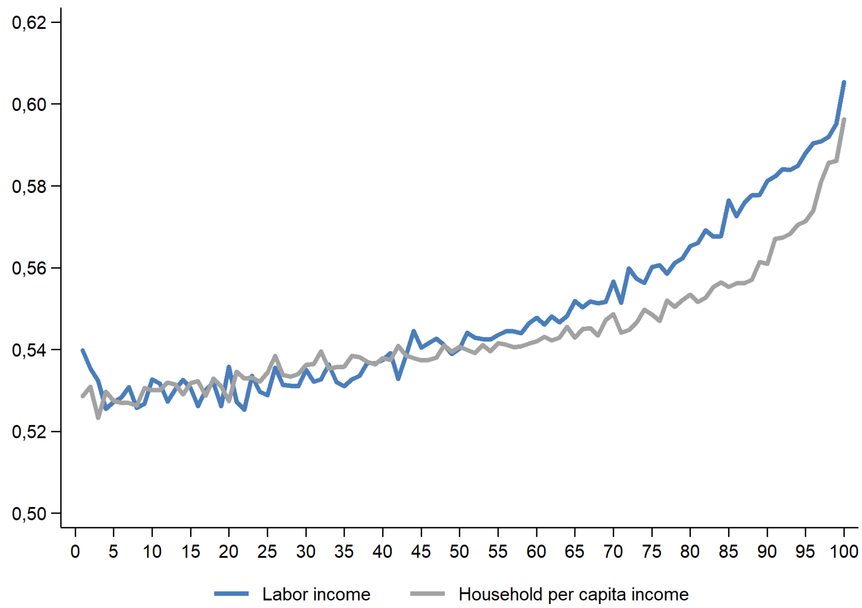
Figure 9: Indices by household per capita income



Source: Authors' calculations based on microdata from national household surveys. Note: values in the vertical axis refer to the standardized values of each index at the level of occupations.

As in the case of educational attainment, the divergence between the AIOE and C-AIOE indexes -and their respective relationships with income levels- can be traced back to differences in occupational complementarity with AI. Figure 10 illustrates a clear positive association between income (measured by either labor earnings or household per capita income) and an occupation's complementarity score. This pattern helps explain why the positive correlation between income and AI exposure weakens when using the C-AIOE: higher-income workers are more likely to hold jobs where AI complements rather than substitutes labor.

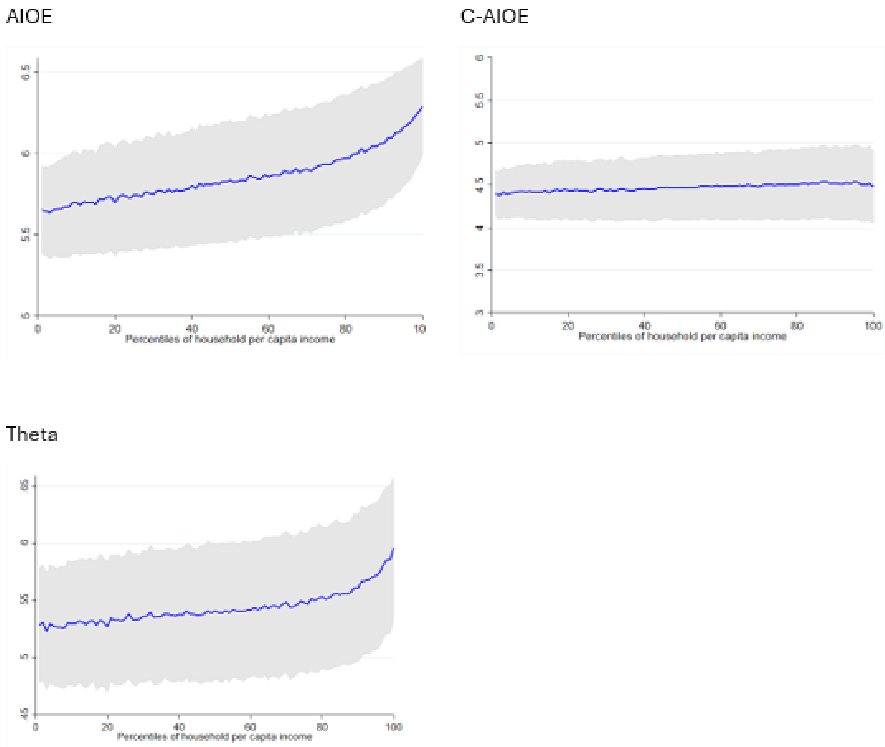
Figure 10: Complementarity theta and income percentiles (labor and household per capita).



Source: Authors' calculations based on microdata from national household surveys. Note: values in the vertical axis refer to the standardized values of each index at the level of occupations.

It is also informative to examine how the dispersion of the indices varies across the income distribution. Figure 11 displays the mean values of each index along with bands representing one standard deviation above and below the mean. The variability of the AIOE exhibits an inverted U-shape, peaking around the middle of the income distribution and declining at both ends. In contrast, the variability of theta increases steadily with income. As a result, the variability of the C-AIOE, which incorporates theta, also rises with income.

Figure 11: Indices by household per capita income percentiles - Std deviations



Source: Authors' calculations based on microdata from national household surveys. Note: values in the vertical axis refer to the standardized values of each index at the level of occupations.

The finding that the variability in complementarity with AI increases with income is particularly noteworthy. This pattern suggests that while lower-income households tend to cluster around similar, relatively low levels of complementarity with AI, higher-income households exhibit much greater heterogeneity in how their work interacts with AI technologies.

This growing dispersion implies that among high-income households, some occupations or tasks are highly complementary to AI — allowing workers to leverage AI to increase productivity and potentially earn even more — while others face greater redundancy or reduced relevance, despite being in the upper part of the income distribution. In other words, high-income positions are more diverse in terms of how exposed or adaptable they are to AI, leading to a wider spread in the theta measure.

This result challenges the simplistic assumption that higher income necessarily correlates with greater protection or benefit from AI. Instead, it points to a segmentation within high-income groups, where some individuals are positioned to thrive in an AI-enhanced economy, while others may be more vulnerable than their earnings would suggest.

This growing heterogeneity in AI complementarity at the top of the income distribution also has important implications for inequality: it could lead to further stratification within high-income groups and greater volatility in income trajectories, as AI amplifies differences in skill relevance and adaptability even among relatively privileged workers.

Finally, in Table 12, we divide the Latin American population by poverty status using the international threshold of 6.85 dollars per day (PPP). AI exposure is somewhat higher among the non-poor across all indices considered.

Table 12: Indices of AI-exposure, by per capita income quintiles and poverty status

	AIOE	**GBB**	**C-AIOE**	**GENOE**
Quintiles				
1	5.69	0.21	4.42	0.27
2	5.76	0.23	4.44	0.28
3	5.83	0.26	4.48	0.29
4	5.91	0.28	4.50	0.29
5	6.10	0.33	4.52	0.28
Poverty status				
Non-poor	5.93	0.28	4.49	0.28
Poor	5.70	0.21	4.42	0.27
Total	5.85	0.26	4.47	0.28

Source: Authors' calculations based on microdata from national household surveys.

In sum, some results remain robust regardless of how AI exposure is measured: risks are higher among women, young adults, and salaried workers. Other findings are more nuanced. AI exposure generally increases with education, earnings, and income across all indices, but only up to a certain point, after which the patterns diverge. According to the AIOE and

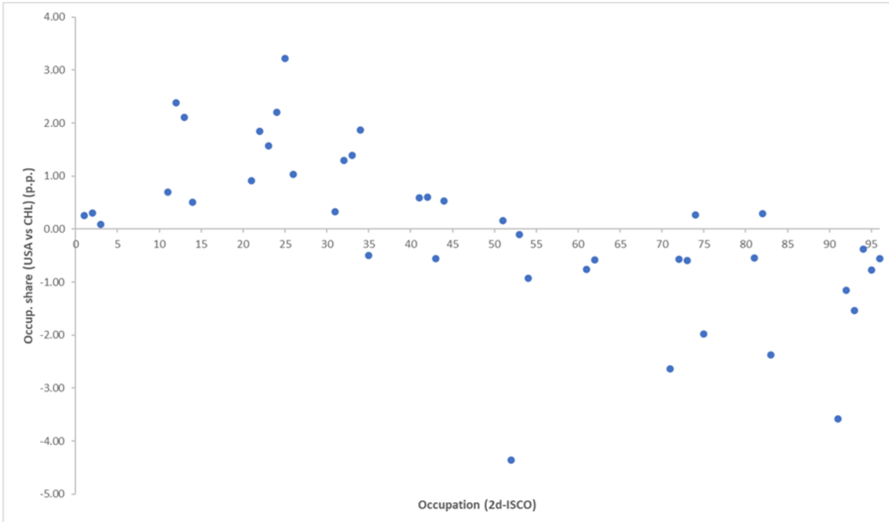
GBB indices, the risk of displacement rises monotonically with these variables. However, the C-AIOE and GENOE indices suggest that factors such as complementarity with AI and institutional constraints mitigate the risk of displacement for the most educated, well-paid workers and wealthier households. If this interpretation holds, AI could lead to a polarization pattern, where workers and households in the upper-middle segment of the distribution face the greatest threat from the implementation of new AI technologies.

5 External validity of task-based AI measures

A key challenge in applying AI exposure indexes to Latin American countries lies in the external validity of these measures. The four indexes we use in this paper—GBB, GENOE, AIOE, and C-AIOE—are based on the O*NET database, which describes the skills and task profiles associated with occupations in the United States. While these indexes are useful for quantifying potential exposure to AI-driven displacement in industrialized contexts, their direct application to developing economies, particularly those in Latin America, raises several concerns. Differences in occupational structure, the content of tasks within occupations, and broader institutional and labor market conditions suggest that exposure levels derived from developed-country data may not translate directly to the Latin American context.

To illustrate the first source of discrepancy, Figure 12 compares the distribution of employment by two-digit ISCO occupational codes between the United States and Chile, used here as a representative case for Latin America. The figure reveals a stark divergence in occupational composition. The Chilean labor force exhibits a significantly lower share of employment in high-skilled categories—such as managers, professionals, and technicians—than the United States economy, along with a higher concentration in operational occupations. Consequently, even if occupational exposure indexes were valid across countries, aggregate exposure levels and potential labor market impacts in Latin America would be shaped by a markedly different occupational mix.

Figure 12: Differences in occupational shares (United States vs. Chile)



Source: Authors' calculations based on microdata from PIAAC and national household surveys. Note: values in the vertical axis refer to the percentage point difference in each occupation share of total employment, United States minus Chile.

A second issue concerns differences in task content within similarly defined occupations. The direct application of O*NET-based indexes assumes that the tasks performed in a given occupation are relatively homogeneous across countries. This assumption may lead to substantial measurement error when estimating AI exposure for Latin American workers.

To test for these cross-country differences in task content, we implement an empirical strategy that predicts AI exposure indexes using country-specific information on job characteristics, drawing on data from the Programme for the International Assessment of Adult Competencies (PIAAC). Specifically, we exploit the rich set of task-related questions in the PIAAC survey to estimate the relationship between AI exposure and task performance in the United States, and then apply this relationship to Chilean data. The procedure is as follows.

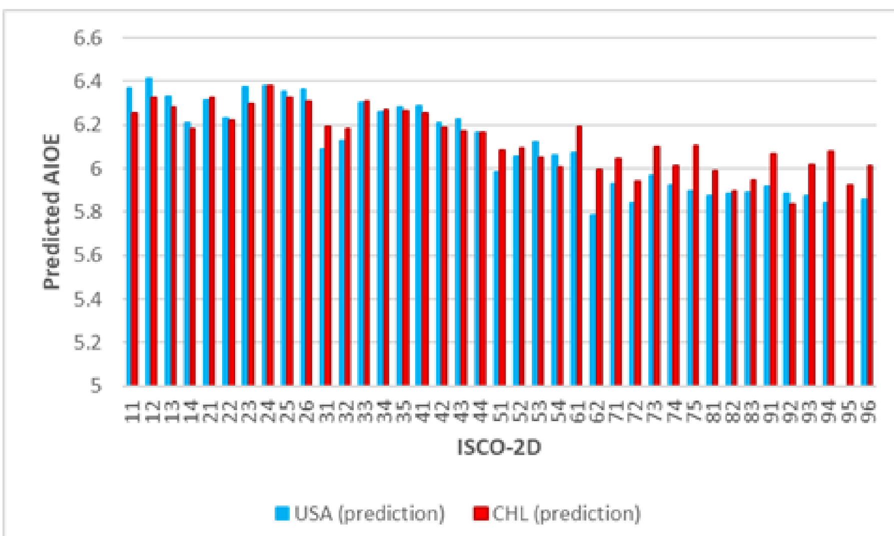
We begin by estimating a regression model using the United States sample, where the AIOE index serves as the dependent variable, and a broad set of task indicators—summarized as task discretion, learning at work, influence, planning, reading, writing, numeracy, and ICT use—are included as explanatory variables, alongside controls for education, age, and gender.[4] A LASSO procedure is used to select the most relevant predictors and estimate

[4]Note that a C-AIOE prediction can easily be performed by predicting the AIOE and then applying to each occupation its corresponding θ coefficient.

their coefficients, which are then used to generate predicted AI exposure scores for the United States.

Next, we apply the estimated coefficients from the United States model to predict AI exposure levels for Chilean workers, based on their reported task profiles in the PIAAC survey. This approach allows us to construct an adjusted AI exposure index that reflects the actual task content within job titles in the Chilean labor market, rather than relying on assumed similarity with United States occupations. Figure 13 compares the predicted exposure levels in both countries at the two-digit ISCO level. The figure suggests that task content across occupations is broadly similar in the United States and Chile, providing support to the applicability of United States-based AI exposure indexes to Latin America. However, the next section considers an additional source of divergence that may challenge the direct application of these indexes in the region: differences in the institutional and labor market context, which can influence the levels and patterns of AI adoption.

Figure 13: Task-based exposure predictions (United States vs. Chile)



Source: Authors' calculations based on microdata from PIAAC and national household surveys.

6 Contextual factors shaping AI adoption

Even when tasks and occupations are similar across countries and new technologies are widely accessible, significant differences in the impact of technological shocks can still arise if labor market and institutional contexts vary between economies. For instance, a new technology adopted in a developed country may not be adopted—or its adoption may be delayed—in a developing country if it replaces a type of labor that is relatively inexpensive in the latter, or if institutional factors, such as stronger labor unions, hinder its rapid adoption.

This section offers a discussion and presents evidence on cross-country differences in factors that may influence the likelihood and pattern of AI adoption. We focus on two levels of comparison: (i) between Latin America and the United States, and (ii) among Latin American countries themselves. Specifically, we examine factors that are likely to shape the diffusion of new technologies and for which we have comparable information in our primary data source—national household surveys. These include: (i) the prevalence of self-employment and informality, (ii) the role and influence of labor unions, and (iii) the structure of wages. We end this section with a simple proposal to incorporate these factors into the AI indexes and illustrate it with an example for Brazil.

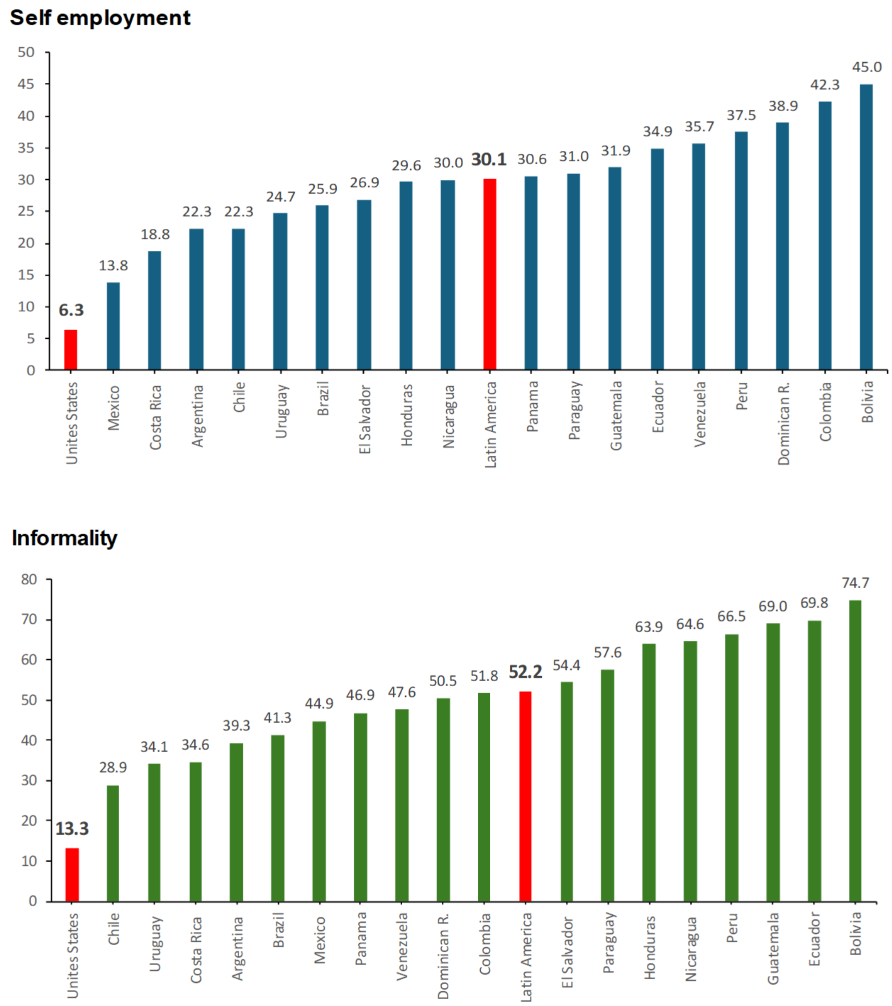
6.1 Self-employment and informality

Similar occupations may be carried out in different contexts, leading to significant differences in exposure to new technologies. In particular, in Latin America—as in other developing economies—a large fraction of jobs are informal, i.e., low-productivity jobs in marginal, small-scale, and often family-based activities. While the definition and measurement of informality are plagued by methodological issues, the underlying concept is straightforward. Informality is typically associated with self-employment or employment in very small firms with limited access to capital and technology, usually involving manual, non-routine tasks that are less susceptible to automation. ILO (1991) defines the informal sector as economic units "with scarce or even no capital, using primitive technologies and unskilled labor, and then with low productivity". Maloney (2004) includes in the informal sector the "small-scale, semi-legal, often low-productivity, frequently family-based, perhaps pre-capitalistic enterprises". Limited access to capital (including human capital) and technology, small scale, low integration into formal markets, and the absence of a dynamic environment are factors that could slow the adoption of new technologies—and, consequently, the direct displacement effect—in the informal sector. Since informal jobs are more prevalent in Latin America than in developed economies, this factor may lead to a slower adoption of new technologies and, consequently, a milder impact on the labor market—particularly on jobs.

In this section, we illustrate differences in labor informality by presenting simple descriptive statistics for Latin American countries and the United States. The analysis is based on harmonized microdata from various Latin American national household surveys and the CPS, the primary household survey in the United States.

Figure 14 reveals substantial differences in labor arrangements across Latin American economies. The share of self-employed workers ranges from nearly 14% in Mexico to 45% in Bolivia. The Latin American average is 30.1%, considerably higher than the corresponding figure for the United States (6.3%).

Figure 14: Share of self employed and informal workers by country



Source: Authors' calculations based on microdata from national household surveys.

We define "informal jobs" as those in one of three categories: self-employed workers, salaried workers in small firms (with five or fewer employees), and family workers. The average share of informal jobs in Latin America is 52.2%, much higher than in the United States (13.3%) (second panel in Figure 14). The dispersion across Latin America is wide, ranging from 28.9% in Chile to 74.7% in Bolivia. These figures highlight the potentially large differences in the impact of AI adoption driven by current labor market structures.

We broadened the comparison between Latin America and the United States by incorporating differences in self-employment and informality across occupations. This extension is particularly relevant given the distinctive structure of labor markets in the two regions.

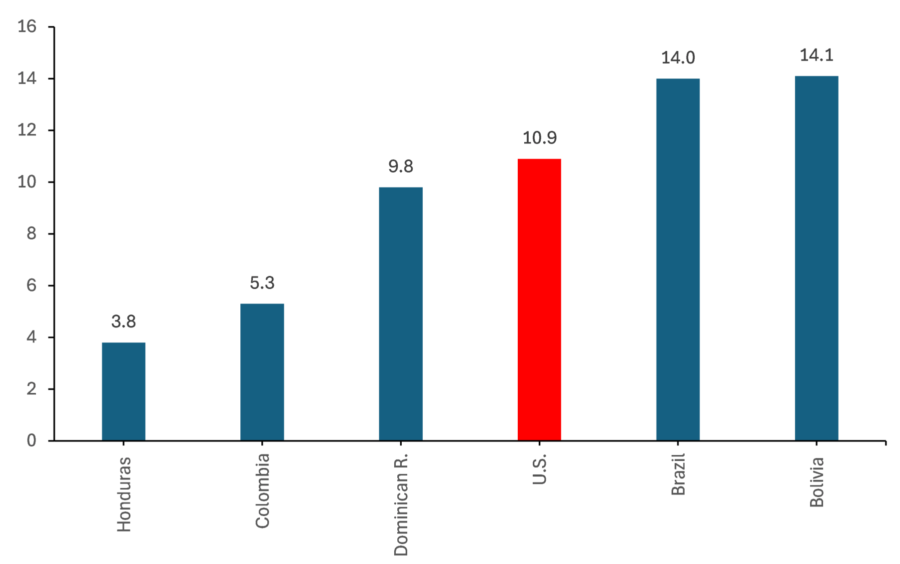
However, the comparison presents a methodological challenge: occupational data in Latin America are typically classified using the International Standard Classification of Occupations (ISCO), while U.S. data—specifically from the Current Population Survey (CPS)—rely on the Standard Occupational Classification (SOC) system. These classifications differ in structure, granularity, and terminology, making a direct mapping between them nontrivial. To address this issue, we developed a crosswalk between ISCO and SOC categories, based on the use of AI to compare titles of occupational categories in both systems. After applying this crosswalk, we find that in most occupational categories, the share of self-employment (78%) and informality (65%) is higher in Latin America than in the United States.

6.2 Unions

Stronger labor unions can play a significant role in delaying the adoption of AI technologies by increasing the cost or difficulty of workforce restructuring. Unions often negotiate collective agreements that protect existing jobs, set limits on layoffs or job reassignments, and promote job security, all of which can constrain employers' ability to swiftly implement labor-displacing technologies. In some cases, unions may actively resist the introduction of new technologies perceived as threats to employment, particularly if reskilling or job transition mechanisms are weak. Moreover, in highly unionized sectors, firms may face additional institutional or political pressures to preserve employment levels, which can reduce the short-term economic incentives to adopt AI solutions. As a result, the pace and pattern of technological adoption are not solely determined by technical feasibility or cost-efficiency, but also by the strength of labor institutions and the bargaining power of workers.

Figure 15 reveals substantial differences in union incidence among those Latin American countries with information in their national household surveys. The share of salaried workers who report being union members ranges from 3.8% in Honduras to 14.1% in Bolivia. The mean for the Latin American countries included in the sample is 9.4%, roughly similar to the corresponding figure for the United States (10.9% in 2024), according to CPS data.

Figure 15: Share of unionized workers



Source: Authors' calculations based on microdata from national household surveys.

6.3 Relative wages

The fact that a machine or algorithm is technically capable of replacing a human job does not necessarily imply that it is economically profitable to do so. If wages are sufficiently low, firms may have little incentive to adopt more capital-intensive technologies. In this sense, "cheap" jobs may be less exposed to technological displacement than "expensive" ones.

It is well beyond the scope of this study to rigorously estimate this contextual factor. Nonetheless, we offer a simple approximation by computing the ratio of occupational wages in Latin America to those in the United States as a proxy for relative labor costs. The intuition is straightforward: if a particular occupation is relatively "cheap" in a Latin American country—meaning that wages for that occupation are significantly lower than in the United States—then the economic incentive to replace labor with capital or technology is likely to be lower than what standard automation indexes, developed using United States data, would suggest. This "cheapness" may reflect genuinely lower wages within that occupation or differences in occupational skill composition between countries. Regardless of the source, the implication is the same: where labor is inexpensive, the cost-saving potential of new technologies is reduced, which may delay or dampen their adoption.

We compute the wage ratio between each Latin American country and the United States by occupation. For the U.S., we use data from the Occupational Employment Statistics (OES) Survey, as it relies on the Standard Occupational Classification (SOC) system, which facilitates a relatively straightforward crosswalk with the ISCO classification used in Latin America.

Occupations with particularly low ratios are relatively cheaper in Latin America, implying weaker incentives to replace them with technology. For example, in the case of Brazil, the following occupations fall within the first decile of the relative wage distribution:

6.4 Adjusted indexes

As discussed above, the threat posed by AI to employment is mitigated—relative to what AI exposure indexes developed for advanced economies would predict—when workers exhibit certain characteristics, particularly when they are informal, unionized, or employed in relatively low-wage occupations.

To make this issue operational, we define three variables: a binary variable $I_i = 1$ if worker i holds an informal job; a binary variable $S_i = 1$ if the worker is unionized; and a categorical variable W_{io} that captures the relative wage position of the occupation.

To construct W_{io}, we rank occupations based on their wage level in Latin America relative to the United States. Specifically, we set $W_{io} = 1$ if the worker's occupation falls in the 10th decile of this distribution (i.e., occupations with particularly low relative wages in Latin America). For the 9th decile we assign $W_{io} = 0.5$, and for the 8th decile $W_{io} = 0.25$. We test the robustness of our results to changes in these arbitrary thresholds.

We then define a contextual adjustment variable ϕ_i, which combines the three dimensions in a simple average:

$$\phi_{io} = \frac{I_i + S_i + W_{io}}{3}$$

Let A_o denote an AI exposure index for occupation o, such as those discussed throughout this paper. We then define a contextually adjusted exposure index for individual i in occupation o, A^c_{io}, as follows:

$$A^c_{io} = A^{min} + (A_o - A^{min})(1 - \tau\phi_{io})$$

where τ captures the intensity of the adjustment. In the extreme case where $\tau = 1$, workers with $\phi_i = 1$ face the lowest level of displacement threat in the economy across all occupations.

We illustrate the effect of the adjustments using the case of Brazil. In addition to being the largest economy in Latin America, Brazil is one of the few countries in the region with worker-level data on unionization, available through its national household survey (PNAD). Table 13 presents the AIOE and C-AIOE indices after applying the adjustments discussed in this section. For simplicity, we report results for $\tau = 1$. To aid interpretation, we show the impact of each adjustment—informality, unionization, and wages—separately for each index, and include a final column displaying the combined effect of all adjustments.

Table 13: Adjustments to AI indexes - Brazil

	AIOE					C-AIOE				
		Adjustments					Adjustments			
	Original	Informality	Unions	Wages	All	Original	Informality	Unions	Wages	All
All	5.94	5.88	5.91	5.88	5.79	4.51	4.41	4.48	4.45	4.33
Gender										
Female	6.02	5.95	5.99	5.94	5.84	4.65	4.53	4.62	4.58	4.42
Male	5.88	5.82	5.85	5.83	5.75	4.40	4.33	4.38	4.36	4.26
Area										
Rural	5.69	5.62	5.67	5.67	5.58	4.37	4.23	4.33	4.35	4.18
Urban	5.97	5.91	5.94	5.90	5.82	4.53	4.44	4.50	4.47	4.35
Age										
15-24	5.94	5.88	5.93	5.89	5.82	4.59	4.49	4.58	4.54	4.42
25-34	5.98	5.92	5.96	5.91	5.83	4.53	4.45	4.51	4.47	4.36
35-44	5.93	5.88	5.91	5.87	5.79	4.49	4.39	4.46	4.43	4.31
45-54	5.90	5.84	5.87	5.84	5.75	4.48	4.37	4.44	4.43	4.29
55-64	5.90	5.83	5.87	5.84	5.74	4.48	4.36	4.44	4.43	4.28
Education										
Low	5.67	5.60	5.66	5.66	5.58	4.40	4.26	4.38	4.39	4.23
Medium	5.93	5.86	5.91	5.89	5.80	4.56	4.45	4.53	4.51	4.38
High	6.34	6.31	6.28	6.15	6.07	4.57	4.55	4.53	4.42	4.36
Earnings decile										
1	5.98	5.92	5.95	5.91	5.83	4.53	4.44	4.50	4.46	4.35
2	5.70	5.63	5.69	5.69	5.60	4.43	4.28	4.41	4.42	4.24
3	5.73	5.62	5.72	5.71	5.59	4.48	4.27	4.46	4.46	4.23
4	5.77	5.68	5.77	5.74	5.64	4.49	4.31	4.48	4.46	4.27
5	5.86	5.79	5.85	5.82	5.75	4.58	4.46	4.57	4.54	4.41
6	5.83	5.77	5.81	5.79	5.73	4.56	4.46	4.54	4.53	4.41
7	5.87	5.82	5.85	5.83	5.77	4.56	4.49	4.53	4.52	4.42
8	5.92	5.87	5.90	5.87	5.80	4.52	4.45	4.50	4.47	4.37
9	5.95	5.90	5.93	5.89	5.82	4.48	4.42	4.46	4.43	4.33
10	6.01	5.97	5.98	5.93	5.85	4.47	4.41	4.43	4.40	4.31

Source: Authors' calculations based on microdata from national household surveys.

As an illustration, Figure 16 shows the impact of the adjustments on the C-AIOE index across education levels. The informality adjustment has a stronger effect on the low-skilled group, while the unionization and relative wage factors offer greater protection for the skilled. Overall, the adjustments have a somewhat larger impact on more skilled individuals, though the differences across groups remain modest.

Figure 16: Impact of adjustments on the C-AIOE index - Brazil

Source: Authors' calculations based on microdata from national household surveys.

7 Microsimulations

AI is a shock with consequences that are very difficult to predict. In this context, estimating its potential impact on employment and income distribution is a highly speculative exercise. Workers displaced by AI could become unemployed, find new roles within the same firm by performing different tasks, or transition to employment in other sectors of the economy. Some occupations will lose relevance or disappear altogether (displacement), while entirely new ones may emerge (reinstatement). In addition, the adoption of AI is likely to bring about dramatic changes in the productivity of individual tasks and occupations, as well as in the overall productivity of the economy. Estimating the combined effects of all these changes on income distribution is clearly beyond the scope of this paper. In light of this complexity, we present a set of very simple—yet hopefully illustrative—exercises to explore some of the potential impacts of AI adoption on income distribution in Latin American countries.

Our exercises are motivated by the observation that one of the primary concerns surrounding AI is job loss due to occupational displacement, and the resulting negative impact on the incomes of affected workers. These effects could have significant implications for inequality and poverty. The question we address at this stage is straightforward: if predictions about the replacement of occupations by AI are borne out—and setting aside other positive effects that new technologies might generate—what would be the expected impact of AI on incomes, inequality, and poverty? Clearly, this exercise does not offer a precise forecast of future developments, as such a forecast would need to account for positive effects that are difficult to predict (such as reinstatement, productivity gains, and general equilibrium effects). Rather, the analysis provides an estimate of the potential magnitude of negative outcomes in a scenario where displacement effects dominate. It could be viewed as a warning signal for public policy.

Our simulations are based on the most recent national household survey available for each country. We simulate changes from this baseline scenario driven by the adoption of AI, focusing on the displacement effects of this technological shock.

7.1 Identification of displaced workers in the microsimulation

To estimate the possible distributional consequences of artificial intelligence (AI)-driven labor displacement, we construct a simple simulation that reallocates to unemployment or informality a fixed number of displaced workers across occupations. The allocation is guided by both the prevalence of occupations in the labor market and their relative exposure to AI, measured using the C-AIOE index.

Let i denote an occupation classified at the ISCO-2 digit or ISCO-4 digit level, depending on data availability. We denote by L_i the number of workers employed in occupation i in a given country. The share of total employment corresponding to occupation i is defined as:

$$\theta_i = \frac{L_i}{\sum_i L_i}$$

This term captures the weight of each occupation in the economy and serves as the baseline probability of a randomly chosen worker belonging to that occupation.

We denote by CAIOE_i the complementarity-adjusted AI exposure index for occupation i, based on Pizzinelli et al. (2023). This index incorporates both the degree to which AI technologies could replace tasks in occupation i and the potential complementarity between human labor and AI.

To determine each occupation's contribution to aggregate displacement risk, we compute a weighted exposure score:

$$\alpha_i = \theta_i \cdot \text{CAIOE}_i$$

This metric reflects the idea that displacement risk is a function of both how exposed a task is to AI and how many people are employed in it.

The weighted exposures are then normalized to derive displacement weights, ω_i, which represent the fraction of all displaced workers that will be drawn from occupation i:

$$\omega_i = \frac{\alpha_i}{\sum_j \alpha_j}$$

These weights ensure that occupations with a high product of exposure and employment share will absorb a proportionally larger share of the simulated displacement shock.

Finally, let D denote the total number of displaced workers assumed in the simulation. Then, the number of displaced workers from occupation i is given by:

$$d_i = \omega_i \cdot D$$

This final allocation captures the simulated distribution of job loss across occupations as a function of both AI exposure and occupational employment prevalence, and this will be the number of workers in each occupation that will be displaced to unemployment or informality.

To account for the possibility that displacement risks could increase more than proportionally with AI exposure, we also explore a non-linear variant of the model. Specifically, we apply a power transformation to the exposure index:

$$\text{CAIOE}_i^{(\gamma)} = (\text{CAIOE}_i)^{\gamma}, \quad \gamma > 1$$

This transformation enhances the contrast between highly and weakly exposed occupations, effectively modeling convex displacement risks. The new weighted exposure becomes:

$$\alpha_i^{(\gamma)} = \theta_i \cdot \text{CAIOE}_i^{(\gamma)}$$

The rest of the procedure, including the calculation of displacement weights $\omega_i^{(\gamma)}$ and the assignment of displaced workers $d_i^{(\gamma)}$—follows as in the baseline case.

This approach offers a flexible and transparent methodology for simulating AI-driven labor displacement. By using exposure indices grounded in task-based analyses, and weighting them by actual employment distributions in Latin American countries, we provide a realistic benchmark for assessing distributional risks. Moreover, the inclusion of nonlinear scenarios serves to highlight how differing assumptions about displacement risks may change the composition of affected workers. In all cases, we emphasize that these are stylized simulations designed to explore potential vulnerabilities in the labor market, rather than to predict exact employment losses. [5]

We assume two scenarios for displaced workers. The first scenario involves job loss and unemployment, leading to a complete reduction of labor income to zero. This outcome is more likely in the very short term, as displaced workers may eventually find new employment. In the second scenario, we assume a less dramatic but still negative outcome: the worker finds a job in the informal sector. There is considerable evidence that Latin American economies are characterized by large informal labor markets, which often function as buffers during economic shocks.

To impute potential earnings in the informal sector for displaced workers, we estimate a wage using a regression model based on observed earnings of informal workers. We combine the estimated coefficients from this model with the observable characteristics of each displaced worker. To account for unobservable factors, we compute each displaced worker i's percentile in the distribution of residuals from a baseline Mincer earnings regression. We then add the

[5] We also carried out an alternative exercise in which only the occupations with the highest exposure to AI are affected. The results, available upon request, are not substantially different from our main alternative.

corresponding residual from the informal-sector regression (based on that same percentile) to the predicted earnings for worker i. The imputation proceeds in four steps:

1. Estimate a Mincer regression for informal workers:

$$\ln(w_i^{\text{informal}}) = X_i \beta^{\text{informal}} + \varepsilon_i^{\text{informal}} \tag{1}$$

   where:

   - w_i^{informal} is the wage of informal worker i,
   - X_i is a vector of observable characteristics (e.g., education, experience),
   - β^{informal} is the vector of estimated coefficients,
   - $\varepsilon_i^{\text{informal}}$ is the error term.

2. Compute the percentile of each displaced worker in the residual distribution from a baseline Mincer regression:

$$\text{percentile}_i = F(\hat{\varepsilon}_i^{\text{baseline}}) \tag{2}$$

   where F is the empirical cumulative distribution function (CDF) of residuals from a baseline Mincer regression for the overall labor market.

3. Assign the corresponding residual from the informal-sector regression based on the same percentile:

$$\hat{\varepsilon}_i^{\text{informal}} = F_{\text{informal}}^{-1}(\text{percentile}_i) \tag{3}$$

   where F_{informal}^{-1} is the quantile function (inverse CDF) of the informal-sector residual distribution.

4. Impute the predicted log-wage in the informal sector:

$$\widehat{w_i^{\text{informal}}} = \exp\left(X_i \hat{\beta}^{\text{informal}} + \hat{\varepsilon}_i^{\text{informal}}\right) \tag{4}$$

We assume no other changes occur at the individual or household level beyond the earnings adjustments resulting from the displacement effects of AI adoption. Naturally, we do not assume that such a major shock would leave behaviors unaffected. Instead, our simulations aim to capture the first-round impact of the technological shock, which can serve as a useful reference point for the potential magnitude of its effects.

7.2 Results

Table 14 presents an example of the results we compute for each country. In this case, we focus on Chile and use the AIOE and C-AIOE indexes. The first column reports selected social indicators for the year of the most recent national household survey available (CASEN 2022, in the case of Chile). These indicators include the unemployment rate, informality rate, measures of earnings inequality, and the share of workers earning below the poverty line (referred to as "vulnerability").

Each panel displays results for a different value of δ, which represents a shock displacing δ percent of the workforce. Within each panel, two scenarios are shown: in the first column, all displaced workers are assumed to become unemployed; in the second, they are assumed to transition into informal employment.

For instance, in the case of Chile, using the AIOE index, a shock displacing 10% of workers who become unemployed would raise the unemployment rate from 6.3% to 15.3%, while mean (median) labor income would decline by 11.2% (12.2%). The share of displaced workers is mildly increasing along the earnings distribution. Accordingly, proportional income losses are more pronounced in the upper part of the distribution: earnings would fall by around 13% in the top decile, compared to 8% in the bottom decile.

The results for earnings inequality are highly dependent on whether displaced workers are included in the calculations. When they are included, all inequality measures increase sharply. For instance, the Gini coefficient rises from 0.437 to 0.489. In contrast, if displaced workers are excluded and earnings inequality is computed only for those who remain employed, all indices show a modest decline in inequality.

Finally, as a result of the AI shock that displaces 10% of workers, the share of vulnerable workers increases substantially, from 4% to 13.4%.

We then consider a less extreme scenario in which displaced workers transition into informal jobs. In this case, unemployment remains unchanged by construction, while informality rises from 26.1% to 33.6%. Income losses are less severe: mean and median earnings decline by around 3%, and the share of workers earning below the poverty line increases only slightly, from 4% to 4.3%. Income losses are mildly asymmetric, with somewhat larger declines at both the bottom and the top of the distribution, resulting in negligible changes in inequality.

The last panel under the AIOE simulations illustrates the effects of a more severe AI shock, in which 25% of workers are displaced. In the extreme scenario where all displaced workers become unemployed, the unemployment rate would rise sharply to 29.3%, mean earnings would decline by 28%, the share of poor workers would surge from 4% to 28%, and inequality would increase dramatically. In the more plausible scenario where displaced workers transition into informal employment, the consequences are still significant but less extreme: mean and median incomes would fall by around 7%, vulnerability would rise to nearly 5%, and, once again, changes in inequality would remain modest.

The right section of the table presents results based on the C-AIOE index. This index accounts for potential complementarities with AI, implying a smaller shock for more skilled workers. As a result, the pattern of displacement becomes more regressive, with a higher concentration of displaced workers in the bottom decile—those with limited opportunities to leverage such complementarities. This leads to a more regressive impact on the earnings distribution, reflected in higher inequality measures. However, in the scenario where displaced workers transition into informal employment, the impact on inequality remains modest. For instance, the Gini coefficient would increase only slightly, from 0.437 to 0.439 if $\delta = 0.1$, and to 0.441 under a more severe shock of $\delta = 0.25$.

Table 14: Simulations - Chile

	Inicial distribution	AIOE				C-AIOE			
		d = 10%		d = 25%		d = 10%		d = 25%	
		Unemployed	Informal jobs	Unemployed	Informal jobs	Unemployed	Informal jobs	Unemployed	Informal jobs
Unemployment rate	6.3%	15.3%	6.3%	29.3%	6.3%	15.3%	6.3%	29.3%	6.3%
Informality rate	26.1%	26.4%	33.8%	26.9%	46.0%	25.9%	33.1%	26.0%	44.3%
% displaced									
Mean		9.6%	9.6%	24.5%	24.5%	9.8%	9.8%	24.5%	24.5%
Decile 1		8.2%	8.2%	22.6%	22.6%	13.0%	13.0%	30.2%	30.2%
Decile 2		8.1%	8.1%	20.9%	20.9%	9.9%	9.9%	24.6%	24.6%
Decile 3		8.3%	8.3%	21.2%	21.2%	9.0%	9.0%	23.8%	23.8%
Decile 4		8.7%	8.7%	20.3%	20.3%	9.4%	9.4%	23.7%	23.7%
Decile 5		8.6%	8.6%	22.7%	22.7%	9.9%	9.9%	22.9%	22.9%
Decile 6		9.2%	9.2%	23.9%	23.9%	10.2%	10.2%	24.0%	24.0%
Decile 7		9.9%	9.9%	26.6%	26.6%	8.7%	8.7%	23.4%	23.4%
Decile 8		11.3%	11.3%	25.9%	25.9%	7.9%	7.9%	24.0%	24.0%
Decile 9		11.3%	11.3%	29.6%	29.6%	8.8%	8.8%	23.6%	23.6%
Decile 10		12.7%	12.7%	31.9%	31.9%	9.8%	9.8%	24.2%	24.2%
Proportional change in earnings									
Mean		-11.2%	-2.7%	-27.9%	-7.3%	-9.2%	-2.2%	-23.9%	-5.9%
Median		-12.2%	-3.1%	-22.4%	-7.7%	-10.8%	-2.5%	-20.9%	-6.2%
Decile 1		-7.9%	-2.2%	-22.3%	-6.4%	-12.4%	-3.8%	-29.4%	-8.2%
Decile 2		-8.1%	-1.7%	-21.0%	-4.7%	-9.8%	-2.2%	-24.5%	-5.0%
Decile 3		-8.3%	-1.3%	-21.2%	-3.6%	-9.0%	-1.4%	-23.9%	-3.8%
Decile 4		-8.7%	-1.5%	-20.4%	-3.4%	-9.4%	-1.7%	-23.7%	-3.9%
Decile 5		-8.6%	-1.8%	-22.7%	-4.7%	-10.0%	-1.9%	-22.9%	-4.1%
Decile 6		-9.2%	-1.7%	-23.8%	-5.0%	-10.2%	-1.9%	-24.1%	-5.1%
Decile 7		-9.9%	-2.3%	-26.6%	-6.2%	-8.7%	-2.0%	-23.4%	-4.7%
Decile 8		-11.3%	-2.8%	-26.1%	-6.9%	-7.9%	-1.8%	-24.1%	-6.0%
Decile 9		-11.3%	-3.0%	-29.8%	-8.5%	-8.7%	-2.2%	-23.6%	-7.1%
Decile 10		-13.4%	-3.6%	-32.3%	-9.5%	-9.0%	-2.6%	-23.4%	-6.8%
Inequality (including displaced									
Gini	0.437	0.489	0.437	0.571	0.437	0.491	0.439	0.575	0.441
Theil	0.370	0.468	0.371	0.644	0.369	0.473	0.374	0.655	0.378
CV	1.168	1.268	1.175	1.437	1.154	1.280	1.177	1.467	1.174
Inequality (excluding displaced									
Gini	0.437	0.434	0.437	0.430	0.437	0.436	0.439	0.435	0.441
Theil	0.370	0.366	0.371	0.360	0.369	0.370	0.374	0.371	0.378
CV	1.168	1.164	1.175	1.143	1.154	1.176	1.177	1.172	1.174
Vulnerability	4.0%	13.4%	4.3%	27.8%	4.8%	13.1%	4.4%	27.4%	4.9%

Source: Authors' calculations based on microdata from national household surveys.

In Table 15, we extend the results to all countries with information on occupations at the 4-digit ISCO level: Chile, Ecuador, El Salvador, Honduras, Peru, the Dominican Republic, and Uruguay. The results are mostly in line with those obtained for Chile.

For example, taking the Latin American average and using the AIOE index, a shock displacing 10% of workers into unemployment would increase the unemployment rate from 4.1% to 13.8%. Mean labor income would decline by 11.5%, while the median would fall by 10%. The share of displaced workers increases slightly along the earnings distribution—though less markedly than in Chile. As a result, proportional income losses are somewhat larger at the top of the distribution: earnings in the top decile would fall by approximately 12.8%, compared to 9.4% in the bottom decile.

As in the case of Chile, all inequality measures rise sharply when displaced workers are included in the analysis. The average Gini coefficient across our sample of countries increases from 0.415 to 0.476. In contrast, when focusing only on those who remain employed, all inequality indices reflect a modest decline. Finally, following an AI shock that displaces 10% of workers, the average share of vulnerable workers in our sample of Latin American countries increases significantly—from 9.8% to 19.9%.

In a less extreme scenario—where displaced workers move into informal employment rather than becoming fully unemployed—the negative impact on income is notably reduced. Average and median earnings drop by less than 3%, and the proportion of workers living below the poverty line rises only marginally, from 9.8% to 10.9%. The income losses are mildly uneven, with slightly greater declines observed at both ends of the distribution, leading to a modest decrease in inequality. In contrast, under a more severe AI shock that displaces 25% of the workforce, average and median incomes would decline by approximately 7%, the vulnerability rate would increase to 11.5%, and inequality would still show only minor changes.

When accounting for complementarities with new technologies (as in the C-AIOE panel of the table), the shock is less severe for more skilled workers. However, in our sample of countries, this moderating effect is weaker than in Chile. As a result, the displacement pattern appears neutral rather than regressive. This produces a relatively uniform effect across the earnings distribution, leading to only minimal changes in inequality measures. For example, under the scenario in which displaced workers move into informal employment, the average Gini coefficient would decrease marginally from 0.415 to 0.414 if $\delta = 0.1$, and would rise slightly to 0.418 under a more intense shock of $\delta = 0.25$.

Table 15: Simulations - all countries with ISCO at 4 digits

	Inicial distribution	AIOE				C-AIOE			
		d = 10%		d = 25%		d = 10%		d = 25%	
		Unemployed	Informal jobs	Unemployed	Informal jobs	Unemployed	Informal jobs	Unemployed	Informal jobs
Unemployment rate	4.1%	13.8%	4.1%	27.4%	4.1%	13.9%	4.1%	27.5%	4.1%
Informality rate	50.8%	51.4%	56.3%	51.9%	63.7%	51.0%	56.0%	50.9%	63.0%
% displaced									
Mean		10.1%	10.1%	24.3%	24.3%	10.3%	10.3%	24.4%	24.4%
Decile 1		9.2%	9.2%	22.5%	22.5%	11.0%	11.0%	26.9%	26.9%
Decile 2		8.6%	8.6%	21.5%	21.5%	10.7%	10.7%	25.1%	25.1%
Decile 3		9.1%	9.1%	21.7%	21.7%	9.8%	9.8%	25.4%	25.4%
Decile 4		8.9%	8.9%	22.5%	22.5%	9.9%	9.9%	25.4%	25.4%
Decile 5		9.9%	9.9%	23.8%	23.8%	10.4%	10.4%	24.5%	24.5%
Decile 6		10.3%	10.3%	23.1%	23.1%	9.2%	9.2%	23.7%	23.7%
Decile 7		9.6%	9.6%	23.6%	23.6%	10.5%	10.5%	22.7%	22.7%
Decile 8		10.7%	10.7%	25.3%	25.3%	9.8%	9.8%	22.8%	22.8%
Decile 9		11.8%	11.8%	28.4%	28.4%	10.2%	10.2%	22.9%	22.9%
Decile 10		13.8%	13.8%	31.7%	31.7%	10.9%	10.9%	24.4%	24.4%
Proportional change in earnings									
Mean		-11.8%	-3.0%	-27.7%	-7.4%	-11.0%	-2.7%	-24.9%	-6.1%
Median		-9.9%	-2.7%	-27.6%	-6.3%	-8.7%	-2.5%	-24.8%	-6.1%
Decile 1		-9.1%	-2.4%	-22.2%	-5.9%	-10.9%	-3.0%	-26.4%	-6.7%
Decile 2		-8.5%	-2.2%	-21.5%	-5.3%	-10.8%	-2.6%	-25.0%	-5.8%
Decile 3		-9.1%	-2.0%	-21.7%	-4.8%	-9.8%	-2.1%	-25.4%	-5.4%
Decile 4		-9.0%	-1.9%	-22.6%	-4.8%	-10.0%	-2.0%	-25.4%	-5.3%
Decile 5		-9.9%	-2.2%	-23.8%	-5.5%	-10.4%	-2.3%	-24.5%	-5.3%
Decile 6		-10.3%	-2.3%	-23.1%	-5.5%	-9.2%	-2.1%	-23.7%	-5.3%
Decile 7		-9.6%	-2.3%	-23.7%	-5.6%	-10.5%	-2.4%	-22.7%	-5.1%
Decile 8		-10.7%	-2.7%	-25.3%	-6.5%	-9.8%	-2.4%	-22.8%	-5.8%
Decile 9		-11.9%	-3.3%	-28.5%	-7.9%	-10.2%	-2.7%	-22.9%	-5.9%
Decile 10		-14.3%	-4.2%	-32.4%	-10.3%	-11.7%	-3.3%	-24.9%	-7.4%
Inequality (including displaced)									
Gini	0.411	0.471	0.412	0.555	0.412	0.472	0.414	0.557	0.417
Theil	0.325	0.431	0.324	0.604	0.320	0.432	0.326	0.608	0.329
CV	1.087	1.181	1.069	1.347	1.048	1.191	1.084	1.358	1.067
Inequality (exlucding displaced									
Gini	0.411	0.409	0.412	0.405	0.412	0.409	0.414	0.407	0.417
Theil	0.325	0.320	0.324	0.314	0.320	0.319	0.326	0.317	0.329
CV	1.087	1.069	1.069	1.052	1.048	1.077	1.084	1.060	1.067
Vulnerability	9.8%	19.3%	10.2%	32.6%	10.9%	19.4%	10.4%	32.3%	11.0%

Source: Authors' calculations based on microdata from national household surveys.

Up to this point, our simulations have relied on occupation data at the 4-digit ISCO level. However, for many countries—particularly the largest ones—only 2-digit ISCO data are available. To assess the implications of using a more aggregated classification, Table 16 compares the results for Chile using both the 4-digit and 2-digit ISCO levels. For simplicity, we only show the results for the informality columns for $\delta = 0.25$. The differences between the two approaches are minor, with qualitative findings remaining virtually unchanged. This robustness is encouraging, as it supports the extension of our analysis of AI adoption impacts to a broader set of Latin American countries for which only 2-digit occupational data are available.

Table 16: Simulations - comparison Chile with ISCO at 2 and 4 digits

	AIOE		C-AIOE	
	2d	4d	2d	4d
% displaced				
Decile 1	21.7%	23.4%	25.2%	29.8%
Decile 2	20.1%	19.4%	23.8%	23.7%
Decile 3	20.8%	19.9%	25.8%	24.6%
Decile 4	22.5%	20.3%	24.7%	24.1%
Decile 5	22.4%	21.9%	24.6%	25.1%
Decile 6	24.1%	22.7%	24.7%	24.1%
Decile 7	27.5%	25.9%	24.7%	22.6%
Decile 8	28.9%	28.2%	24.5%	22.8%
Decile 9	30.1%	30.1%	25.4%	23.9%
Decile 10	31.4%	32.8%	25.8%	23.4%
Proportional change in earnings				
Mean	-7.5%	-7.3%	-6.5%	-5.8%
Median	-7.6%	-7.3%	-7.5%	-6.2%
Decile 1	-6.6%	-6.4%	-7.4%	-7.8%
Decile 2	-4.7%	-4.1%	-5.2%	-4.9%
Decile 3	-3.6%	-3.6%	-4.3%	-4.1%
Decile 4	-3.6%	-3.7%	-4.3%	-4.2%
Decile 5	-4.5%	-4.2%	-4.5%	-4.3%
Decile 6	-5.1%	-5.1%	-5.1%	-4.9%
Decile 7	-6.7%	-5.9%	-5.6%	-4.9%
Decile 8	-7.6%	-7.3%	-6.3%	-5.9%
Decile 9	-8.7%	-8.5%	-7.0%	-7.0%
Decile 10	-9.7%	-9.5%	-7.9%	-6.5%
Inequality (including displaced)				
Gini	0.436	0.436	0.441	0.442
Theil	0.366	0.371	0.371	0.381
CV	1.139	1.170	1.125	1.197
Inequality (excluding displaced)				
Gini	0.436	0.436	0.441	0.442
Theil	0.366	0.371	0.371	0.381
CV	1.139	1.170	1.125	1.197
Vulnerability	4.7%	4.7%	4.8%	4.9%

Source: Authors' calculations based on microdata from national household surveys.

Table 17 reports the unweighted average outcomes for the broader group of countries for which only 2-digit occupational data are available. The findings largely align with those presented in Table 15, which is based on the smaller sample with 4-digit occupational detail.

To illustrate, using the AIOE index and focusing on the Latin American average, a shock that pushes 10% of workers into unemployment would raise the unemployment rate from 4.9% to 14.3%. Average labor income would drop by 11.3%, while the median would decrease by 9%. Similar to the 4-digit sample, the proportion of displaced workers grows slightly across the earnings distribution, leading to somewhat greater relative income losses at the upper end. Specifically, earnings in the top decile would fall by 12.8%, compared to an 8.6% drop in the bottom decile.

As with the results in Table 15, incorporating displaced workers into the analysis leads to a marked increase in all measures of inequality. On average, the Gini coefficient rises from 0.431 to 0.489 across the countries in our sample. In contrast, when considering only those who remain employed, inequality indicators show a slight decrease. Lastly, in the wake of an AI-induced shock displacing 10% of the workforce, the average proportion of vulnerable workers across nearly all Latin American countries in our sample jumps from 9.8% to 19.6%.

In a less severe scenario, where displaced workers shift into informal employment rather than falling into full unemployment, the adverse effects on income are considerably mitigated. Average earnings decline by roughly 3%, and the share of workers living below the poverty line increases only slightly—from 9.8% to 10.8%. Income losses are modestly uneven, with somewhat larger reductions at both the lower and upper ends of the distribution, resulting in almost no changes in inequality.

By contrast, a more substantial AI-related shock displacing 25% of the labor force would lead to an estimated 8% drop in earnings, raise the vulnerability rate to 11.4%, and still produce only modest shifts in inequality indicators.

When accounting for complementarities between labor and new technologies—as reflected in the C-AIOE panel—the impact of displacement is less pronounced for more skilled workers. This leads to a neutral displacement pattern, similar to what is observed in the sample using 4-digit occupational data. Consequently, the effect is fairly uniform across the earnings distribution, and inequality measures show minimal variation. For instance, under the informality scenario, the average Gini coefficient would increase slightly from 0.431 to 0.434 when $\delta = 0.1$, and to 0.437 in the case of a larger shock $\delta = 0.25$).

Table 17: Simulations - all countries with ISCO at 2 digits

	Inicial distribution	AIOE				C-AIOE			
		d = 10%		d = 25%		d = 10%		d = 25%	
		Unemployed	Informal jobs	Unemployed	Informal jobs	Unemployed	Informal jobs	Unemployed	Informal jobs
Unemployment rate	4.9%	14.3%	4.9%	28.5%	4.9%	14.3%	4.9%	28.5%	4.9%
Informality rate	48.4%	48.9%	54.2%	50.0%	63.0%	48.7%	54.0%	49.3%	62.4%
% displaced									
Mean		9.8%	9.8%	24.8%	24.8%	9.8%	9.8%	24.8%	24.8%
Decile 1		8.6%	8.6%	22.0%	22.0%	10.0%	10.0%	24.7%	24.7%
Decile 2		8.6%	8.6%	22.0%	22.0%	9.8%	9.8%	24.4%	24.4%
Decile 3		9.0%	9.0%	22.6%	22.6%	9.5%	9.5%	25.1%	25.1%
Decile 4		9.2%	9.2%	22.7%	22.7%	9.9%	9.9%	24.6%	24.6%
Decile 5		9.3%	9.3%	23.8%	23.8%	9.9%	9.9%	24.9%	24.9%
Decile 6		10.0%	10.0%	24.0%	24.0%	10.2%	10.2%	24.7%	24.7%
Decile 7		9.8%	9.8%	25.0%	25.0%	9.9%	9.9%	24.9%	24.9%
Decile 8		10.6%	10.6%	26.7%	26.7%	9.8%	9.8%	24.2%	24.2%
Decile 9		11.2%	11.2%	28.8%	28.8%	9.8%	9.8%	25.2%	25.2%
Decile 10		12.7%	12.7%	31.7%	31.7%	9.5%	9.5%	24.9%	24.9%
Proportional change in earnings									
Mean		-11.3%	-3.1%	-28.2%	-7.8%	-10.1%	-2.6%	-25.5%	-6.6%
Median		-9.0%	-1.9%	-28.6%	-6.1%	-8.0%	-1.9%	-26.4%	-6.0%
Decile 1		-8.6%	-2.3%	-21.9%	-5.9%	-9.8%	-2.7%	-24.5%	-6.7%
Decile 2		-8.6%	-2.2%	-21.9%	-5.5%	-9.9%	-2.4%	-24.5%	-6.0%
Decile 3		-9.0%	-2.1%	-22.6%	-5.2%	-9.5%	-2.2%	-25.1%	-5.7%
Decile 4		-9.2%	-2.1%	-22.8%	-5.1%	-9.8%	-2.1%	-24.6%	-5.5%
Decile 5		-9.4%	-2.2%	-23.8%	-5.8%	-9.9%	-2.2%	-24.9%	-5.7%
Decile 6		-10.0%	-2.4%	-24.0%	-5.8%	-10.2%	-2.5%	-24.7%	-5.8%
Decile 7		-9.8%	-2.5%	-25.0%	-6.3%	-9.9%	-2.4%	-24.9%	-6.2%
Decile 8		-10.6%	-2.8%	-26.8%	-7.3%	-9.8%	-2.5%	-24.1%	-6.2%
Decile 9		-11.3%	-3.2%	-28.9%	-8.6%	-9.8%	-2.7%	-25.2%	-6.9%
Decile 10		-12.8%	-4.1%	-31.7%	-10.0%	-9.4%	-2.8%	-24.6%	-7.4%
Inequality (including displaced)									
Gini	0.431	0.489	0.432	0.575	0.432	0.490	0.434	0.578	0.437
Theil	0.366	0.472	0.365	0.661	0.365	0.476	0.370	0.664	0.373
CV	1.194	1.295	1.178	1.523	1.184	1.310	1.197	1.520	1.199
Inequality (excluding displaced)									
Gini	0.431	0.430	0.432	0.429	0.432	0.432	0.434	0.432	0.437
Theil	0.366	0.364	0.365	0.364	0.365	0.368	0.370	0.369	0.373
CV	1.194	1.183	1.178	1.206	1.184	1.197	1.197	1.205	1.199
Vulnerability	9.8%	19.6%	10.8%	33.6%	11.4%	19.5%	10.8%	33.3%	11.5%

Source: Authors' calculations based on microdata from national household surveys.

7.3 Simulations with contextual adjustment

In this final section, we present simple simulations that incorporate contextual factors which may cause the diffusion of AI to have different effects in Latin America compared to the United States. As discussed earlier, we focus on three key factors: informality, unionization, and relative wages. The simulation procedure follows the approach described previously but now relies on the context-adjusted indices developed and analyzed in Section 6.

We focus on the case of Brazil, one of the few countries in the region with worker-level data on unionization. Table 18 presents the results of a simulated shock displacing 10 percent of jobs, showing the AIOE and C-AIOE indices after applying all the adjustments discussed in the previous section, with the parameter set at $\tau = 1$.

Overall, the adjustments imply a less severe impact of AI-driven job displacements on the upper deciles of the distribution, leading to a lower fall in earnings in those groups and therefore a greater impact on inequality. However, since the asymmetries in the oveарall adjustments for contextual factors are small, the asymmetries in the results of the simulations across income deciles are also minor. For instance, while in the original estimations, and using the AIOE index, mean earnings in the upper decile fall 3.3%, the reduction would be 3.1% when considering the impact of contextual factors.

Table 18: Results of the simulations with adjusted AI indexes - Brazil

	AIOE		C-AIOE	
	Original	With adjustments	Original	With adjustments
% displaced				
Decile 1	9.5%	9.6%	9.8%	9.7%
Decile 2	10.1%	9.8%	9.6%	10.1%
Decile 3	9.9%	10.3%	10.1%	10.0%
Decile 4	10.0%	9.8%	10.4%	10.1%
Decile 5	10.0%	10.0%	10.1%	9.7%
Decile 6	9.7%	9.6%	9.7%	10.4%
Decile 7	9.6%	10.5%	10.0%	9.8%
Decile 8	9.3%	9.8%	9.6%	9.8%
Decile 9	10.8%	10.5%	9.9%	9.5%
Decile 10	10.8%	10.0%	10.6%	9.7%
Proportional change in earnings				
Decile 1	-3.6%	-3.7%	-3.7%	-3.7%
Decile 2	-3.0%	-2.9%	-2.9%	-3.0%
Decile 3	-2.8%	-2.9%	-2.9%	-2.8%
Decile 4	-2.6%	-2.5%	-2.7%	-2.6%
Decile 5	-2.5%	-2.5%	-2.5%	-2.4%
Decile 6	-2.3%	-2.4%	-2.4%	-2.5%
Decile 7	-2.4%	-2.6%	-2.5%	-2.6%
Decile 8	-2.3%	-2.4%	-2.4%	-2.5%
Decile 9	-2.9%	-2.9%	-2.6%	-2.5%
Decile 10	-3.3%	-3.1%	-3.2%	-3.0%
Inequality				
Gini	0.496	0.499	0.498	0.498
Theil	0.516	0.530	0.526	0.527
CV	1.53	1.66	1.64	1.64
Vulnerability	0.10	0.10	0.10	0.10

Source: Authors' calculations based on microdata from national household surveys.

8 Conclusion

This paper examined the potential distributional consequences of AI adoption in Latin American labor markets, leveraging harmonized household survey data from 14 countries and multiple AI occupational exposure indices to assess which workers and countries face greater exposure to AI-driven changes. A key contribution of our analysis lies in the adaptation of these indices to the regional context by incorporating structural and institutional features—such as informality, unionization, and labor costs—that are often overlooked in studies focused on high-income countries. This adjustment allows for a more comprehensive picture of vulnerability across the region. Additionally, we validated the applicability of these indices—originally developed for advanced economies—by comparing task profiles using task content data.

We document considerable heterogeneity in exposure both across and within countries. Workers in more formal, service-oriented economies—particularly those in professional, clerical, and service occupations—tend to show a higher exposure to AI developments. Disaggregated analysis by demographic and labor characteristics shows that women, younger individuals, more educated workers, and those employed in the formal sector are more likely to experience task content changes in their jobs, which could potentially increase their risk of displacement. This might suggest that workers in the right tail of the income distribution are more affected by the AI. However, once AI-task complementarities are taken into account, these gradients flatten substantially, suggesting that productivity-enhancing interactions may help mitigate displacement risks, especially among higher-income and more educated workers.

A broad set of microsimulation exercises further suggests that, in the absence of compensatory labor market policies, AI-induced displacement could lead to modest yet non-negligible increases in poverty and inequality. The size of these effects varies significantly across countries, reflecting differences in occupational structures and institutional settings.

Taken together, our findings provide novel empirical evidence on how AI adoption interacts with the structural characteristics of labor markets in the Global South. By applying and adjusting AI exposure measures to the Latin American context—a region marked by high heterogeneity in both economic development and institutional configurations—this paper offers a comprehensive framework for evaluating distributive risks and informing future policy design. The potential ”reinstatement effects”, productivity gains and general equilibrium impacts of AI adoption represent interesting avenues for future research.

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