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Labor Market Exposure to AI: Cross-country Differences and Distributional Implications

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Labor Market Exposure to AI: Cross-country Differences and Distributional Implications

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Abstract

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1 Introduction

The rapid development of Artificial Intelligence (AI) has sparked considerable discussion regarding its impact on labor markets.[1] By automating tasks, personalizing experiences, and improving quality control, AI could dramatically enhance productivity across various sectors, presenting an unprecedented revolution in the workplace. Despite this promising outlook, the swift progress of AI, coupled with continued R&D, creates substantial uncertainty surrounding its socioeconomic implications (Lane and Saint-Martin, 2021; Agrawal et al., 2018). Economists largely agree that AI could bolster societal wealth in the long run, yet concerns persist over its potential to disrupt employment in many industries.

In this fast-evolving landscape, three significant areas of uncertainty stand out. First, it remains unclear how AI technologies might serve as either substitutes or complements for human labor in specific tasks and occupations, ultimately leading to "winners and losers" in the job market (Autor, 2022). Second, there is interest in understanding how exposure to AI varies across countries, and in particular whether there are systematic differences between Advanced Economies (AEs) and Emerging Markets (EMs). Third, within countries, exposure to the risks and benefits of AI is likely to differ across demographic groups and skill levels, making implications for economic disparities difficult to predict.

In this paper, we offer preliminary insights into these questions. First, we propose an adjustment to a standard measure of AI occupational exposure (AIOE) to capture AI's potential to complement or substitute for labor in each occupation. Second, we apply both the original measure and the complementarity-adjusted one to labor force microdata from six countries, with a particular emphasis on EMs. Our analysis sheds light on differences in exposure to AI across countries, disentangling those with greater potential to benefit from complementarity and those at greater risk from substitution. Finally, within each country, we examine how exposure varies across demographic groups, skill levels, and the income distribution.

Recent research has focused on "exposure" to AI across the spectrum of occupations. The proposed definitions of exposure consider how AI applications overlap with the human

[1] It has been argued that AI fulfills the definition of a General-Purpose Technology (GPT) and therefore holds the potential to spur a sustained wave of economic growth and innovation. Lipsey et al. (2005) define a GPT as a technology that (i) is widely used, (ii) has the potential for continuous innovation, (iii) generates complementary innovations. Examples of GPTs are the steam engine, electricity, and the internet. Scholars generally agree that AI, as a suite of technologies, is a GPT (Agrawal et al., 2018) and potentially some of its individual sub-fields, such as Generative AI and Machine Learning, individually fulfill the definition (Goldfarb et al., 2023).

abilities needed to perform a given occupation (as in the AIOE index of Felten et al., 2021, 2023) or could significantly accelerate the performance of tasks in each job (Eloundou et al., 2023; Briggs and Kodnani, 2023). So defined, this concept purposely remains agnostic to the potential for AI to serve as either a substitute or complement for human labor in key tasks and possibly to replace an occupation altogether. Given the large degree of uncertainty regarding future innovations and their application to specific productive processes, precise predictions are challenging and require significant caveats. Nevertheless, it is important for academics and policymakers to consider the consequences of AI's interactions with each occupation. For instance, workers in occupations more vulnerable to substitution by AI will be more likely to experience adverse income shocks while those in complemented occupations could experience higher returns to their labor. Such exercise would allow for an informed discussion of how AI may pose greater risks of adverse labor market outcomes for some workers and greater opportunities for others, drawing aggregate implications for its economy-wide impact.

This paper thus contributes to the debate on how AI may impact the labor market by proposing an extension to the widely used AI Occupational Exposure (AIOE) measure by Felten et al. (2021) to account for potential complementarity. To this aim, we first build an index of potential for AI complementarity at the occupation level based on the same data source used by these authors, the Occupational Information Network (O*NET) repository. Specifically, we draw on two areas of O*NET: work contexts and occupations' "job zones". The former capture "physical and social factors that influence the nature of work", and hence are informative of the likelihood that key activities of an occupation would be assigned to AI without human supervision -that is, as a substitute to labor. For instance, society is presumably less likely to fully delegate to AI in contexts in which there are grave consequences to errors, like piloting an airplane or diagnosing diseases. Meanwhile, job zones reflect the amount of education and training required to perform an occupation. Longer training may entail greater ability to integrate the knowledge needed to operate AI into the skill set of an occupation, translating into greater potential to use the technology to support human tasks.

Equipped with this index, we then construct a complementarity-adjusted AI occupational exposure (C-AIOE) measure, where the exposure of occupations is mitigated by their potential for complementarity. In this alternative measure, a higher value of exposure more closely corresponds to greater risk of substitution and hence of an adverse labor market effect from AI. We find that some high-skill occupational groups with high exposure to AI, such as professionals and managers, also hold the highest potential for complementarity and thus have low C-AIOE values. Meanwhile, clerical support occupations are highly exposed but have on average low complementarity, therefore scoring highest in the C-AIOE measure.

A second question concerns the magnitude of disparities in AI exposure across countries and whether, within each country, similar patterns emerge in how exposure is distributed across the labor force. Most of the analysis of exposure so far has focused on Advanced Economies (AEs), with only limited discussion of Emerging Markets (EMs). This latter group of countries, encompassing a wide range of diverse economic realities, is characterized by distinct labor market compositions with respect to occupations and worker demographics. Labor market exposure to AI in EMs, and its differences with AEs, hence deserve a deeper discussion.

The second contribution of this paper is thus to provide a detailed cross-country analysis of AI exposure using worker-level microdata from six economies: two advanced economies (UK and US) and four EMs (Brazil, Colombia, India, South Africa). We combine microdata from recent labor force surveys with the AIOE and C-AIOE measures at a very granular occupational level (more than 400 ISCO-08 codes) to paint a detailed picture of AI exposure both across countries and within each country. The use of microdata also allows for a deeper analysis of heterogeneity throughout the labor market of individual countries, based on demographic groups and along the income distribution, uncovering similarities and differences in exposure patterns in AEs and EMs.

The main findings can be summarized as follows. There are substantial cross-country disparities in the baseline AIOE, with EMs generally exhibiting lower exposure levels than AEs. This variation primarily hinges on different employment compositions, with AEs characterized by larger proportions of high-skill occupations such as professionals and managers. In line with the findings of previous studies, these professions are the most exposed to AI due to their high concentration of cognitive-based tasks (Felten et al., 2021, 2023; Briggs and Kodnani, 2023; Eloundou et al., 2023). However, because those high-skill occupations also show higher potential for AI complementarity, these cross-country disparities in terms of potentially disruptive exposure diminish significantly once complementarity is factored in. Nevertheless, AEs remain more exposed even under the C-AIOE measure. Meanwhile, EMs with a large share of agricultural employment, like India, remain relatively less exposed under both measures, as occupations in this sector have very low baseline exposure to AI. Overall, the results suggest that the impact of AI on labor markets in AEs may be more "polarized," as their employment structure better positions them to benefit from growth opportunities but also makes them more vulnerable to likely job displacements.

Our analysis uncovers within-country disparities in AI exposure, both adjusted and unadjusted, across demographic variables such as gender, education, and age, among both EMs and AEs. These patterns exhibit notable parallels across countries. Women are more exposed to AI than men in almost all countries in our sample, primarily due to their predominant employment in middle-skill service and retail occupations, which bear a relatively higher exposure than manual labor roles. The only exception is India, where women have lower exposure than men due to their substantial employment in agriculture. In terms of educational attainment, in both AEs and EMs workers with at least a college degree are more exposed than those with lower educational credentials. However, the former also carry a greater potential to benefit from AI due to their concentration in professional and managerial jobs. No common results emerge with respect to age, most likely due to complex interactions with country-specific secular trends in educational attainment and female labor force participation.

With respect to exposure across the distribution of earnings, a significant finding emerges. High-income workers are more exposed to AI. However, consistent with their generally higher educational attainment, this difference is mostly accounted for by employment in occupations with high potential complementarity. Meanwhile, employment in high-exposure but low-complementarity jobs is evenly distributed across the distribution. This result suggests that while the potential adverse impact may be more evenly spread across the income distribution, the benefits are predominantly concentrated at the top.

Our paper relates to the growing number of works on the impact of AI on labor markets. The majority of empirical studies focus in detail on variation in exposure exclusively in the US (Felten et al., 2021, 2023; Eloundou et al., 2023; Webb, 2020).[2] OECD (2023), Albanesi et al. (2023), Briggs and Kodnani (2023), Gmyrek et al. (2023) provide a cross-country perspective, but only the latter two consider exposure in EMs.[3] Briggs and Kodnani (2023) conduct a broad sectoral analysis extrapolating from coarse industry-level measures of exposure constructed for the US. Gmyrek et al. (2023) have a large coverage of EMs and low-income economies at the occupational level with varying degrees of granularity. Using microdata, our work instead conducts a granular comparison of EMs and AEs both at the aggregate level and within countries. We thus delve deeper into patterns of AI exposure across demographic groups and the income distribution, providing a more refined

[2]Brynjolfsson et al. (2018) study "automation" of tasks but focus on Machine Learning, which is an important but small subset AI.

[3]Copestake et al. (2023) are an example of an empirical study of the early impact of AI on a single EM economy.

identification of potential "winners" and "losers" in EMs.

Several studies have made methodological contributions by developing measures of occupation-level exposure to AI (Felten et al., 2023; Eloundou et al., 2023; Webb, 2020; Briggs and Kodnani, 2023). Through the O*NET repository, these works construct measures of exposure that are generally agnostic regarding the likelihood of AI complementing or substituting for human labor in a given task, activity, or occupation. Following the long-standing literature on routine-biased automation, recent works making a distinction between complementarity and substitution have adopted a task-based framework (Acemoglu and Restrepo, 2018, 2022; Autor et al., 2022; Gmyrek et al., 2023). Despite its rigorous conceptualization of the interactions between human and machine abilities, as acknowledged by Autor (2022), the task model also has some limitations when applied to AI. First, as the technology continues to develop, it is difficult to say what tasks AI can and cannot perform fully unsupervised. Second, this approach holds a narrow view on the factors determining which jobs are exposed to replacement from AI. Recent studies from the OECD, based on surveys of workers and firms, clearly show the rich variety of concerns and individual experiences in AI adoption (Lane et al., 2023; Milanez, 2023). Our contribution is thus to construct a measure of complementarity to AI by examining a broad set of factors beyond tasks, related to the social and physical context in which work is performed. We thus provide a more nuanced view of which occupations and workers face the greatest risks and opportunities in the years ahead.

Our methodology naturally carries caveats. First, the selection of contexts from O*NET relies on our own judgement of which factors matter for the interaction between AI and workers. However, we present a set of tests to show that these contexts are not all systematically related to each other and thus offer a multifaceted take on potential complementarity, factoring in a plurality of angles. We also test the robustness of the C-AIOE to different specifications of the adjustment. Furthermore, we acknowledge that the importance of complementarity relies on societal views and on other innovations to support AI. As AI technology improves in precision and garners increased trust, the likelihood of it supplanting human tasks –even in occupations characterized by high levels of responsibility, criticality, and skills– may grow. Consequently, the applicability of the concept proposed in this paper could decrease over time. To illustrate this point, we discuss an exercise in which the weight given to complementarity in the adjustment can be altered.

Before concluding we also make further considerations on the interpretation of the results and the scope for future analysis. For instance, our proposed adjustment to the AIOE measure does not imply that workers in exposed occupations with high complementarity do not face any risk of displacement. Complementarity can only be leveraged if individual workers possess the skills needed to take advantage of AI as a supporting technology. Without such abilities, workers in those occupations would still face reduced employment prospects even if the occupation as a whole may experience rising demand. Moreover, our approach only measures cross-country differences based on occupational composition, abstracting from macro-factors such as the availability of infrastructure needed to implement AI and the potential difference in the task composition of occupations across countries.

The remainder of the paper is structured as follows. Section 2 introduces the concept of complementarity and proposes a potential complementarity-adjusted exposure measure. Section 3 describes the country-specific data sources used for the analysis. Sections 4-5 present the main findings and the sensitivity analysis. Section 6 provides further discussion of the results. Finally, Section 7 concludes.

2 AI Exposure and Adjusting for Potential Complementarity

In this section, we discuss the importance of adding the potential for complementarity or substitutability as a dimension for understanding how AI exposure at the occupational level can pose both risks and opportunities.

2.1 Motivation

Recent analyses have focused their attention on AI exposure. While its precise definition varies across studies, exposure reflects the potential for AI to be integrated into each occupation based the tasks and skills that characterize each job. Given the high degree of uncertainty over the future of this fast-pacing and broadly applicable technology, the concept of exposure is purposely framed as agnostic on the likelihood of AI complementing or replacing labor in the performance of a given task or occupation. For instance, the AIOE index by Felten et al. (2021) measures the degree of overlap between main AI applications and the abilities needed to perform an occupation effectively.[4]

[4] In the context of Generative AI, Eloundou et al. (2023) define exposure "as a measure of whether access to [Large Language Models] would reduce the time required for a human to perform a specific [work activity] or complete a task by at least 50 percent." Meanwhile Webb (2020) measures exposure through the degree of similarity between the described applications of AI patents and the tasks defining an occupation. Finally, Briggs and Kodnani (2023) manually identify work activities exposed to AI and whether, within an

Given AI's potential to perform highly complex functions, understanding how it could augment workers or reduce the demand for their labor is of great importance for policymakers and researchers alike. While some studies differentiate between substitution and complementarity, they build this distinction on a task-based framework. For instance, Gmyrek et al. (2023) defines occupations as having high "automation" or "augmentation" potential based on the distribution of the AI-automation scores of the individual tasks defining each occupation.[5] Although this approach has merits, it holds a narrow focus in categorizing the interaction of human work with a technology that will likely have complex repercussions in other realms.

Our proposed framework thus conceives complementarity as driven by a set of factors –social, legal, technical– that are independent of exposure itself. This distinction is conceptually illustrated in Figure 1. Workers in occupations highly exposed, but where AI has the potential to turn into a supporting technology (upper right quadrant) are more likely to experience productivity gains, conditional on access to the necessary infrastructure and the appropriate skills to engage with the technology. On the other hand, workers in highly exposed occupations with lower potential for complementarity, and thus a higher risk of substitution (lower right quadrant), may experience a long-lasting fall in demand for their labor along the lines of the negative shock inflicted by the past wave of routine-biased automation, with reduced employment opportunities and lower earnings (Autor and Dorn, 2013).

At lower levels of AI exposure (left quadrants), a higher complementarity potential may still affect how AI is integrated into each occupation but, given the lower scope for interaction with human skills and tasks, it would likely be less influential for labor demand. In this sense, the importance of potential complementarity is *conditional* on a given exposure level.

It is also worth noting that, while lower complementarity reflects a risk of lower labor demand for workers in a given occupation, higher complementarity does not in itself signify no risks for individual workers. Those employed in a highly complementary occupation who do not possess the skills needed to engage with AI would likely face lower employment opportunities and wages.

occupation, such activities are of a low-enough level of complexity that AI could complete them. Arguably, this last methodology implies a view on exposure that is closer to labor substitution.

[5]More precisely, occupations where the mean task-level automatability score is high and the standard deviation is low are defined as automatable. Occupations with a low mean score and high standard deviation are defined as augmentable.

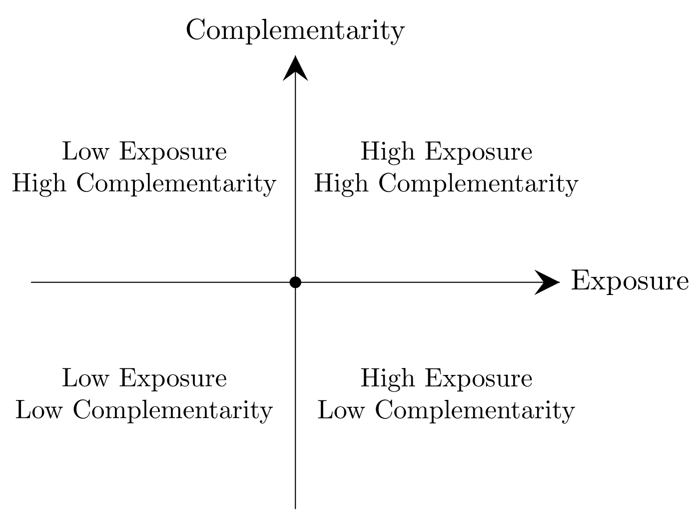
With these caveats in mind, we propose a simple adjustment of AI exposure measures to account for complementarity. In what follows, we use the AIOE index by Felten et al. (2021) as the baseline measure to augment into a complementarity-adjusted AIOE (C-AIOE). However, the same approach could be applied to any measure that does not already capture complementarity.

For a given occupation i, let θ_i be a measure of potential complementarity of AI. The baseline exposure can be adjusted as follows:

$$\text{C-AIOE}_i = \text{AIOE}_i * \big(1 - (\theta_i - \theta_{MIN})\big), \tag{1}$$

where θ_{MIN} is the minimum value of θ_i across all occupations. We adjust for θ_{MIN} to allow the complementariy measure to have a relative interpretation as the original AIOE index. The second term on the right-hand side thus represents a downward adjustment of AIOE relative to the occupation with the lowest potential complementarity (θ_{MIN}), for which the AIOE and C-AIOE measures conicide. Hence a higher value of the C-AIOE index implies a greater risk of replacement at the occupation level.

Figure 1: AI exposure and Complementarity Diagram



It should be noted that the original AIOE index by Felten et al. (2021) is a measure of *relative* exposure, meaning that it aims to describe which occupations, and hence workers, are more or less exposed than others. However, it is not apt to provide a headline figure of how many workers are exposed in absolute terms. As the same issue applies to our measure of potential complementarity, the proposed adjustment to the AIOE is intentionally made relative to the occupation with the lowest value of θ. Despite this caveat, the relative interpretation of both measures helpfully centers the discussion around differences across countries and workers. Furthermore, given the high amount of uncertainty and rapid pace of developments in AI, attempting to provide an absolute quantification would not be prudent at this stage.

2.2 AIOE Methodology from Felten et al. (2021)

Before describing the construction of the complementary measure, we give a brief overview of the AIOE measure constructed by Felten et al. (2021). The AIOE index is derived by connecting 10 AI applications, such as image recognition and text creation, with 52 occupational abilities like oral comprehension and inductive reasoning. The mapping is based on a crowd-sourced matrix that scores the relatedness between each AI application and ability. Moreover, each occupation can be viewed as a weighted combination of the 52 abilities using two sets of weights: i) *Prevalence*, which measures how common the ability is within the occupation, and ii) *Importance*, which indicates how crucial the ability is to performing tasks in that occupation. Data on AI applications and abilities come from the Electronic Frontier Foundation and O*NET, respectively.[6]

Specifically, the AIOE for each occupation i can be calculated as follows:

$$AIOE_i = \frac{\sum_{j=1}^{52} A_{kj} \cdot L_{ji} \cdot I_{ji}}{\sum_{j=1}^{52} L_{ji} \cdot I_{ji}} \tag{2}$$

where k represents the AI application, while j indexes the occupational ability, and i stands for the occupation itself. A_{kj} is the exposure to AI of ability j, which is calculated as the sum of the "relatedness" scores of the ability with each of the 10 individual AI applications.[7] This

[6]The O*NET repository was initiated by the U.S. Department of Labor in 1998 and provides comprehensive data on nearly 1,000 occupations, including requisite skills and abilities, collected via surveys. Although O*NET focuses on the US, its data has often used to study other labor markets and cross-country comparisons. For example, Bluedorn et al. (2023) uses O*NET study "green jobs", while and Soh et al. (2022) study "digital jobs" in the US and UK. Cross-country analysis relies on the assumption that key tasks and skills comprising an occupation do not change across countries. As countries vary in the degree of capital intensity, there may be differences in the level of use of some technologies within the same occupation. However, this is unlikely to alter the essential activities and abilities defining the occupation itself to the point of invalidating cross-country comparisons. Moreover, to the extent that skills and use of machinery are already taken into account in the definition of the occupations themselves, workers carrying out similar functions with different equipment would be assigned to different occupations. For instance, a worker in a factory where very limited machinery is used would be classified as a "manufacturing laborer" –an elementary occupation according to international classification standards– rather than as some type of "machine operator."

[7]For example, the O*NET ability "oral comprehension" has a mapping of 0.89 with the AI application "translation" and of 0.37 with "image recognition." These two values are summed with the other 8 scores to obtain A_{kj}.

term is subsequently weighted and scaled by the ability's prevalence (L_{ji}) and importance (I_{ji}) within each occupation. This results in the AIOE for each occupation i. Details can be found in Felten et al. (2021).

As Felten et al. (2021) note, this measure focuses on "narrow" AI, which refers to "software that relies on highly sophisticated algorithmic techniques to find patterns in data and make predictions about the future." While this definition encompasses Generative AI, such as large language models and image generation, it does not capture exposure to "general" AI, which refers to computer software that can think and act autonomously and is combined with automation and robot technologies.

2.3 AI Exposure and Adjusting for Potential Complementarity

To construct our complementarity measure θ, we employ the same source of occupation-level data as Felten et al. (2021): the O*NET repository. We leverage two lesser used parts of the O*NET repository: work contexts and "job zones." O*NET's defines work context as the "physical and social factors that influence the nature of work." Out of the 57 contexts, we select 11 that we consider most relevant for the likelihood of AI replacing human activities or being adopted in a supervised manner, which we aggregate in 5 groups following O*NET's own grouping. The selection of these specific contexts, which we further discuss below, is motivated by the choices societies will plausibly make regarding the modalities of AI application or the likely need for supporting technologies (e.g., more advanced automation and robots) to fully implement AI in a given physical context.[8]

O*NET defines job zones as groups of occupations characterized by similar levels of education, on-the-job training, and professional experience needed to perform the work. The rationale for considering job zones is that occupations with longer periods of required professional development would have a greater ability to integrate AI knowledge into their training programs and thus equip future workers with complementary skills.

Together, the 11 contexts and the job zone are grouped into six components as follows:

1. **Communication**: i) Face-to-Face, ii) Public Speaking. As AI tools continue to evolve, they will undoubtedly enhance various aspects of communication. However, the subtle intricacies of face-to-face interactions and the art of public speaking largely remain the domain of humans. Societal norms may dictate the preservation of these sophisticated

[8] Tables A.1 and A.2 report all the work contexts from O*NET.

human communication skills in professional environments. For example, a trial lawyer employing rhetoric to persuade a jury or a physician explaining a diagnosis to a patient relies on nuanced understanding, empathy, and adaptability that AI currently cannot fully replicate. Moreover, in many circumstances, human interactions are affected by personal bias (for instance, based on gender or race). In these cases, AI can complement workers by attenuating their bias when carrying out essential in-person interactions that require lack of implicit influences.[9]

2. **Responsibility**: i) Responsibility for outcomes, ii) Responsibility for others' health. AI can certainly transform many sectors by augmenting tasks that bear significant responsibility for outcomes. Consider the healthcare sector, where AI assists with predictive analytics for patient risk or even the real-time monitoring of vital signs in critical care. Yet, the accountability and ethical decision-making inherent in these tasks demand human oversight, judgment, and, importantly, compassion. Even as AI capabilities expand, such responsibilities are likely to see a coexistence of AI and human labor, emphasizing complementarity over substitutability.

3. **Physical Conditions**: i) Exposure to Outdoors Environments, ii) Physical Proximity to Others. Roles necessitating substantial outdoor exposure and physical proximity require great level of adaptability and sensory acumen. These human skills are likely to continue to be invaluable in diverse professional contexts, such as the swift decision-making of a firefighter or the ability to operate in diverse environments of construction workers. Replacing these abilities and adaptability to conditions requires integrating AI technologies into highly advanced and costly machinery, suggesting greater likelihood of complementary co-existence of human labor and AI.

4. **Criticality**: i) Consequence of Errors, ii) Freedom of Decisions, iii) Frequency of Decisions. The critical importance of human oversight may become even more apparent to society as AI automates decision making processes over time. For instance, in professions such as air traffic controller or critical care nurses –which score high in these components– human judgment plays a vital role, relying on both data and instinct to act in often unexpected scenarios. At the same time AI can provide valuable data and suggestions, with the potential to reduce human error rates and speed up the time needed to make decisions.[10]

[9] A literature review by Hall et al. (2015) notes that many studies find significant levels of implicit bias by healthcare providers in the US towards certain ethnic groups "related to patient–provider interactions, treatment decisions, treatment adherence, and patient health outcomes."

[10] Good examples can be found in the use of AI to support radiologists in diagnostics, seeRajpurkar et al.

5. **Routine**: i) Degree of Automation, ii) Unstructured vs Structured Work. Occupations whose essential functions are easily codifiable in a set of routine actions have historically been substituted by technology to a greater degree (Autor et al., 2003; Autor, 2015; Autor et al., 2022). Despite the differences between AI and older forms of innovation, routine-intensive occupations reasonably remain more exposed to replacement, while less structured jobs may require more advanced technologies for AI to operate autonomously. For instance, telephone customer service assistants dealing with a large number of similar inquiries may follow routinized protocols of action which could be followed by software. Meanwhile, fashion designers, who score the lowest in automation and the highest in unstructured work, may use image-generation software or can leverage data-driven predictions on fashion trends, but they mostly work through a hard-to-codify creative process.

6. **Skills**: Job Zones. AI technologies demand a certain level of expertise to operate effectively, interpret outcomes accurately, and make informed decisions based on AI-generated insights. Occupations with already high education and long training requirements may have greater scope to integrate skills complementary to AI into their curricula. Although this reasoning is mainly applicable to future workers, who are yet to acquire the skills, these occupations also tend to feature regular training throughout workers' careers (e.g., summer schools for researchers, executive courses for managers, practical training, conferences).

Each work context in O*NET has a value between 0 to 100.[11] The automation score is inverted so that occupations with a low degree of automation have higher values to capture the fact that occupations that are already highly automated are more likely to face substitution as AI continues to advance. Job zones have an ordered categorical value from 1 to 5, which we multiply by 20 to convert into values from 20 to 100.[12] To align with Felten et al. (2021), the occupation classification in O*NET is converted to the US SOC 2010 classification.[13] This conversion ensures consistency and comparability between the

(2018), Sim et al. (2020), and Gaube et al. (2023)

[11] The original data source is available at https://www.onetonline.org/find/descriptor/browse/4.C/4.C.1/4.C.1.b

[12] Turning an ordinal variable into a cardinal variable has the implicit consequence of assuming a quantitative relationship, which may have non-trivial consequences. However, as also shown by the robustness checks below, the final complementarity index is not excessively sensitive to the "Skills" component relative to the other components.

[13] The US Bureau of Labor Statistics utilizes the Standard Occupational Classification (SOC) Code system at the 6-digit level, which has been updated in three editions: 2000, 2010, and 2018. O*NET utilizes a more granular 8-digit classification that is easily convertible to the SOC. This, in turn can be converted into the 4-digit ISCO-08, which can be applied to data from other countries.

two datasets for accurate analysis and interpretation. The score for each of the 6 groups is computed as the arithmetic mean of the scores of the individual contexts. Subsequently, θ is computed as the arithmetic mean of the six components and then divided by 100 to be bounded between 0 and 1. The lowest value, used as θ_{MIN}, is 0.31, corresponding to Hand Cutters and Trimmers (US SOC 2010 code 51-9031).[14] With the currently limited knowledge of how AI would be adopted in all sectors and jobs, taking the average of the various components represents a cautious stance regarding the relative importance of each factor. Moreover, while all components represent salient dimensions, none of them is necessarily applicable to all occupations. For instance, there may be occupations that, despite lengthy training processes, simply cannot integrate AI in their work in a complementary manner.

2.4 The Complementarity-Adjusted AIOE

Figure 2 plots the AIOE score against our measure of potential complementarity, consistent with our conceptual framework. Quadrants are segmented using the medians of both AIOE and complementarity θ, illustrating various interactions of AI exposure and complementarity. For instance, professions such as lawyers and judges, despite their high AI exposure, might harness AI as a valuable supporting tool. This would lead to productivity enhancements if they possess the requisite skills for this new tech interaction. In contrast, telemarketers, despite sharing a similar AI exposure level with lawyers, display minimal complementarity. This can be attributed to the fact that many of their duties, like detailing products or capturing customer data, can be easily taken over by AI applications. Occupations in the bottom left quadrant have both low exposure and low complementarity. Nonetheless, even within this group there may be some differences in the way workers could interact with AI. For instance, plausibly dancers could more easily leverage some form of AI application, as part of the creative process of their work, compared to dishwashers. Surgeons, although categorized in the low-AI exposure bracket, have the highest potential AI complementarity among all jobs analyzed. This can be attributed to the widespread adoption of AI in healthcare, particularly in areas like enhanced medical diagnostics.

Figure 3a) examines the distribution of potential complementarity and Felten et al. (2021)'s AIOE across broad occupations, categorized at the 1-digit ISCO-08 level. High-skill occupations such as managers, though as highly exposed to AI as clerical support workers, typically exhibit greater complementarity than their low-skill counterparts. Notably, a significant variability in complementarity exists within certain occupational groups, especially

[14] In contrast, the highest value of θ is 0.78, corresponding to Oral and Maxillofacial Surgeons (US SOC 2010 code 29-1022). The median value is 0.58.

among craft and trade workers, services and sales, as well as plant and machine operators. However, this variance is more subdued among clerical and support workers, as well as skilled agricultural and fishery workers. Figure 3b) shows that the complementarity adjustment reduces average differences among broad occupation groups. Simultaneously, it also results in increased within-occupation variance of AI exposure. Managers and professionals, who previously had high exposure under AIOE, now experience lower complemented-adjusted AI exposure. On the other hand, clerical jobs, which exhibited high AIOE, now demonstrate the highest C-AIOE. Agricultural workers, in comparison, rank relatively low on both measures.

2.5 Robustness Checks on the Complementarity Adjustment

As our measure of potential complementarity is novel and the selection of O*NET variables relies on our own judgement, we conduct robustness and sensitivity analyses, including examining the correlation between individual components of complementarity (Table A.3). We also compare each component with Felten et al. (2021)'s AIOE (Figure A.2; Table A.4) and assess how complementarity compares with other AI exposure measures previously discussed in the literature (Figure A.7). Our goal here is to understand how effectively our chosen components capture diverse dimensions of complementarity and to gauge the alignment between different AI exposure measures and the complementarity metric. Additionally, we check whether any components have an excessive influence on complementarity variations both graphically (Figure A.1) and by excluding one component at a time and computing complementarity based on the remaining five components – a method termed "leaving-one-out" analysis (Figures A.3 and A.4; Table A.5). The results of these checks strongly suggest that the selected components effectively encapsulate diverse and significant factors crucial to the interaction between AI and workers, providing a comprehensive and multifaceted measure of complementarity.

To further examine our component selection, we also conduct a principal component analysis (PCA) on the complementarity measure. The findings from the PCA indicate that the components under consideration are not all systematically interrelated, implying, when combined with other checks aforementioned, that our choice of work contexts and skills can indeed provide a multifaceted take on potential complementarity (Figure A.5). Importantly, the first two principal components only explain about 65 percent of the total variation in the 6 individual components of complementarity. Notably, the PCA results emphasize the importance of components like criticality, responsibility, and physical condition in grasping complementarity in professions such as pilots and surgeons. On the other hand, roles like economists are closely tied to components of communication, skills, and routine.

In this paper, we exclusively utilize the AI exposure measures introduced by Felten et al. (2021) to construct our complementarity-adjusted counterpart and perform subsequent analyses. Therefore, it is important to compare Felten et al. (2021)'s measures with other existing ones in the literature. As shown in Figure A.6, the baseline measure exhibits a positive correlation with other frequently cited AI exposures, such asWebb (2020). This correlation is also positive when considering the measure by Felten et al. (2023) that includes only exposure to Large Language Models (LLMs).[15] The only exception is Briggs and Kodnani (2023), where the relationship is negative.[16] Overall, our findings derived from the baseline AI exposure measure should be robust and applicable to most alternative measures as well.

Finally, we examine how AIOE and C-AIOE compare to exposure to routine-biased technical change. Table A.6 reports the share of employment in occupations that are cognitive, routine, and manual above given thresholds of AIOE, θ, and C-AIOE.[17] The main takeaways of the table are as follows. High-AIOE occupations are tilted towards cognitive jobs, but it is only at uppermost quantiles of exposure that almost all jobs are cognitive. Similarly, high-complementarity occupations have a greater association with cognitive jobs than routine and manual ones. Consequently, the C-AIOE measure shows a much lower overlap with cognitive occupations, and a larger one with routine and manual jobs. As professions and managerial positions mostly fall into the cognitive categories, the tabulations from Table A.6 are well aligned with our main results on the effect of the complementarity adjustment.

3 Country-Specific Data

We use worker-level microdata for 6 countries from labor force and household surveys. Table 1 lists the full name of the surveys used, the years used, and the most granular level of occupations for the ISCO-08. We use the most recent year of the survey available outside of the COVID-19 years (2020 and 2021).[18]

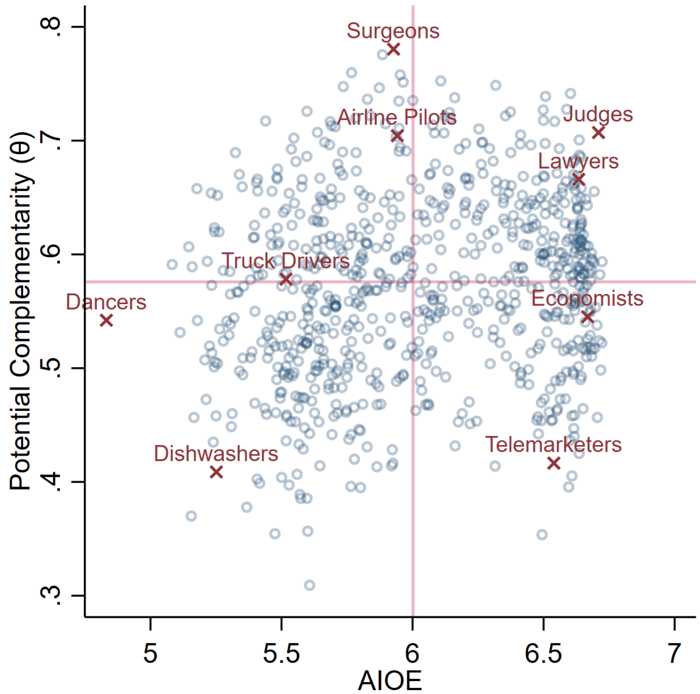
[15] "AIOE" represents the occupation-level AI exposure measure, considering all 10 AI applications, while "AIOE: LLM" focuses solely on LLMs.

[16] We replicate the AI exposure measure of Briggs and Kodnani (2023) solely relying on the methodology described in their text, without access to the original data or the exact coding procedure. As a result, it is important to exercise caution when interpreting the related findings.

[17] The division into (non-routine) cognitive, (non-routine) manual, and routine jobs is taken from Cortes et al. (2020).

[18] A potential caveat is that in some countries, particularly in AEs, wage growth since the pandemic has been more pronounced for low-wage occupations (Duval et al., 2022). This could partially affect the results presented in Section 4 related to exposure by the earnings distribution. However, differential wage growth

Figure 2: AI Exposure (AIOE) and Potential Complementarity (θ)



Note: "AIOE" is the occupation-level AI exposure from Felten et al. (2021). "Potential complementarity (θ)" utilizes 11 work contexts and 1 skill variable ("job zone") from O*NET. All occupations adhere to the US SOC 2010 coding. The diagram contains red reference lines that are based on the medians of both AIOE and θ. These lines serve to categorize occupations into four distinct quadrants, each indicating a unique blend of AI exposure and complementarity. For visual emphasis, 9 occupations are distinctly marked in red.

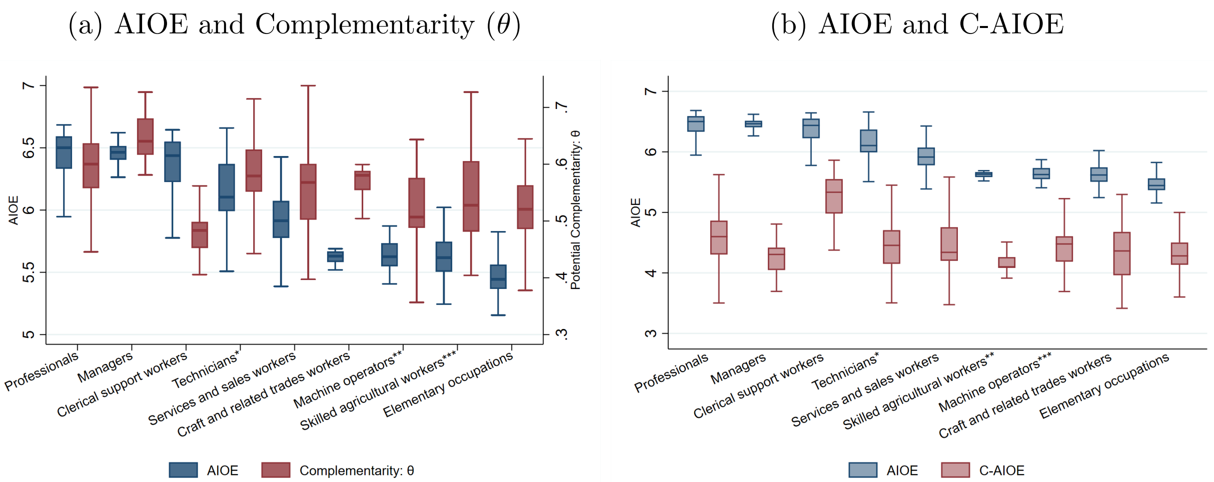
In all surveys we restrict the sample to individuals aged 16 to 64 who are employed[19] in the reference period of the survey. The lower bound of the age interval corresponds to the legal working age in the US for a 40-hour work week. In several countries, the statistical definition of working age starts below 16 years of age. However, we make this harmonized choice for the sake of comparison. Similarly, 64 is two to three years below the minimum eligibility age for state-provided social security pensions in the US and UK but roughly aligns with the effective retirement age in these countries (OECD, 2021).

We group educational attainment in four different categories in order to conduct the cross-country analyses. The categories considered are, in terms of the US educational system, middle school and below (or equivalent); high school (or equivalent); higher education or

of a few percentage points over one or two years is unlikely to significantly change the key results presented. Moreover, several studies, focused on AEs, find that the pandemic did not spark long-term structural changes Duval et al. (2022); Jaumotte et al. (2023). Hence, survey years prior to COVID-19 likely reflect well the employment composition in 2023, when the COVID-19 pandemic disruptions to the labor market have almost fully waned.

[19]Employment considers both formal and informal as well as self-employed workers.

Figure 3: AI Complementarity and Exposure across Major Occupation Groups



Note: The figure plots the distribution of the values of complementarity θ, unajusted exposure AIOE, and adjusted exposure C-AIOE across occupations specified by ISCO-08 codes. The grouping is at the 1-digit ISCO-08 code level. *: Technicians and associate professionals. **: Skilled agricultural, forestry and fishery workers. ***: Plant and machine operators and assemblers.

Table 1: Data Sources

Country	**Survey**	**Year**	**ISCO-08 Digits**
Brazil	Pesquisa Nacional por Amostra de Domicílios Contínua	2022	4
Colombia	Gran Encuesta Integrada de Hogares	2022	4
India	Period Labour Force Survey	2018-19	3
South Africa	Labor Market Dynamics in South Africa Survey	2019	4
UK	Labour Force Survey	2022	4
US	American Community Survey	2019	4

incomplete college degree (or equivalent); and college degree or higher (or equivalent). For India, there is no category in the survey that corresponds to higher education or incomplete college education.

Earnings are computed as gross (pre-tax) income from the main job or activity. For most countries, this corresponds to monthly gross earnings, except for the UK, which reports the gross weekly earnings, and the US, which reports the gross annual earnings.

To apply the AIOE and C-AIOE measures to labor force surveys we convert the measures from the US SOC 2010 to ISCO-08 using a crosswalk from the Bureau of Labor Statistics. When the mapping is not one-to-one, we take simple averages of the individual scores.[20] Whenever the national labor force surveys are coded using other classifications,

[20] Sensitivity analysis using employment-weighted averages using the American Community Survey yielded

these are also converted to ISCO-08 using crosswalks.

4 Cross-Country Results

In this section, we first present baseline results on aggregate cross-country variation in AI exposure using both the unadjusted AIOE measure and our complementarity-adjusted C-AIOE one. Subsequently, we examine how these differences are driven by countries' employment composition by exposure and complementarity. Last, we analyze the exposure of AI across different demographic groups and the income distribution.

4.1 Aggregate Results

We begin our analysis by studying AI exposure across countries, focusing on the cumulative employment share at different levels of AIOE. Figure 4a presents this share at a given level of exposure for all countries. The x-axis reports the percentiles of the distribution of AIOE across unique occupation titles (at the ISCO-08 4-digit level). Lower percentiles represent individual occupations with lower values of AIOE. The y-axis reports the share of employment in all occupations with an exposure up to the respective percentile for each country. For instance, the UK has about 25 percent of employment below the lowest 40^{th} percentile of AIOE (value of 0.4 on the x-axis) while Brazil has 50 percent and India 70 percent. This simple observation indicates already that Brazil and India have a higher share of workers employed in occupations with lower potential to be impacted by AI than the UK has.

Our findings reveal a substantial proportion of workers demonstrating higher exposure in both the US and the UK. The UK emerges as the country with the highest aggregate exposure levels, as indicated by its curve lying to the right of the others, with 40 percent of employment concentrated above the 80^{th} percentile of AIOE. This fact is attributable to its small proportion of workforce in low-exposure occupations. The US ranks second in terms of highest exposure levels with almost 30 percent of employment concentrated above the 80^{th} percentile of AIOE.

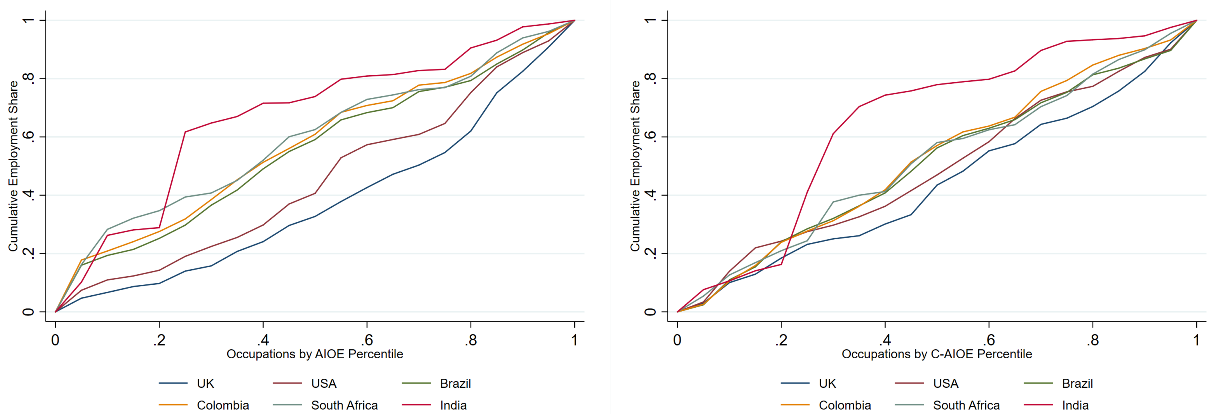
Turning our attention to EMs, AI exposure levels are strikingly similar across Brazil, Colombia, and South Africa, with less than 15 percent of employment concentrated above the 80^{th} percentile of AIOE. Meanwhile, India, the leftmost curve, exhibits the lowest levels of exposure due to its sizable worker population within the agricultural sector. We delve further

extremely similar results.

into this aspect when exploring the variances in employment across different occupations in various countries in the next section.

Figure 4: Cumulative Employment Distribution: AIOE and Complementarity-Adjusted (C-AIOE).

(a) AIOE (b) C-AIOE

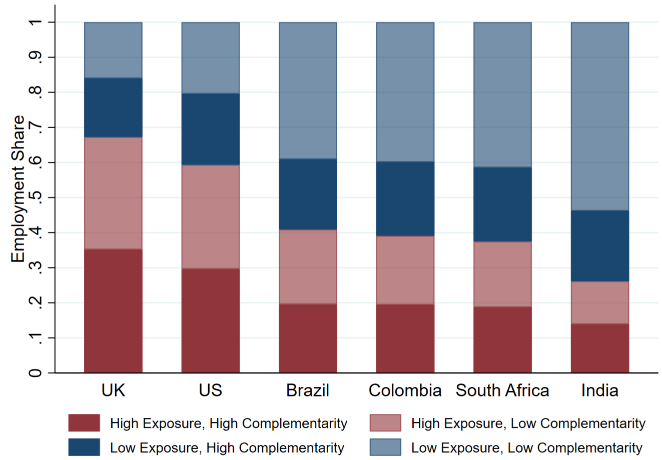


Note: The figures plot the cumulative employment share with respect to the AIOE and C-AIOE measures for each country. The y-axis shows the cumulative employment share in the occupations, and the x-axis the AIOE or C-AIOE normalized to be between 0 and 1, where 0 is the occupation with lowest exposure and 1 the occupation with the highest exposure.

When we account for potential complementarity and adjust the AI exposure accordingly, two significant findings come to the fore. First, as shown in Figure 4b), the previously observed differences in AI exposure between countries substantially diminish. The UK maintains its position as the country with the highest level of complementarity-adjusted exposure. However, the gap in exposure across AEs and most EMs is almost fully closed, indicating a more uniform pattern of AI-adjusted exposure. The exception remains India, where the adjustment for complementarity has only a marginal impact due to the predominance of workers employed in the agricultural sector.

To delve deeper into the role of complementarity, we categorize occupations into four distinct groups: (i) High Exposure and High Complementarity; (ii) High Exposure and Low Complementarity; (ii) Low Exposure and High Complementarity; and (vi) Low Exposure and Low Complementarity. These categories are determined based on whether an occupation's AI exposure (AIOE) and complementarity fall above or below the respective median values. Among these, our principal focus resides on two categories. High Exposure and Low Complementarity represents occupations most vulnerable to potential adverse effects of widespread AI adoption. Meanwhile High Exposure and High Complementarity includes occupations poised to benefit the most from AI.

Figure 5: Employment Share by AI Exposure and Complementarity



Note: The figure plots the share of employment in each quadrant of Figure 1 for each country. "High" and "Low" values are constructed as being above and below the median of exposure AIOE and complementarity θ.

A visual representation of the employment share in each of these groups across countries is provided in Figure 5. As previously established, the US and UK host the largest proportion of workers exposed to AI. In addition, they also have the largest share of workers in occupations with *both* high exposure and high complementarity. The UK leads in this metric, with 51.9 percent of workers engaged in highly complementary occupations, while the US follows with 49.8 percent. Moreover, these countries also report the largest proportion of workers in occupations characterized by high exposure but low complementarity - 32 percent in the UK and 29.7 percent in the US.

Turning to EMs, a common pattern emerges for Brazil, Colombia, and South Africa. Nearly 40 percent of workers in these countries are in high-exposure occupations. Among these, approximately half, or 20 percent, are in occupations with high complementarity potential, while the remaining half work within occupations exhibiting low complementarity potential. As remarked earlier, India stands apart, with the lowest aggregate level of exposure. A total of 26 percent of workers are in high-exposure occupations, divided into 14 percent in occupations with high complementarity and 12 percent in those with low complementarity.

In conclusion, the US and UK point to greater "polarization" in exposure to AI for AEs. One the one hand, with their substantial share of workers in high-exposure yet low-complementarity occupations, AEs appear most vulnerable to adverse labor market effects, as workers in these jobs are more likely to bear the brunt of labor displacement. On the other hand, AEs also have an equally significant proportion of employment in high-exposure and high-complementarity occupations. These are the workers more likely to gain from AI integration, potentially experiencing substantial productivity gains. Overall, the two AEs in the sample, offer a picture of both opportunities and risks from AI. Meanwhile, reduced aggregate exposure in EMs suggests that these countries may face less short-term disruption but are also less equipped to directly leverage the new AI technologies to enhance productivity without a deeper structural transformation of their economies.

4.2 Occupations

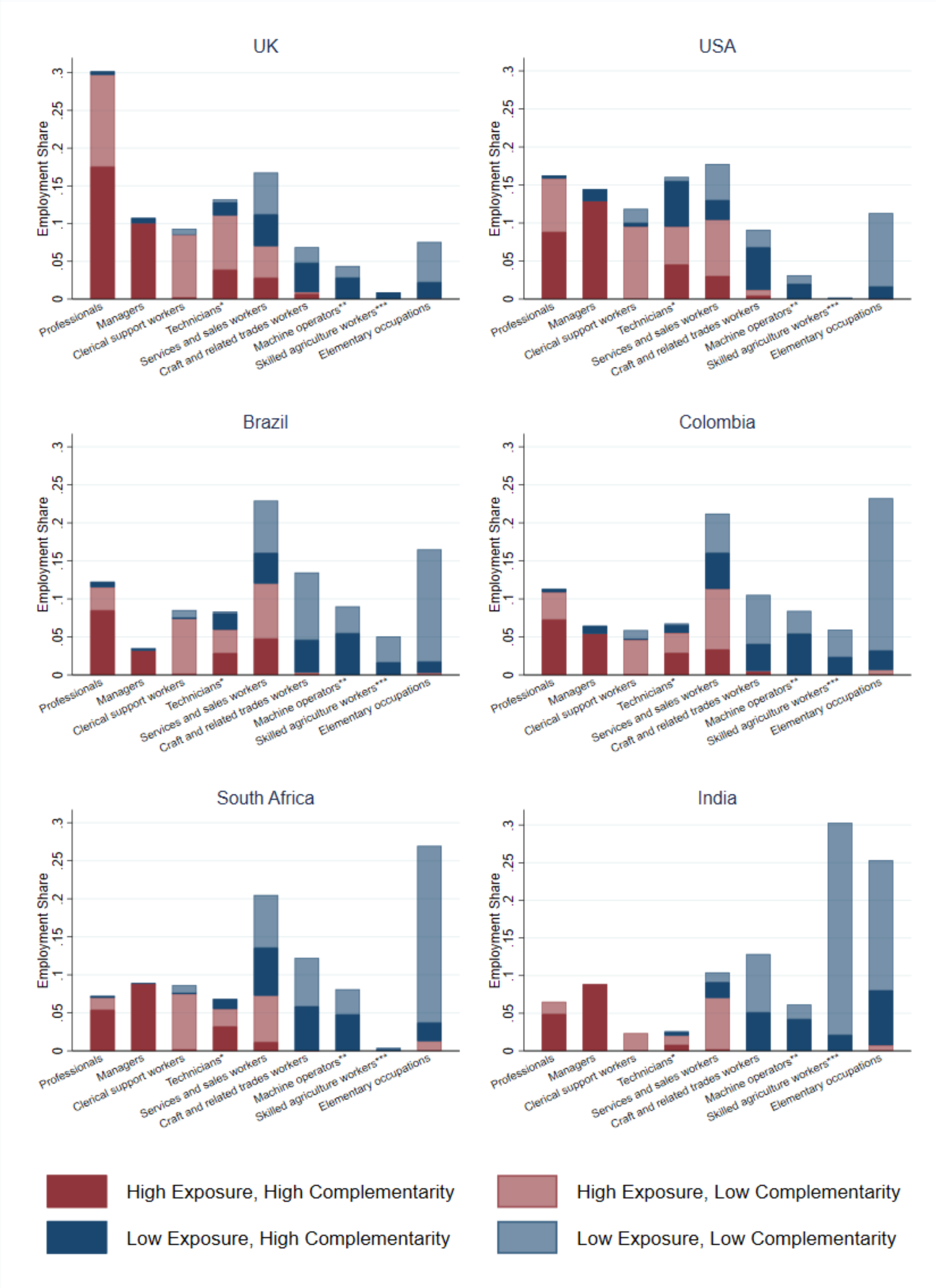
To further unpack the aggregate country-level results, we now zoom into countries' occupational composition in greater detail, scrutinizing their respective AI exposure and complementarity. We compute the employment share across nine main occupational categories (as per the ISCO-08 1-digit level). In line with the previous section, employment in each group is segmented into four categories depending on whether the workers' are employed in (4-digit) occupations with AI exposure and complementarity above or below their respective median values. Using the intersection of occupation groups and these four categories as our analytical framework, Figure 6 provides a detailed breakdown of employment composition in each country.

Figure 6 highlights how the large share of professional and managerial occupations, which are almost entirely in the high-exposure categories, underpin the UK's high aggregate exposure, followed by the US. Nearly 30 percent of workers in the UK are employed in professional occupations, while the corresponding figure for the US stands just above 15 percent. Although the US hosts a larger share of managers, an occupation that exhibits the highest degree of complementarity, the difference between the US (14.4 percent) and UK (10.7 percent) remains relatively small. As these occupational groups are also marked by high complementarity, the figures also explains why the UK and the US exhibit the largest differences between the AIOE and C-AIOE measures in Figure 4. [21]

In EMs, the primary driver of lower AI exposure is the substantial proportion of workers in elementary occupations, a category characterized by low exposure levels. In India, this result is magnified by the extensive employment of workers in agriculture –over 30 percent– which also falls under occupations exhibiting low levels of AI exposure (either in elementary occupations or in skilled agricultural workers).

[21] In Annex A, Figure B.1, we show the employment-weighted average degree of complementarity in each occupation group by country. Managers, followed by professionals, display the highest potential for complementarity.

Figure 6: Employment Share by Exposure and Complementarity



Note: The figure plots the share of employment in each quadrant of Figure 1 for each country across the 1-digit ISCO-08 occupation codes. "High" and "Low" values are constructed as being above and below the median of exposure and complementarity, respectively. *: Technicians and associate professionals. **: Plant and machine operators and assemblers. ***: Skilled agricultural, forestry and fishery workers.

Investigating the intersection of high exposure and high complementarity, we find that, in comparison to the US and UK, developing economies house a smaller proportion of workers in occupations with potential for complementarity. This is reflected in the modest share of professional occupations, especially in India and South Africa with less than 10 percent, and managerial roles, particularly noticeable in Brazil, constituting less than 5 percent of the workforce. Meanwhile, the share of clerical workers –a group with high exposure yet low complementarity– is also lower in developing economies, standing under 10 percent in Brazil, Colombia, and South Africa and less than 5 percent in India.

4.3 Demographics

We now explore how AI exposure and complementarity varies with workers' demographic characteristics. This study allows us to better identify which subsets of workers are most vulnerable, as well as those most likely to reap benefits from AI adoption. To guide the analysis, Figure 7 plots the share of employment in high-exposure occupations, sub-divided by complementarity, by gender, education, and age.

4.3.1 Gender

Focusing first on gender, in Figure 7a) we observe that in five out of six countries in the sample, women face a higher exposure to AI compared to men. For instance, in the US, 68 percent of women are in high exposure occupations compared to 51 percent of men. Comparable figures in Brazil are 52 percent for women and 32 percent for men. This outcome is primarily attributable to the occupational distribution across genders. Female employment is more concentrated in service and retail occupations, which are relatively more exposed to AI, while men are more likely to be in occupations intensive in manual labor, which are less exposed.[22] India differs from the other countries, with 24 percent of women employed in high-exposure occupations compared to 28 percent for men. The higher share of females in elementary and agricultural jobs drives this result.

Despite the higher exposure, focusing our attention to the potential for complementarity suggests that women may have a higher likelihood of benefiting from the proliferation of AI. Appendix Figure B.2 shows that in all countries women have a larger share of employment in professional occupations, which rank second in potential complementarity to AI. Conversely, although men generally exhibit a larger share of managerial jobs, which have the

[22] In Annex B, Figure B.2, we present the employment share of women and men across different occupation groups based on their degree of exposure and complementarity.

highest degree of complementarity, the total shares of managers compared to professionals is relatively small.

Nevertheless, women are also more susceptible to potential negative impacts from AI adoption, particularly in the UK, US, Brazil, and South Africa. This vulnerability arises from their greater representation in clerical jobs, a category characterized by high exposure and low complementarity, thus at higher risk from AI adoption.

4.3.2 Education

With respect to education, Figure 7b) suggests that workers with college-level degrees are more exposed to AI than those with lower educational attainment. Approximately 90 percent of college-educated workers across most countries are in occupations with high exposure, primarily in professional roles. In contrast, those without a high school diploma are predominantly involved in elementary occupations, which results in a significantly reduced AI exposure. In most countries, less than 20 percent of these workers find themselves in high-exposure occupations. The only exception is the the UK, where 40 percent of workers with only a middle school education or less are in high-exposure occupations.

When considering the potential for complementarity, we observe that in all countries within our sample, workers holding a college degree or higher are predominantly concentrated within occupations that exhibit greater potential to benefit from the widespread adoption of AI. In contrast, among those with an education level of middle school or below, workers in exposed occupations display the lowest prospects of benefiting from AI adoption.

Furthermore, our analysis suggests that the potential adverse impacts of AI might be distributed more evenly than the potential gains. For instance, in the UK, the difference in the proportion of workers in high exposure and low complementarity occupations, conditional on their education level, is less than 10 percentage points — ranging from 26 percent among workers with middle school education or below to 36 percent among workers with a college education or higher. Conversely, the discrepancy in the potential to benefit from AI is considerably larger. Only 17 percent of workers with middle school education or below find themselves in high-exposure and high-complementarity occupations, as opposed to over 50 percent of workers with a college education or higher.

4.3.3 Age

Based on Figure 7c), we do not observe a straightforward association between age and AI exposure. Overall, age patterns are likely very intertwined with country-specific long-term trends in educational attainment and female labor force participation, which can substantially blur the underlying life-cycle profiles.[23] One general observation is that the youngest workers tend to have lower AI exposure than prime-age workers. Moreover, conditional on being in high-exposure occupations, younger workers are also less likely to be in jobs with high complementarity, and thus are more susceptible to potential negative impacts stemming from widespread AI adoption.

4.4 Earnings

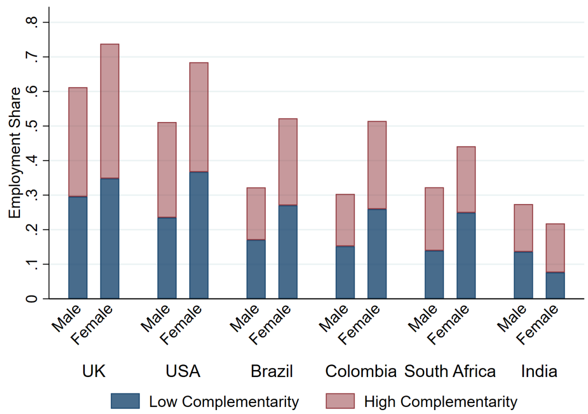
We now shift our attention to the potential impact of AI over the income distribution. To this aim, Figure 8a) plots the employment share of workers in high-exposure occupations, defined as the occupations above the AIOE median, across the earnings distribution. A positive association between earnings and share of employment in high-exposure occupations emerges in all countries. Consistent with our earlier findings, the US and UK possess a higher proportion of highly exposed workers across the entire earnings distribution. In the UK, for example, almost all workers in the top decile are in highly exposed occupations. In Brazil, Colombia, and South Africa AI exposure patterns across the earnings distribution appear relatively similar, with high-income workers exhibiting greater exposure, especially noticeable in Colombia. Meanwhile, in India, AI exposure is exceptionally low at the lower end of the distribution and progressively increases with income.

Interestingly, our analysis reveals a more equal distribution of workers with high AI exposure and low complementarity across the income distribution (Figure 8b), indicating that the risks from widespread AI adoption may be broadly evenly distributed across the earnings distribution. In contrast, upon assessing which workers stand to benefit most, in all countries in the sample, employment in high-complementarity occupations is concentrated in the top deciles of the earnings distribution (Figure Figure 8c). This pattern is more pronounced in EMs, and more gradual in AEs, particlularly in the UK, where the top four deciles are fairly levelled.

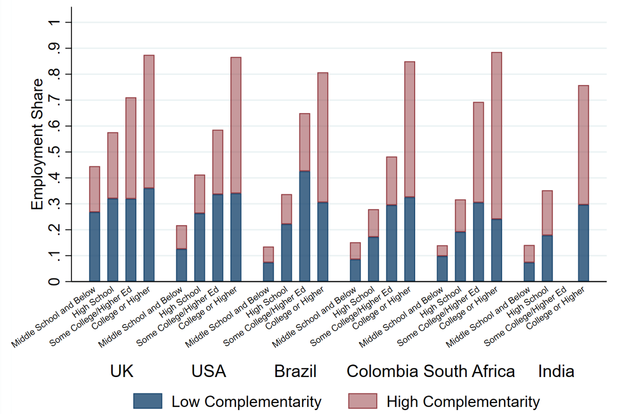
[23]For instance, while younger workers in AEs are more likely to be in low-skill occupations, they also have higher educational attainments than older workers.

Figure 7: AI Exposure and Complementarity Distribution by Demographic Characteristics

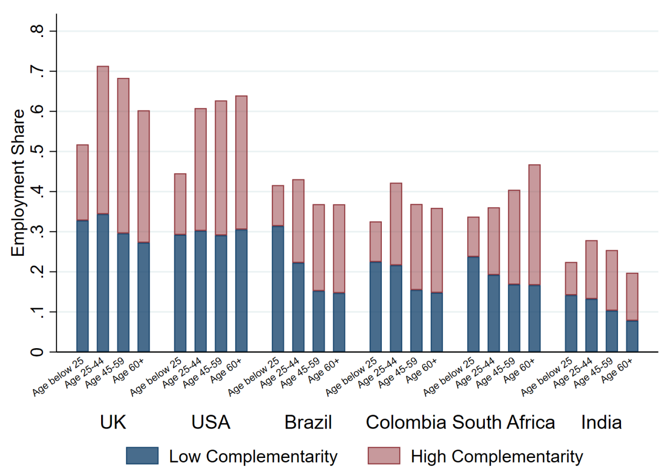
(a) Gender



(b) Education



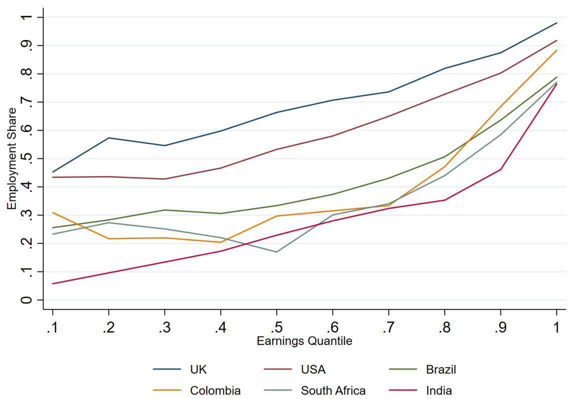
(c) Age



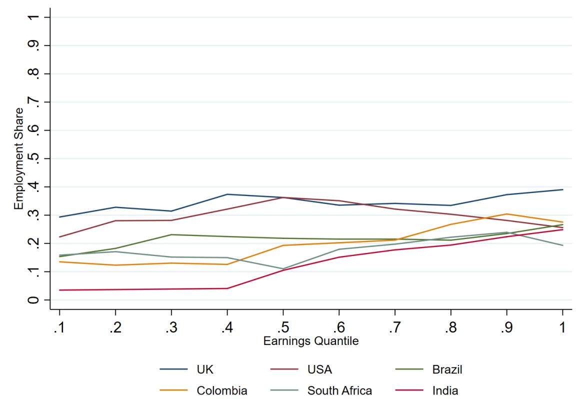
Note: The figures plot the distribution of employment in high-exposure, high-complementarity, and low-complementarity occupations conditional on (a) gender, (b) education, and (c) age. "High" and "Low" are defined as being above or below the median of exposure and complementarity. For India, there is no corresponding category in the survey for "Some College or Higher Education" in the education plot (b).

Figure 8: Share of Employment in High Exposure Occupations by Earnings Decile

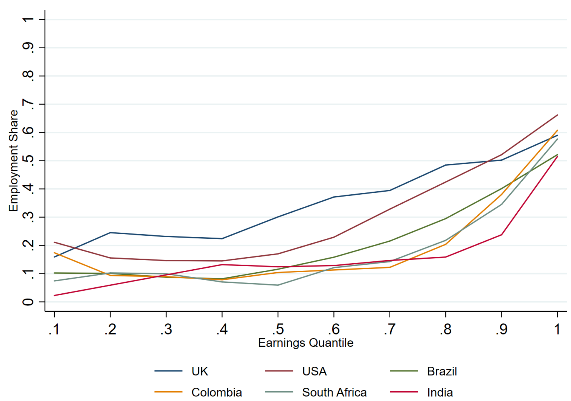
(a) High Exposure



(b) High Exposure, Low Complementarity



(c) High Exposure, High Complementarity



Note: The figures plot the share of employment in (a) high-exposure occupations, (b) high-exposure and low-complementarity, and (c) high-exposure and high-complementarity conditional on each earnings decile. "High" and "low" are defined as being above or below the median exposure and complementarity.

5 Sensitivity Analysis

This section presents robustness checks to the main results, discussing how the impact of the complementarity adjustment changes when societal considerations are included, and considering an alternative functional form.

5.1 Complementarity Weight

As discussed above, our proposed adjustment of the baseline AIOE measure produces a marked reduction in aggregate cross-country differences in exposure. The exercise is meant to provide a proof-of-concept for how societal norms and the need for supporting innovation plausibly affect the relative probability that, for a given level of exposure, AI would function as a complementary technology. However, the extent to which norms could shape adoption and the pace at which technologies will develop is highly uncertain and may differ across countries. For instance, some societies may feel less averse to delegating highly consequential tasks (such as driving a transport vehicle or diagnosing diseases) to non-monitored algorithms. Moreover, norms could evolve over time, either becoming more permissive –as societies learn more about how AI-powered tools are adapted and safety systems improve– or stricter, e.g., if the technology proves less reliable or if social backlash against it emerges.

The complementarity adjustment can easily be augmented to capture these considerations by assigning a weight to mitigate the effect of θ on AIOE as follows:

$$\text{C-AIOE}_i = \text{AIOE}_i * (1 - w * (\theta_i - \theta_{MIN}))$$

where $0 \leq w \leq 1$. Since this specification nests both the unadjusted AIOE (for $w = 0$) and the baseline C-AIOE (for $w = 1$), a value of w below 1 would capture a milder adjustment for complementarity. In a dynamic sense, a changing value of w can also be thought of as reflecting societal preferences and infrastructure evolving over time. A higher w would represent early cautions and technical impediments, and a gradually lower w would capture the progressive overcoming of technical constraints and societal reservations.

As an illustration, in this section we consider how the baseline results change for a partial complementarity adjustment by setting the value of w to 0.5. Importantly, given the joint distribution of the AIOE index and θ, the effect of higher/lower w on cross-country differences in exposure need not be linear.[24]

[24]In other words, a value of 0.5 w does not necessarily imply a the gap in exposure between, say, the UK

Figure 9a) shows the cumulative share of employment for each country by percentile of C-AIOE over occupations. As expected, the differences across countries are more muted than for the baseline C-AIOE in Figure 4b) and substantial gaps remain between advanced economies and most EMs. Interestingly the $w = 0.5$ specification narrows the gap between these groups of countries in the lower tail of the exposure distribution (up until the 20$^{\text{th}}$ percentile) but much less so at higher percentiles of exposure.[25]

5.2 Exponential Adjustment

We also check whether the results are robust to an alternative functional form for the complementarity adjustment. Specifically, we test an exponential adjustment:

$$\text{C-AIOE}_i = \text{AIOE}_i * \mathrm{e}^{-(\theta_i - \theta_{MIN})}$$

The difference of this specification is the nonlinear form of the adjustment. A marginal increase in θ_i will yield a larger decrease in C-AIOE for lower levels of θ. This could be relevant since the baseline results show that the complementarity adjustment dampens differences between AEs and services-intensive EMs more than between the latter and agriculture-intensive EMs.

Figure 9b) shows that the result from the baseline specification is robust to the exponential adjustment. Under this functional form, the differences between AEs and Brazil, Colombia and South Africa are strongly dampened while India remains shifted to the left of the exposure distribution.

6 Additional Discussion

Before concluding, we discuss some caveats on the methodology and interpretation of the findings.

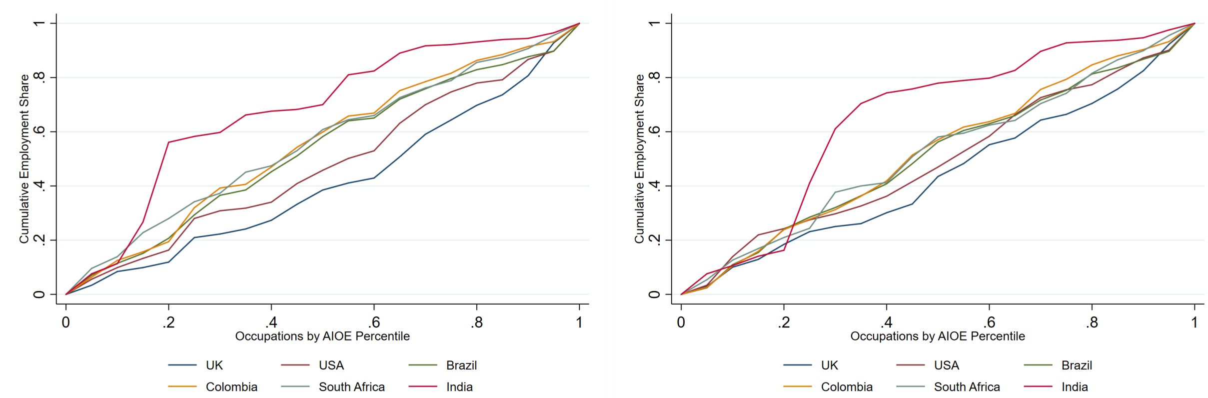
- First, both the AIOE and the C-AIOE focus on a subset of dimensions of exposure. The implementation of AI-based technologies and hence total exposure at the occupational and country level will depend also on other factors. These include country-level features such as the availability of IT infrastructure, the relative costs of labor and capital, and

and Brazil, that is mid-way between that of $w = 0$ and of $w = 1$.

[25] Figure B.7 plots the cumulative share of employment for each country individually for $w = 0$, 0.5 and 1.

Figure 9: Robustness Checks: Cumulative Employment Share by C-AIOE Distribution

(a) Baseline adjustment with $w = 0.5$ (b) Exponential adjustment



Note: The figures plot the cumulative employment share in respect to two different specifications of the C-AIOE measure for each country. The y-axis shows the share of employment in the occupations with C-AIOE equal or below the percentile in the x-axis.

even openness to trade. The importance of these factors requires further study.

- The implications of AI exposure for inequality also require further study. The C-AIOE measure suggests the possibility of non-trivial changes in wages between jobs, due to shifts in demand for different occupations, and within jobs, based on workers' skills. The ultimate effect on income inequality will also depend on workers' ability to transition to jobs experiencing growing demand from jobs with shrinking demand. This reallocation could occur through job-to-job switches or through generational turnover with new cohorts of workers entering into growing jobs in greater proportions.

- Even with the complementarity adjustment, AI exposure as considered in this work does not account for the creation of new tasks. As shown by Acemoglu and Restrepo (2019) and Autor et al. (2022), new technologies have historically also created new tasks and new jobs. This mechanism would contribute to reducing country-level AI exposure over the long term when considering workers' ability to change occupations.

- As discussed above, AI exposure and, importantly, the weight given to the contexts defining complementarity depend on societal preferences. These could differ across countries and may evolve. For instance, while at first societies may be reluctant to fully delegate some tasks to AI, such as controlling means of transportation or making medical diagnoses, regulatory frameworks and social conventions may change over time to allow for these applications. These changes would, in turn, affect labor market exposure.

- Our approach abstracts from linkages across occupations and spillovers of AI exposure. Some occupations could indirectly experience changes in demand due to exposure in linked occupations. For instance, as discussed in OECD (2023), "algorithmic management" practices may increase a manager's ability to supervise a larger number of workers completing activities not directly exposed to AI. Thus, a productivity increase for managers would lead to higher labor demand in the occupations of their supervised workers.

- Related to the points above, the analysis is static and in partial equilibrium, providing a snapshot view of exposure in one year. As the speed of AI adoption remains uncertain and could vary across industries, sectors, and countries, exposure in a dynamic sense could differ substantially. Better knowledge of the adoption process is crucial not only to understand the impact of AI on the labor market but also its ultimate implications for productivity (Brynjolfsson et al., 2018, 2021).

- Labor markets in one country are also exposed to AI adoption abroad via trade linkages. For instance, even with low AI adoption in their home country, workers in high-exposure and low-complementarity occupations could face displacement risk if domestic (foreign) firms decide to offshore (re-shore) their tasks with AI technology located overseas. Domestic labor replacement by foreign-located AI automation would be imply not only job displacements but also losses in productivity and capital income for the domestic economy.

7 Conclusion

This study presents an in-depth examination of the potential impact of Artificial Intelligence (AI) on labor markets through a detailed cross-country analysis encompassing both Advanced Economies (AEs) and Emerging Markets (EMs). By leveraging microdata and a granular occupational classification, the paper advances our understanding of AI's potential to both disrupt and augment various occupations. The analysis reveals a nuanced landscape: while AI poses risks of labor displacement due to task automation, it also holds promise in its capacity to enhance productivity and complement human labor, especially in occupations that require a high level of cognitive engagement and advanced skills.

Applying a widely used measure of AI Occupational Exposure (AIOE), this study finds substantial cross-country disparities, with EMs generally characterized by lower exposure levels than AEs. Countries' distinct occupational structures underpin these differences, with the AEs displaying a larger share of employment in high-skill jobs that are highly exposed to AI. Interestingly, these disparities, in terms of potentially disruptive exposure, significantly diminish once AI's potential for complementarity is considered, as high-skill occupations that are more prevalent in AEs, despite being more exposed, can also greatly benefit from AI. Overall, AEs have more employment than EMs in exposed occupations at both ends of the complementarity spectrum. This finding suggests that AEs may expect a more polarized impact of AI on the labor market and are thus poised to face greater risk of labor substitution but also greater benefits for productivity. The potential for both negative and positive outcomes associated with AI is distributed across different demographic and income groups within and across countries in complex patterns. These findings thus challenge simplified narratives of AI as solely a threat to employment.

Looking forward, our analysis highlights the need for future research to delve deeper into understanding the dynamic relationship between AI and the labor market, taking into account the context of specific economies. It also underscores the importance of ongoing assessments of AI's potential for complementarity, which can significantly mitigate its disruptive impact. Furthermore, the potential socioeconomic implications of AI call for carefully calibrated policies to promote skill development and to support displaced workers' transitions. This, in turn, can ensure a smoother transition towards an increasingly AI-integrated economy while mitigating the risk of labor market displacement and wider income disparity. Future studies could also explore the implications of AI exposure on labor mobility, job quality, and overall economic performance within and across countries, further enriching our understanding of this transformative technology.

References

Acemoglu, D. and P. Restrepo (2018). Artificial intelligence, automation, and work. In A. Agrawal, J. Gans, and A. Goldfarb (Eds.), *The economics of artificial intelligence: An agenda*, pp. 197–236. University of Chicago Press.

Acemoglu, D. and P. Restrepo (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives 33*(2), 3–30.

Acemoglu, D. and P. Restrepo (2022). Tasks, automation, and the rise in us wage inequality. *Econometrica 90*(5), 1973–2016.

Agrawal, A., J. Gans, and A. Goldfarb (2018). Introduction. In A. Agrawal, J. Gans, and A. Goldfarb (Eds.), *The economics of artificial intelligence: An agenda*, pp. 197–236. University of Chicago Press.

Albanesi, S., A. D. da Silva, J. F. Jimeno, A. Lamo, and A. Wabitsch (2023). New technologies and jobs in europe. Technical Report DP18220, CEPR Discussion Papers.

Autor, D., The labor market impacts of technological change: From unbridled enthusiasm to qualified optimism to vast uncertainty. Working Paper.

Autor, D., C. Chin, A. M. Salomons, and B. Seegmiller (2022). New frontiers: The origins and content of new work, 1940–2018. Technical report, National Bureau of Economic Research.

Autor, D. H. (2015). Why are there still so many jobs? the history and future of workplace automation. *Journal of economic perspectives 29*(3), 3–30.

Autor, D. H. and D. Dorn (2013). The growth of low-skill service jobs and the polarization of the us labor market. *American economic review 103*(5), 1553–1597.

Autor, D. H., F. Levy, and R. Murnane (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics 118*(4), 1279–1333.

Bluedorn, J., N.-J. Hansen, D. Noureldin, I. Shibata, and M. M. Tavares (2023). Transitioning to a greener labor market: Cross-country evidence from microdata. *Energy Economics*, 106836.

Briggs, J. and D. Kodnani (2023). The potentially large effects of artificial intelligence on economic growth. *Global Economics Analyst*.

Brynjolfsson, E., T. Mitchell, and D. Rock (2018, May). What can machines learn, and what does it mean for occupations and the economy? *AEA Papers and Proceedings 108*, 43–47.

Brynjolfsson, E., D. Rock, and C. Syverson (2018). Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics. In A. Agrawal, J. Gans, and A. Goldfarb (Eds.), *The economics of artificial intelligence: An agenda*, pp. 23–57. University of Chicago Press.

Brynjolfsson, E., D. Rock, and C. Syverson (2021). The productivity j-curve: How intangibles complement general purpose technologies. *American Economic Journal: Macroeconomics 13*(1), 333–372.

Copestake, A., M. Marczinek, A. Pople, and K. Stapleton, Ai and services-led growth: Evidence from indian job adverts. Working Paper.

Cortes, G. M., C. J. Nekarda, N. Jaimovich, and H. E. Siu (2020, 8). The dynamics of disappearing routine jobs: A flows approach. *Labour Economics 65*.

Duval, R. A., Y. Ji, L. Li, M. Oikonomou, C. Pizzinelli, I. Shibata, A. Sozzi, and M. M. Tavares (2022). Labor market tightness in advanced economies. (Staff Discussion Note 2022/001).

Eloundou, T., S. Manning, P. Mishkin, and D. Rock, Gpts are gpts: An early look at the labor market impact potential of large language models. Working Paper.

Felten, E., M. Raj, and R. Seamans (2021). Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses. *Strategic Management Journal 42*(12), 2195–2217.

Felten, E., M. Raj, and R. Seamans, How will language modelers like chatgpt affect occupations and industries? Working Paper.

Gaube, S., H. Suresh, M. Raue, E. Lermer, T. K. Koch, M. F. Hudecek, A. D. Ackery, S. C. Grover, J. F. Coughlin, D. Frey, et al. (2023). Non-task expert physicians benefit from correct explainable ai advice when reviewing x-rays. *Scientific reports 13*(1), 1383.

Gmyrek, P., J. Berg, and D. Bescond (2023). Generative ai and jobs: A global analysis of potential effects on job quantity and quality. *ILO Working Paper 96*.

Goldfarb, A., B. Taska, and F. Teodoridis (2023). Could machine learning be a general purpose technology? a comparison of emerging technologies using data from online job postings. *Research Policy 52*(1), 104653.

Hall, W. J., M. V. Chapman, K. M. Lee, Y. M. Merino, T. W. Thomas, B. K. Payne, E. Eng, S. H. Day, and T. Coyne-Beasley (2015). Implicit racial/ethnic bias among health care professionals and its influence on health care outcomes: a systematic review. *American journal of public health 105*(12), e60–e76.

Jaumotte, M. F., L. Li, A. Medici, M. Oikonomou, C. Pizzinelli, M. I. Shibata, J. Soh, and M. M. Tavares (2023). Digitalization during the covid-19 crisis: Implications for productivity and labor markets in advanced economies. (Staff Discussion Note 2022/003).

Lane, M. and A. Saint-Martin (2021). The impact of artificial intelligence on the labour market: What do we know so far?

Lane, M., M. Williams, and S. Broecke (2023). The impact of ai on the workplace: Main findings from the oecd ai surveys of employers and workers.

Lipsey, R. G., K. I. Carlaw, and C. T. Bekar (2005). *Economic transformations: general purpose technologies and long-term economic growth*. Oup Oxford.

Milanez, A. (2023). The impact of ai on the workplace: Evidence from oecd case studies of ai implementation.

OECD (2021). *Pensions at a Glance 2021*. OECD Publishing, Paris.

OECD (2023). *OECD Employment Outlook 2023: Artificial Intelligence and the Labour Market*. OECD Publishing, Paris.

Rajpurkar, P., J. Irvin, R. L. Ball, K. Zhu, B. Yang, H. Mehta, T. Duan, D. Ding, A. Bagul, C. P. Langlotz, et al. (2018). Deep learning for chest radiograph diagnosis: A retrospective comparison of the chexnext algorithm to practicing radiologists. *PLoS medicine 15*(11), e1002686.

Sim, Y., M. J. Chung, E. Kotter, S. Yune, M. Kim, S. Do, K. Han, H. Kim, S. Yang, D.-J. Lee, et al. (2020). Deep convolutional neural network–based software improves radiologist detection of malignant lung nodules on chest radiographs. *Radiology 294*(1), 199–209.

Soh, J., M. Oikonomou, C. Pizzinelli, I. Shibata, and M. Mendes Tavares (2022). Did the covid-19 recession increase the demand for digital occupations in the united states? evidence from employment and vacancies data. *IMF Working Paper 2022/195*.

Webb, M., The impact of artificial intelligence on the labor market. Working Paper.

A Complementarity Index Additional Information and Analysis

Tables A.1 and A.2 report all the 57 work contexts from O*NET.

We carry two sets of robustness checks.

Firstly, we delve into the components of θ. For instance, as θ is constituted from six distinct components, we investigate the correlation among these components and inspect the correlation between each component and AIOE. Detecting significant variability in these correlations would suggest that each component captures different facets of complementarity. Conversely, little variability might indicate a lack of comprehensiveness in our component selection strategy. Overall, these checks confirm that the chosen components accurately capture a range of important factors essential for the AI and worker interaction.

Second, our results rely heavily on the AI exposure measure introduced by Felten et al. (2021), which we expand with a complementarity adjustment to undertake further analyses. It is therefore imperative to compare Felten et al. (2021)'s measures with other existing ones in the literature to ascertain if our conclusions drawn from the baseline AI exposure measure remain robust and are applicable to other measures as well. The analysis in this appendix suggests that the outcomes obtained using Felten et al. (2021)'s metric could also be replicable with other commonly referenced measures.

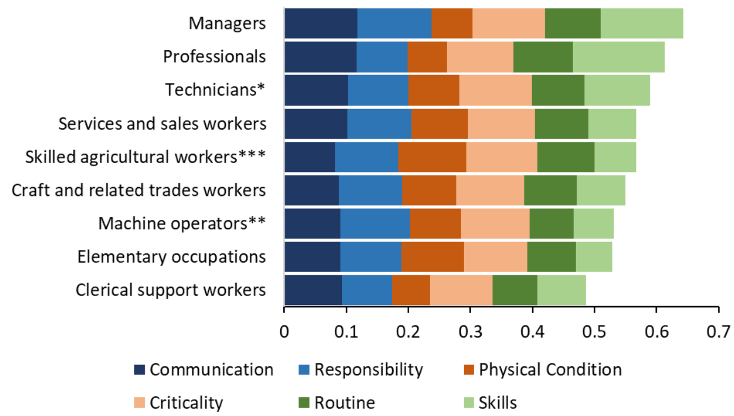
Table A.1: Work Contexts in O*NET

	Work Context	Description
	Interpersonal Relationships	Context of the job in terms of human interaction processes.
	Communication	Types and frequency of interactions with other people that are required as part of this job.
1	Electronic Mail	How often do you use electronic mail in this job?
2	Face-to-Face Discussions	How often do you have to have face-to-face discussions with individuals or teams in this job?
3	Letters and Memos	How often does the job require written letters and memos?
4	Public Speaking	How often do you have to perform public speaking in this job?
5	Telephone	How often do you have telephone conversations in this job?
6	Contact With Others	How much does this job require the worker to be in contact with others (face-to-face, by telephone, or otherwise) in order to perform it?
	Conflictual Contact	Amount of conflict that the worker will encounter as part of this job.
7	Deal With Physically Aggressive People	How frequently does this job require the worker to deal with physical aggression of violent individuals?
8	Deal With Unpleasant or Angry People	How frequently does the worker have to deal with unpleasant, angry, or discourteous individuals as part of the job requirements?
9	Frequency of Conflict Situations	How often are there conflict situations the employee has to face in this job?
	Responsibility for Others	Amount of responsibility the worker has for other workers as a part of this job.
10	Responsibility for Outcomes and Results	How responsible is the worker for work outcomes and results of other workers?
11	Responsible for Others' Health and Safety	How much responsibility is there for the health and safety of others in this job?
	Role Relationships	Importance of different types of interactions with others both inside and outside the organization.
12	Coordinate or Lead Others	How important is it to coordinate or lead others in accomplishing work activities in this job?
13	Deal With External Customers	How important is it to work with external customers or the public in this job?
14	Work With Work Group or Team	How important is it to work with others in a group or team in this job?
	Physical Work Conditions	Context of the job in terms of interactions between the worker and the physical job environment.
	Body Positioning	Amount of time the worker will spend in a variety of physical positions on this job.
15	Spend Time Bending or Twisting the Body	How much does this job require bending or twisting your body?
16	Spend Time Climbing Ladders, Scaffolds, or Poles	How much does this job require climbing ladders, scaffolds, or poles?
17	Spend Time Keeping or Regaining Balance	How much does this job require keeping or regaining your balance?
18	Spend Time Kneeling, Crouching, Stooping, or Crawling	How much does this job require kneeling, crouching, stooping or crawling?
19	Spend Time Making Repetitive Motions	How much does this job require making repetitive motions?
20	Spend Time Sitting	How much does this job require sitting?
21	Spend Time Standing	How much does this job require standing?
22	Spend Time Using Your Hands to Handle, Control, or Feel Objects, Tools, or Controls	How much does this job require using your hands to handle, control, or feel objects, tools or controls?
23	Spend Time Walking and Running	How much does this job require walking and running?
	Environmental Conditions	
24	Cramped Work Space, Awkward Positions	How often does this job require working in cramped work spaces that requires getting into awkward positions?
25	Exposed to Contaminants	How often does this job require working exposed to contaminants (such as pollutants, gases, dust or odors)?
26	Exposed to Whole Body Vibration	How often does this job require exposure to whole body vibration (e.g., operate a jackhammer)?
27	Extremely Bright or Inadequate Lighting	How often does this job require working in extremely bright or inadequate lighting conditions?
28	Sounds, Noise Levels Are Distracting or Uncomfortable	How often does this job require working exposed to sounds and noise levels that are distracting or uncomfortable?
29	Very Hot or Cold Temperatures	How often does this job require working in very hot (above 90 F degrees) or very cold (below 32 F degrees) temperatures?

Table A.2: Work Contexts in O*NET - Continued

Work Context		Description
	Job Hazards	Hazardous conditions the worker could be exposed to, frequency of exposure, likelihood and degree of injury if exposed.
30	Exposed to Disease or Infections	How often does this job require exposure to disease/infections?
31	Exposed to Hazardous Conditions	How often does this job require exposure to hazardous conditions?
32	Exposed to Hazardous Equipment	How often does this job require exposure to hazardous equipment?
33	Exposed to High Places	How often does this job require exposure to high places?
34	Exposed to Minor Burns, Cuts, Bites, or Stings	How often does this job require exposure to minor burns, cuts, bites, or stings?
35	Exposed to Radiation	How often does this job require exposure to radiation?
	Work Attire	Dress requirements of this job.
36	Wear Common Protective or Safety Equipment such as Safety Shoes, Glasses, Gloves, Hearing Protection, Hard Hats, or Life Jackets	How much does this job require wearing common protective or safety equipment such as safety shoes, glasses, gloves, hard hats or life jackets?
37	Wear Specialized Protective or Safety Equipment such as Breathing Apparatus, Safety Harness, Full Protection Suits, or Radiation Protection	How much does this job require wearing specialized protective or safety equipment such as breathing apparatus, safety harness, full protection suits, or radiation protection?
	Work Setting	Description of physical surroundings that the worker will face as part of this job.
38	In an Enclosed Vehicle or Equipment	How often does this job require working in a closed vehicle or equipment (e.g., car)?
39	In an Open Vehicle or Equipment	How often does this job require working in an open vehicle or equipment (e.g., tractor)?
40	Indoors, Environmentally Controlled	How often does this job require working indoors in environmentally controlled conditions?
41	Indoors, Not Environmentally Controlled	How often does this job require working indoors in non-controlled environmental conditions (e.g., warehouse without heat)?
42	Outdoors, Exposed to Weather	How often does this job require working outdoors, exposed to all weather conditions?
43	Outdoors, Under Cover	How often does this job require working outdoors, under cover (e.g., structure with roof but no walls)?
44	Physical Proximity	To what extent does this job require the worker to perform job tasks in close physical proximity to other people?
Structural Job Characteristics		This category involves the relationships or interactions between the worker and the structural characteristics of the job.
	Competition	Amount of competition that the worker will face as part of this job.
45	Level of Competition	To what extent does this job require the worker to compete or to be aware of competitive pressures?
	Criticality of Position	Amount of impact the worker has on final products and their outcomes.
46	Consequence of Error	How serious would the result usually be if the worker made a mistake that was not readily correctable?
47	Freedom to Make Decisions	How much decision making freedom, without supervision, does the job offer?
48	Frequency of Decision Making	How frequently is the worker required to make decisions that affect other people, the financial resources, and/or the image and reputation of the organization?
49	Impact of Decisions on Co-workers or Company Results	What results do your decisions usually have on other people or the image or reputation or financial resources of your employer?
	Pace and Scheduling	Description of the role that time plays in the way the worker performs the tasks required by this job.
50	Duration of Typical Work Week	Number of hours typically worked in one week.
51	Pace Determined by Speed of Equipment	How important is it to this job that the pace is determined by the speed of equipment or machinery? (This does not refer to keeping busy at all times on this job.)
52	Time Pressure	How often does this job require the worker to meet strict deadlines?
53	Work Schedules	How regular are the work schedules for this job?
	Routine versus Challenging Work	The relative amounts of routine versus challenging work the worker will perform as part of this job.
54	Degree of Automation	How automated is the job?
55	Importance of Being Exact or Accurate	How important is being very exact or highly accurate in performing this job?
56	Importance of Repeating Same Tasks	How important is repeating the same physical activities (e.g., key entry) or mental activities (e.g., checking entries in a ledger) over and over, without stopping, to performing this job?
57	Structured versus Unstructured Work	To what extent is this job structured for the worker, rather than allowing the worker to determine tasks, priorities, and goals?

Figure A.1: Average Contribution of Each Component to θ by Occupation Group



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

A.1 Inspecting components of θ

- **Average contribution by occupation group (Figure A.1)**

  Figure A.1 plots the average value of θ in each occupation group broken down into the contribution of each component. The figure highlights how not occupation group systematically scores highest in all components. For example, while professionals score very low in "Responsibility" and "Physical Conditions", but nevertheless have a high average value of due to the high score for skills. At the same time, however, there is not single component that individually drives the results. For example, if the "Skills" component were to be removed, the only occupation group experiencing a large shift in the ranking would be "Professionals". Besides that all, groups in the top (bottom) half of the ranking would remain in the top (bottom) half.

- **Correlation matrix (Table A.3)**

  The relationships between different pairs of complementary components vary in both magnitude and direction. For instance, skills and communication display a robust positive association. However, communication does not seem to have any significant correlation with physical condition. Interestingly, while physical condition demonstrates a moderate positive link with criticality, it negatively aligns with skills. The findings presented in Table A.3 suggest that our chosen components capture distinct facets of complementarity, ensuring that they are not merely echoing similar information.

Table A.3: Pairwise Correlations of the Complementarity Components

Variables	Communication	Responsibility	Physical condition	Criticality	Routine	Skills
Communication	1					
Responsibility	0.083**	1				
Physical condition	-0.071*	0.510***	1			
Criticality	0.121***	0.455***	0.363***	1		
Routine	0.379***	-0.066*	-0.002	0.203***	1	
Skills	0.598***	-0.200***	-0.352***	0.127***	0.476***	1

*** p<0.01, ** p<0.05, * p<0.1

- **Individual association with AIOE (Figure A.2; Table A.4)**

We delve deeper into the relationship between each complementarity component and Felten et al. (2021)'s AIOE as presented in Table A.4. The table reveals a positive correlation of skills, communication, and routine with AIOE. In contrast, responsibility and physical condition have a negative association with AIOE. Similar results emerge when using a sub-indicator of AIOE focusing only on large language models (AIOE: LLM). There appears to be no discernible correlation between criticality and AIOE. Upon observing Figure A.2, which illustrates the relationship between these components and AIOE, it becomes evident that certain professions, like lawyers, might shift within or even between quadrants based on different complementarity components. This movement underscores the distinct influence each component exerts on the interplay between AI exposure and occupation.

Table A.4: Correlations of Complementarity θ_i with AIOE and AIOE: LLM

Variables	AIOE	AIOE: LLM
Communication	0.502***	0.548***
Responsibility	-0.394***	-0.412***
Physical Condition	-0.555***	-0.547***
Criticality	-0.026	-0.058
Routine	0.245***	0.286***
Skills	0.723***	0.724***

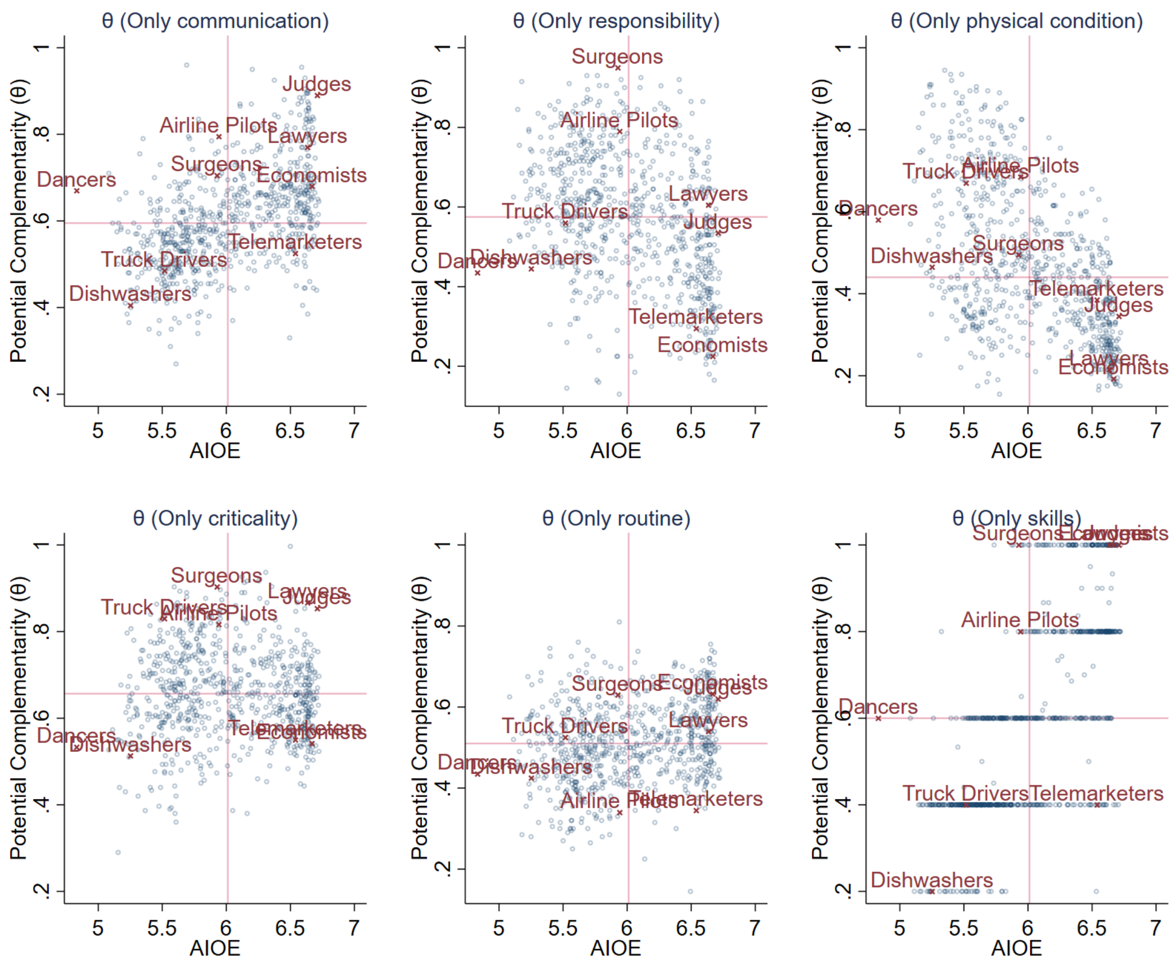
*** p<0.01, ** p<0.05, * p<0.1

Note: "AIOE" represents the occupation-level AI exposure measure, considering all 10 AI applications outlined in Felten et al. (2021), while "AIOE: LLM" focuses solely on large language models (LLM).

- **Leave-one-out analysis (Figures A.3 and A.4; Table A.5)**

Next, we conduct a "leaving-one-out" analysis, where we omit one component at a

Figure A.2: Association between Individual θ Component and AIOE



Note: Potential complementarity in each chart is calculated by using only one of the six categories. The red reference lines are based on the medians of both AIOE and θ. These lines serve to categorize occupations into four distinct quadrants, each indicating a unique blend of AI exposure and complementarity. For visual emphasis, 9 occupations are distinctly marked in red.

time and then calculate complementarity using the remaining five components. This exercise assesses whether any component excessively impacts variations in complementarity. As indicated in Table A.5, the components “skills”, “responsibility”, “communication”, and “physical condition” are particularly influential, exhibiting notable shifts in correlation when excluded. On the other hand, the variations for the “routine”, and “criticality” components are more subtle. Figure A.4 further underscores this pattern, highlighting how the omission of “skills” can alter the linear association between AI exposure and potential complementarity. Additionally, Figure A.3 illustrates that excluding specific components can have a strong impact on the interplay between AI and human work. For instance, for professions such as economists, neglecting the “responsibility" component could lead to an overestimation of the complementarity that AI introduces to these roles. In essence, while all components play a role in determining the relationship between AI exposure and potential complementarity, some are particularly crucial, and their omission can lead to skewed interpretations.

Table A.5: Leave-one-out analysis: Correlations with AIOE and AIOE:LLM

Variables	AIOE	AIOE: LLM
θ_i full set	0.170***	0.179***
W/o communication	0.059*	0.057
W/o responsibility	0.351***	0.369***
W/o physical condition	0.414***	0.421***
W/o criticality	0.200***	0.218***
W/o routine	0.132***	0.134***
W/o skill	-0.209***	-0.199***

*** p<0.01, ** p<0.05, * p<0.1

- **Principal component analysis (Figure A.5)**

On a similar note, we conduct a Principal Component Analysis to inspect whether a small set of orthogonal linear combinations of the components can capture well their total variation.

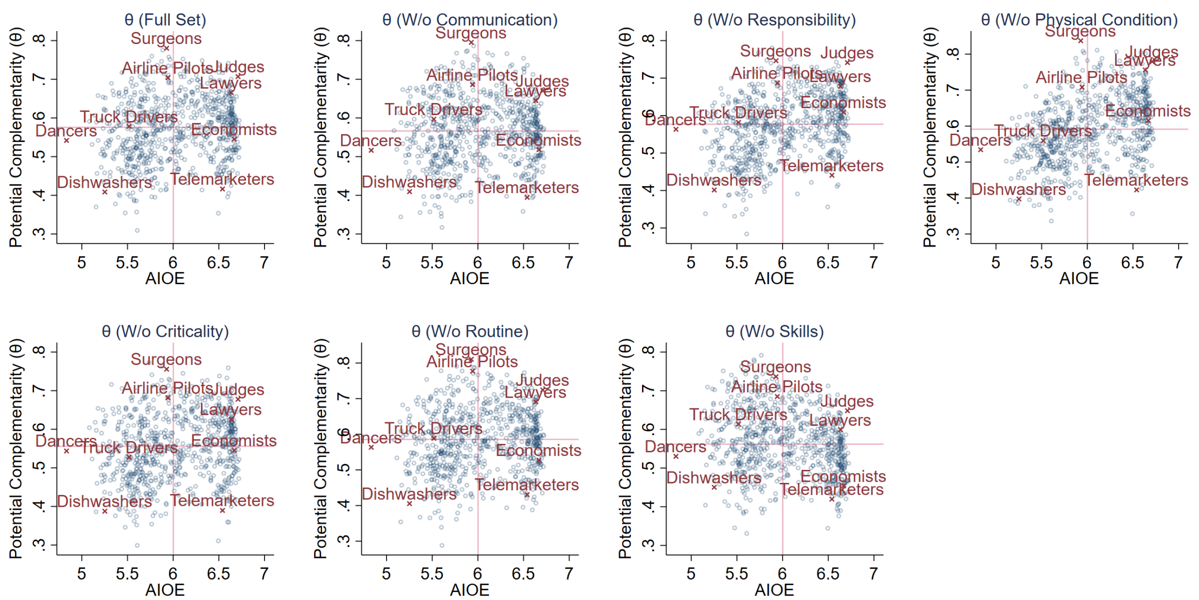
Figure A.5a) shows that the first two principal components only account for about 65% of the total variation in the data. This indicates that complementarity's variability is distributed across multiple dimensions. Our category selection for computing θ encompasses these additional dimensions, which cannot be compressed into only two components without losing important information. Figures A.5b) and A.5c) depict the individual contributions of each category to the formation of the first two principal components. The outcomes highlight the significance of work contexts such as "criticality", "responsibility", and "physical condition" in understanding complementarity for occupations like pilots and surgeons. Conversely, professions like economists are strongly associated with "communication", "skills", and "routine" aspects.

A.2 Evaluating Alternative AI Exposure Measures

- **Scatter plots of different AI exposure measures (Figure A.6)**

In Figure A.6, we observe that both metrics from Felten et al. (2021), referred to as

Figure A.3: Association between Potential Complementarity and AIOE: Leaving-one-out Sensitivity Analysis (A)



Note: Drop one category and use the remaining five to compute θ. The red reference lines are based on the medians of both AIOE and θ. These lines serve to categorize occupations into four distinct quadrants, each indicating a unique blend of AI exposure and complementarity. For visual emphasis, 9 occupations are distinctly marked in red.

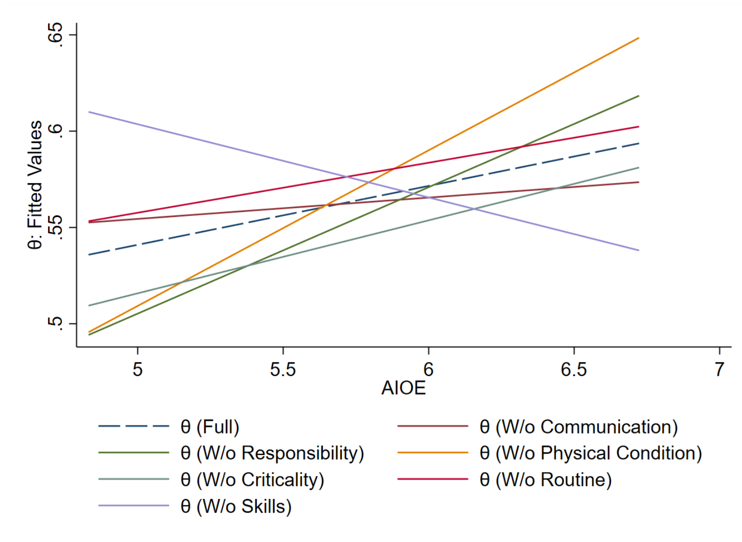
"AIOE" and "AIOE: LLM", have a positive association with other commonly referenced AI exposure measures like Webb (2020) and Eloundou et al. (2023). A notable deviation is Briggs and Kodnani (2023), where there's a negative correlation. Our reproduction of the AI exposure metric from Briggs and Kodnani (2023) follows their documented methodology, without access to their exact coding. Hence, it is crucial to exercise caution in interpreting the corresponding results. Collectively, this analysis shows that the insights from our baseline AI exposure metric carry over to most other metrics as well.

- **Binned scatter plots of θ vs. different AI exposure measures (Figure A.7)**

  The binned scatter plots in Figure A.7 further substantiates the consistency of our potential complementarity with various AI exposure metrics, with the exception of the one we reconstructed based on Briggs and Kodnani (2023). For all other measures, θ exhibits a concave hump-shaped relationship with exposure.

- **Occupational employment share and task intensity by AIOE, θ, and C-AIOE (Table A.6)**

Figure A.4: Association between Potential Complementarity and AIOE: Leaving-one-out Sensitivity Analysis (B)



According to Table A.6, the relationship between AI exposure/complementarity and the task-intensity classification of jobs (cognitive, routine, manual) is not strictly linear.[26] While high-AIOE jobs, those above the median, are largely cognitive-oriented, they are not limited to that category. Indeed, jobs just above the median in AI exposure exhibit a diverse task-intensity distribution, with about 40 percent not falling under cognitive tasks. Nevertheless, the jobs with the utmost AI exposure, specifically those surpassing the 90th percentile, skew heavily towards cognitive tasks. This pattern suggests that while the association is not rigid, jobs that have both high AI exposure and high complementarity tend to concentrate predominantly in cognitive-based roles, such as those in professional spheres and the knowledge economy.

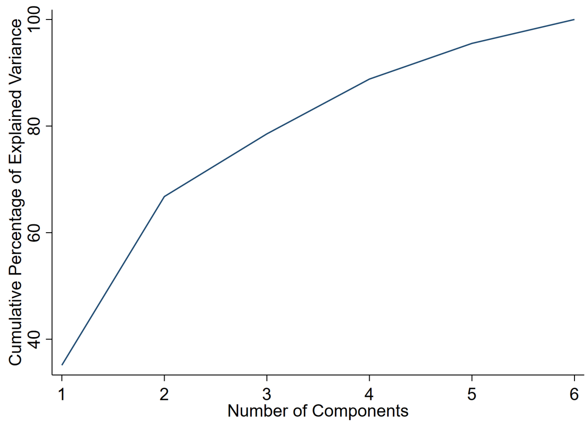
Furthermore, when adjustments are made for potential complementarity, the task-intensity distribution of the jobs that are highly exposed to AI spans more uniformly across cognitive, routine, and manual tasks. Yet, when examining the roles that are most exposed to AI, a notable shift occurs, highlighting that these roles are mainly routine ones, such as routine clerical workers.

An analysis using the Routine Task Intensity index by Autor and Dorn (2013) provides a similar insight. The higher the AIOE and θ, the lower the RTI score, implying less routine intensity. However, this relationship is inverted for the C-AIOE.

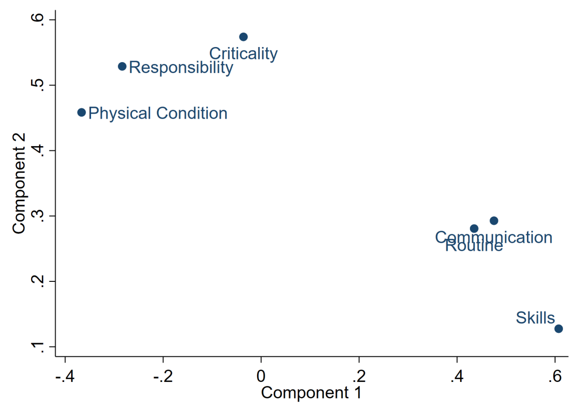
[26]The classification of jobs into these categories is taken from Cortes et al. (2020), where routine-manual and routine-cognitive jobs are grouped into a single routine category.

Figure A.5: Principal Component Analysis for Potential Complementarity (θ)

a. Cumulative Variance Explained by Components



b. Variable Loading to Component 1 and 2



c. Observation Loading to Component 1 and 2

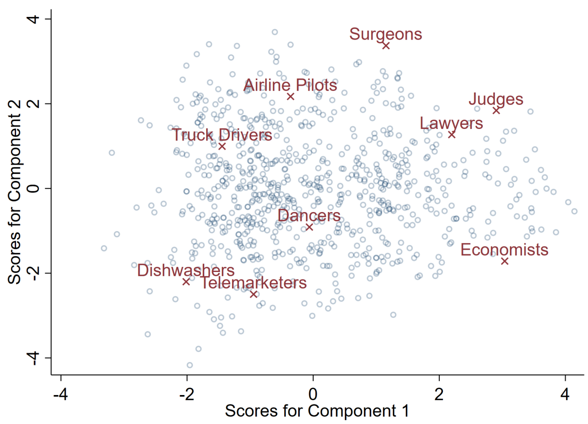


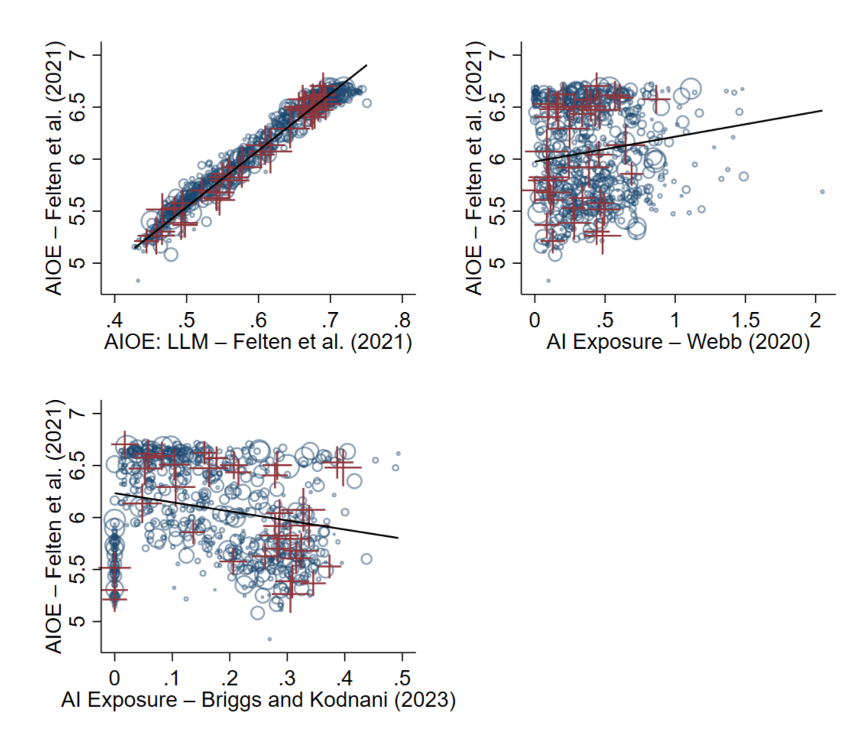
Table A.6: Occupational Employment Share and Routine Task Intensity by AIOE, C-AIOE, and θ

Percentile	AIOE			θ			θ for AIOE $\geq 50^{\text{th}}$		C-AIOE		
Threshold	$\geq 50^{\text{th}}$	$\geq 75^{\text{th}}$	$\geq 90^{\text{th}}$	$\geq 50^{\text{th}}$	$\geq 75^{\text{th}}$	$\geq 90^{\text{th}}$	$\geq 50^{\text{th}}$	$\leq 50^{\text{th}}$	$\geq 50^{\text{th}}$	$\geq 75^{\text{th}}$	$\geq 90^{\text{th}}$
Empl. Share	54.60	26.04	6.89	40.24	20.59	8.29	24.08	30.53	57.62	37.98	17.24
of which											
Cognitive	60.78	69.90	85.71	57.78	64.84	69.25	86.93	40.14	33.03	30.91	30.28
Routine	36.51	29.88	14.29	29.59	27.33	17.81	11.66	56.10	47.66	49.41	69.44
Manual	2.70	0.22	0.00	12.52	7.62	12.84	1.41	3.72	18.54	19.61	0.28
Avg. RTI	-1.36	-2.01	-2.10	-1.82	-1.70	-3.63	-3.18	-0.23	-0.31	-0.28	1.25

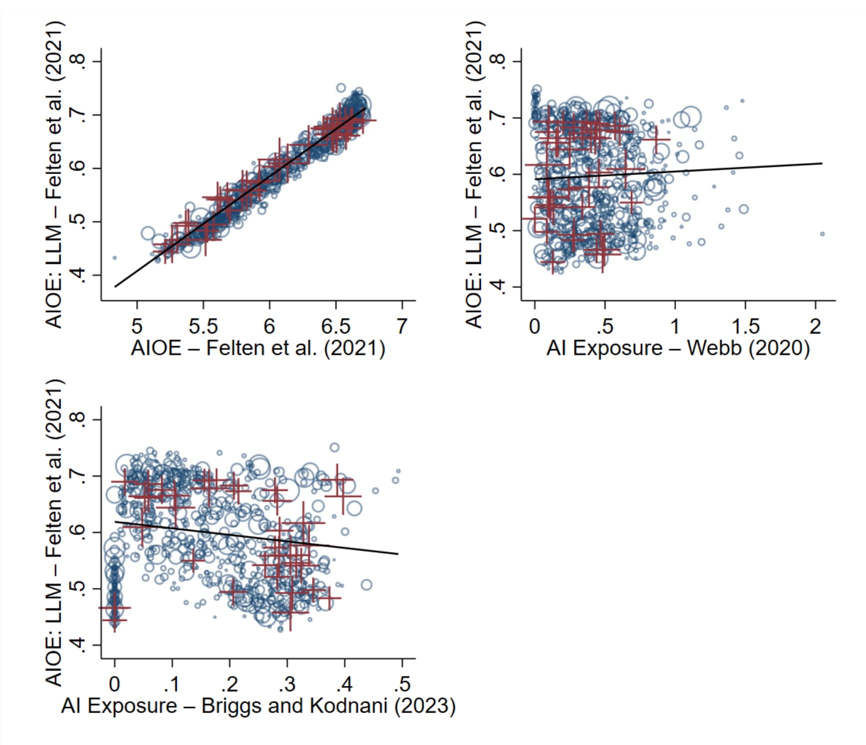
Note: "AIOE" represents the occupation-level AI exposure measure, considering all 10 AI applications outlined in Felten et al. (2021), while "C-AIOE" is the complementarity-adjusted AIOE. "Avg. RTI" is the employment-weighted mean of ln(RTI). RTI stands for relative routine intensity index from Autor and Dorn (2013), and the occupational breakdown into cognitive, routine and manual is sourced from Cortes et al. (2020). All occupations are coded in US SOC 2010. Employment shares are already in percentage.

Figure A.6: Comparing Existing AI Exposure Measures in the Literature

a. AIOE

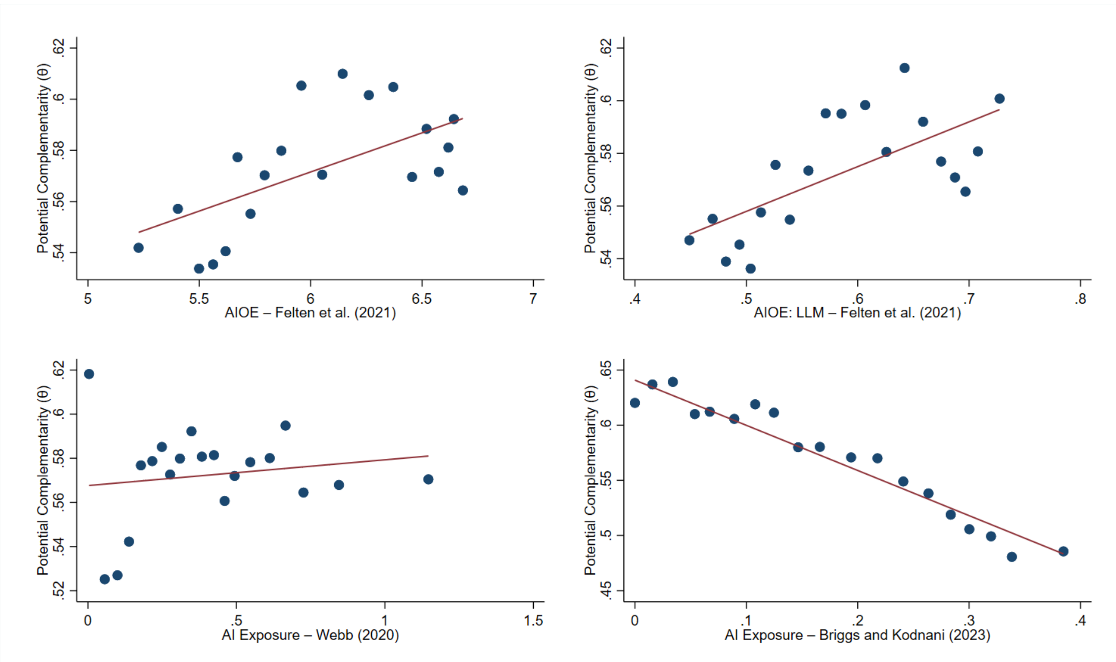


b. AIOE: LLM



Note: "AIOE" represents the occupation-level AI exposure measure, considering all 10 AI applications, while "AIOE: LLM" focuses solely on large language models (LLM). Both measures are from Felten et al. (2021). All measures presented here are AI-related, and occupations are coded in the US SOC 2010. Notably, the AI measure adopted from Briggs and Kodnani (2023) is a replicated version based on their methodology. The red crosses indicate occupations with employment shares greater than the 95th percentile.

Figure A.7: Comparing θ with AI Exposure Measures

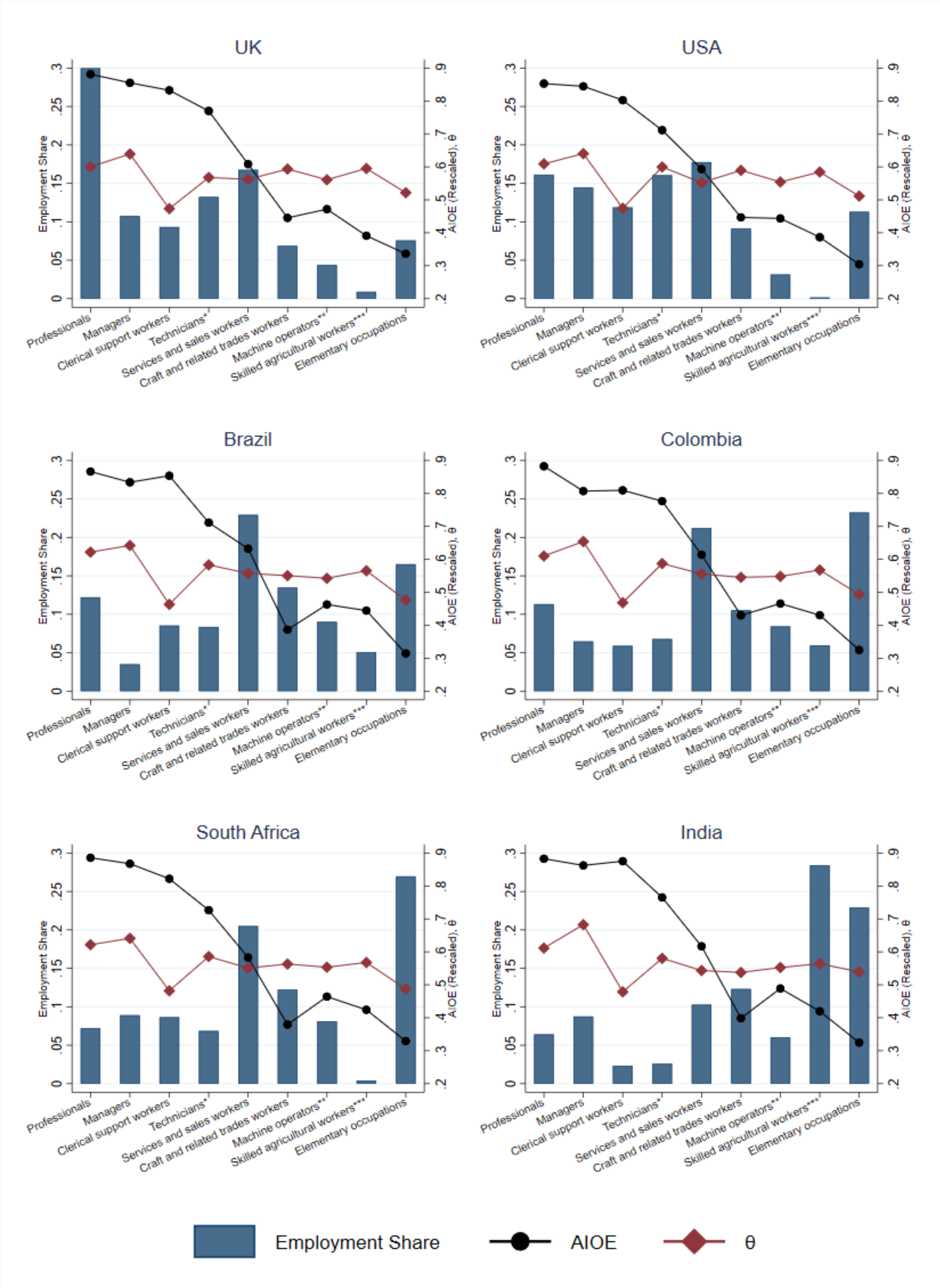


Note: "AIOE" represents the occupation-level AI exposure measure, considering all 10 AI applications outlined in Felten et al. (2021), while "AIOE: LLM" focuses solely on large language models (LLM). All measures presented here are AI-related. Notably, the AI measure adopted from Briggs and Kodnani (2023) is a replicated version based on their methodology. All occupations are coded in US SOC 2010.

B Labor Market Exposure to AI Additional Analysis

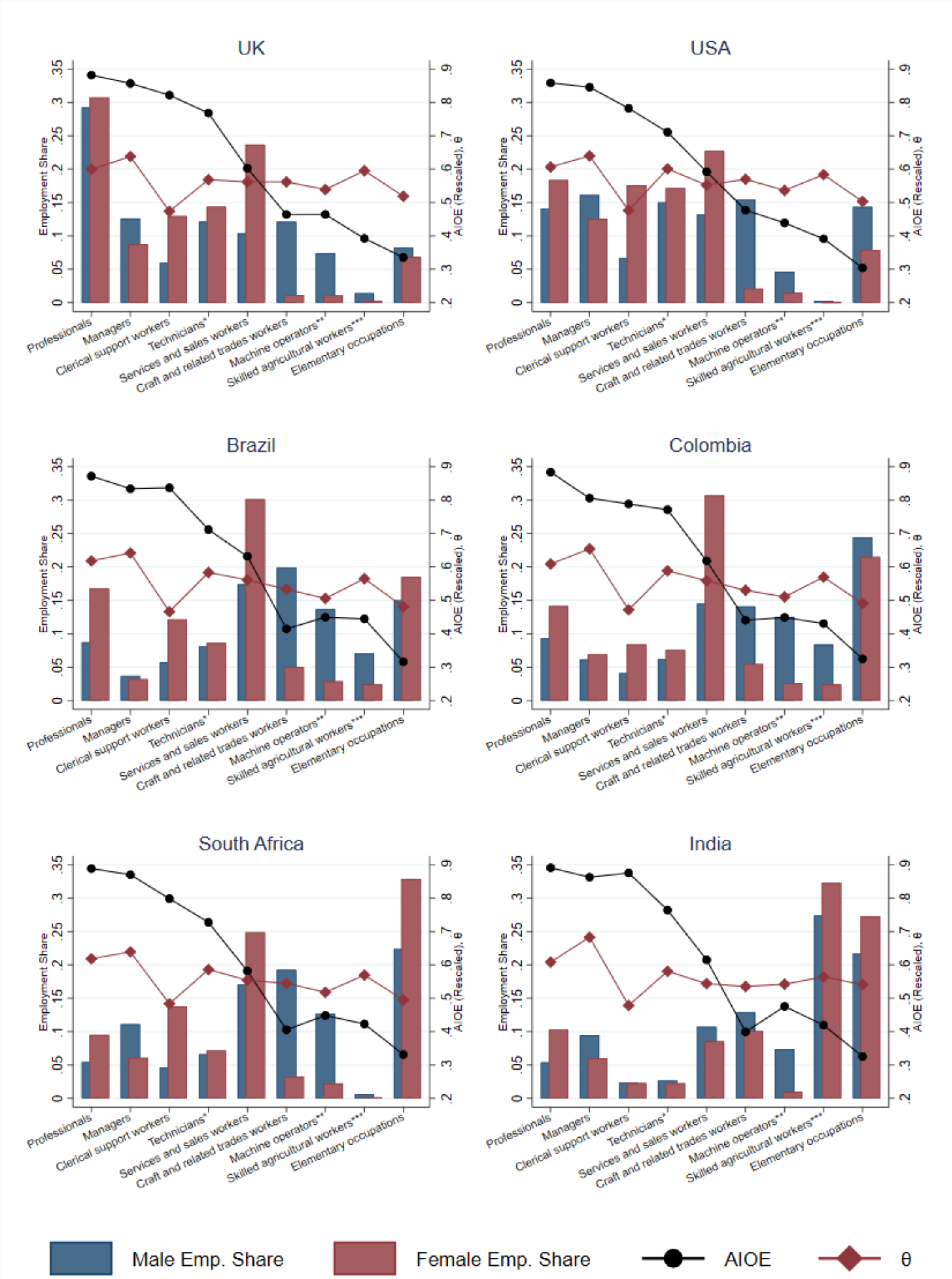
In this Annex, we present further analysis of the distributional impact of AI adoption. In Figure B.1, we present the employment share in each major occupation across countries, in Figure B.2 by gender, Figure B.3 by age, Figure B.4 by education, and Figure B.5 by earnings quintile. In Figure B.6, we plot AI exposure and complementarity as a share of total employment by gender, education, and age. Last, in Figure B.7, we show the impact of different C-AIOE specifications across countries.

Figure B.1: Employment Share by Major Occupation Group



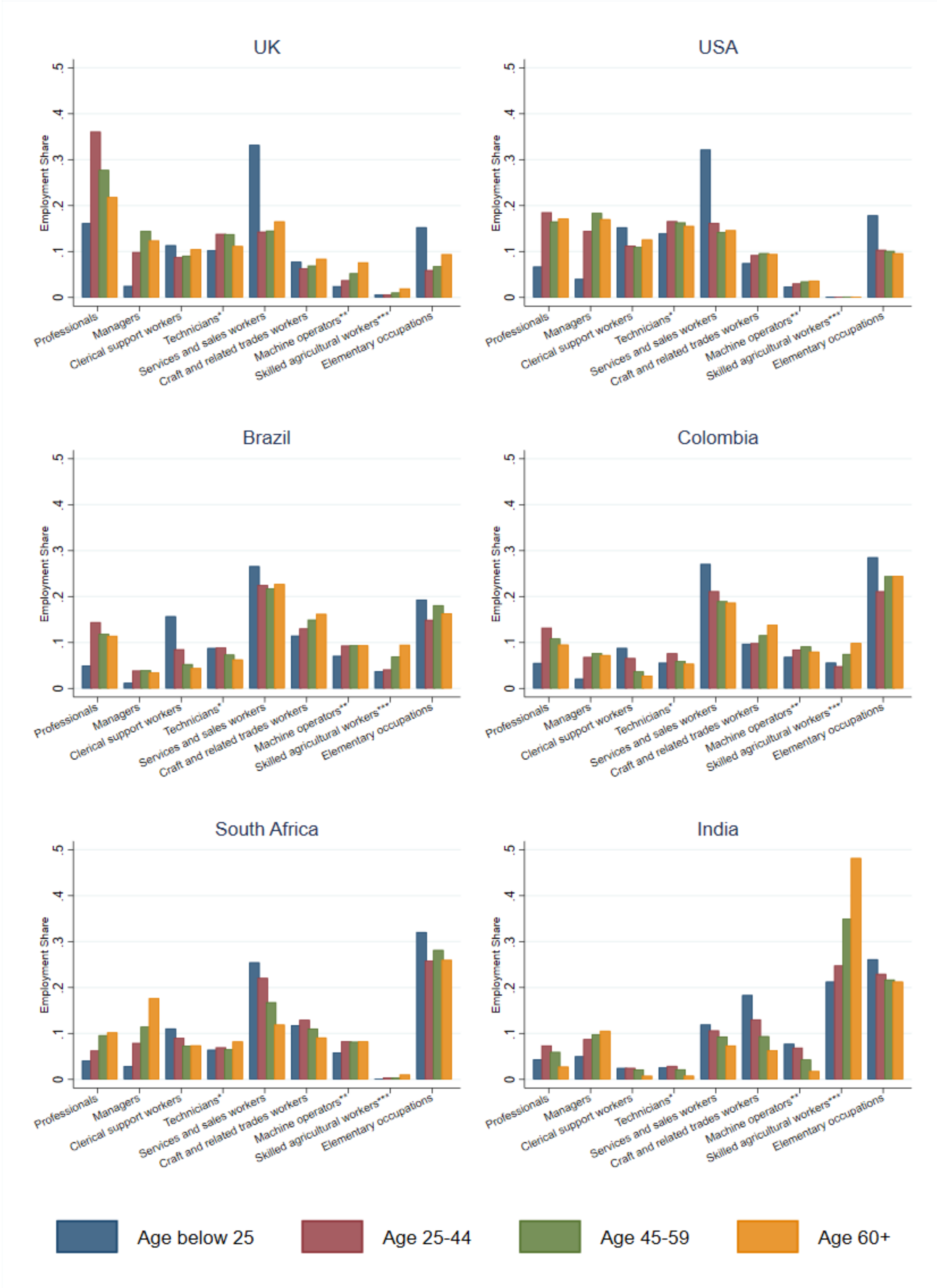
Note: The figure plots the share of employment in each quadrant of Figure 1 for each country across the 1-digit ISCO-08 occupation codes in the left y-axis. The right y-axis corresponds to the mean values of the rescaled AIOE and theta for each 1-digit ISCO-08 occupation code. *: Technicians and associate professionals. **: Plant and machine operators and assemblers. ***: Skilled agricultural, forestry and fishery workers.

Figure B.2: Employment Share by Major Occupation Group and Gender



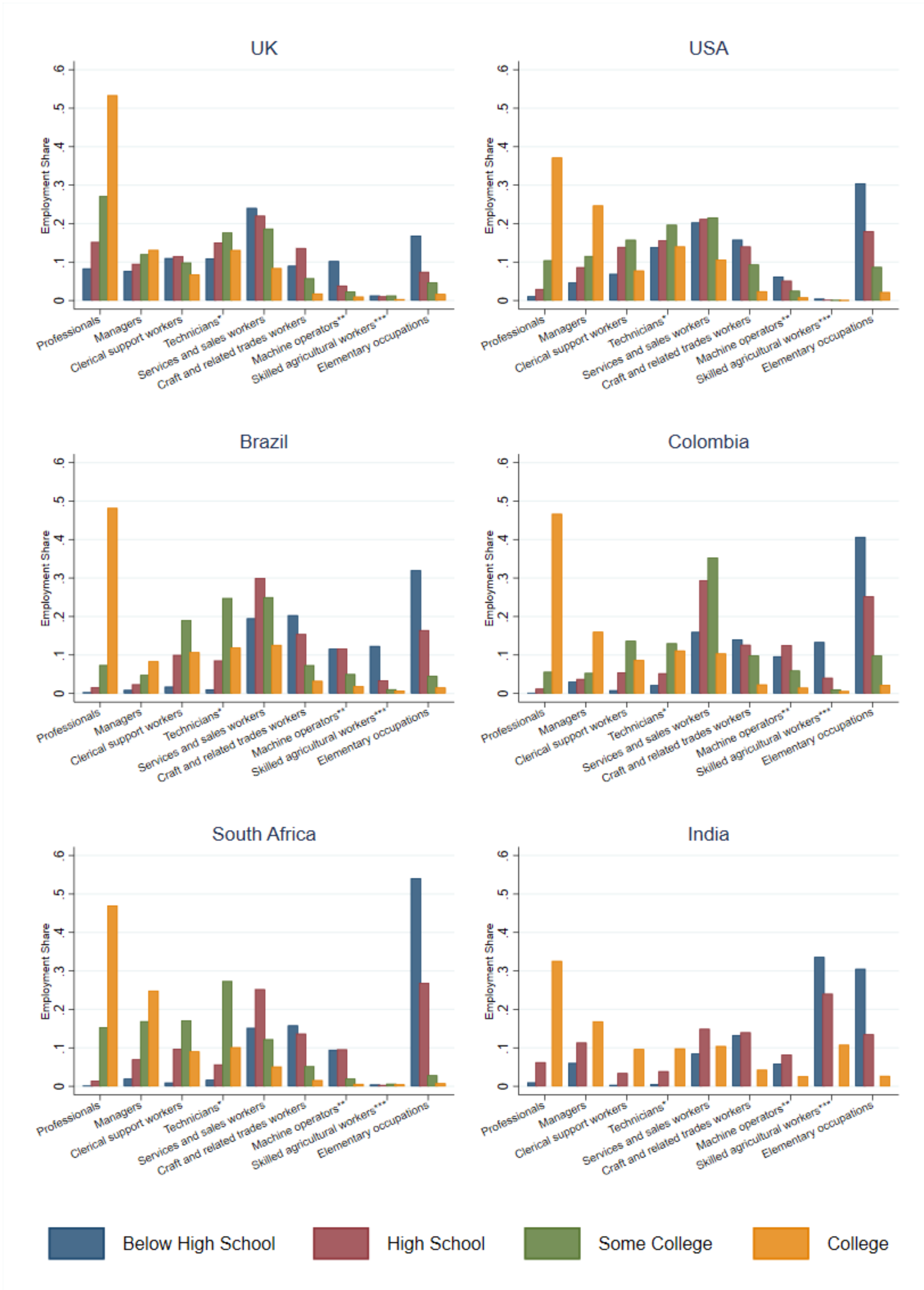
Note: The figure plots the share of employment in each quadrant of Figure 1 for each country across the 1-digit ISCO-08 occupation codes in the left y-axis. The right y-axis corresponds to the mean values of the rescaled AIOE and theta for each 1-digit ISCO-08 occupation code. Employment shares are conditional on gender. *: Technicians and associate professionals. **: Plant and machine operators and assemblers. ***: Skilled agricultural, forestry and fishery workers.

Figure B.3: Employment Share by Major Occupation Group and Age



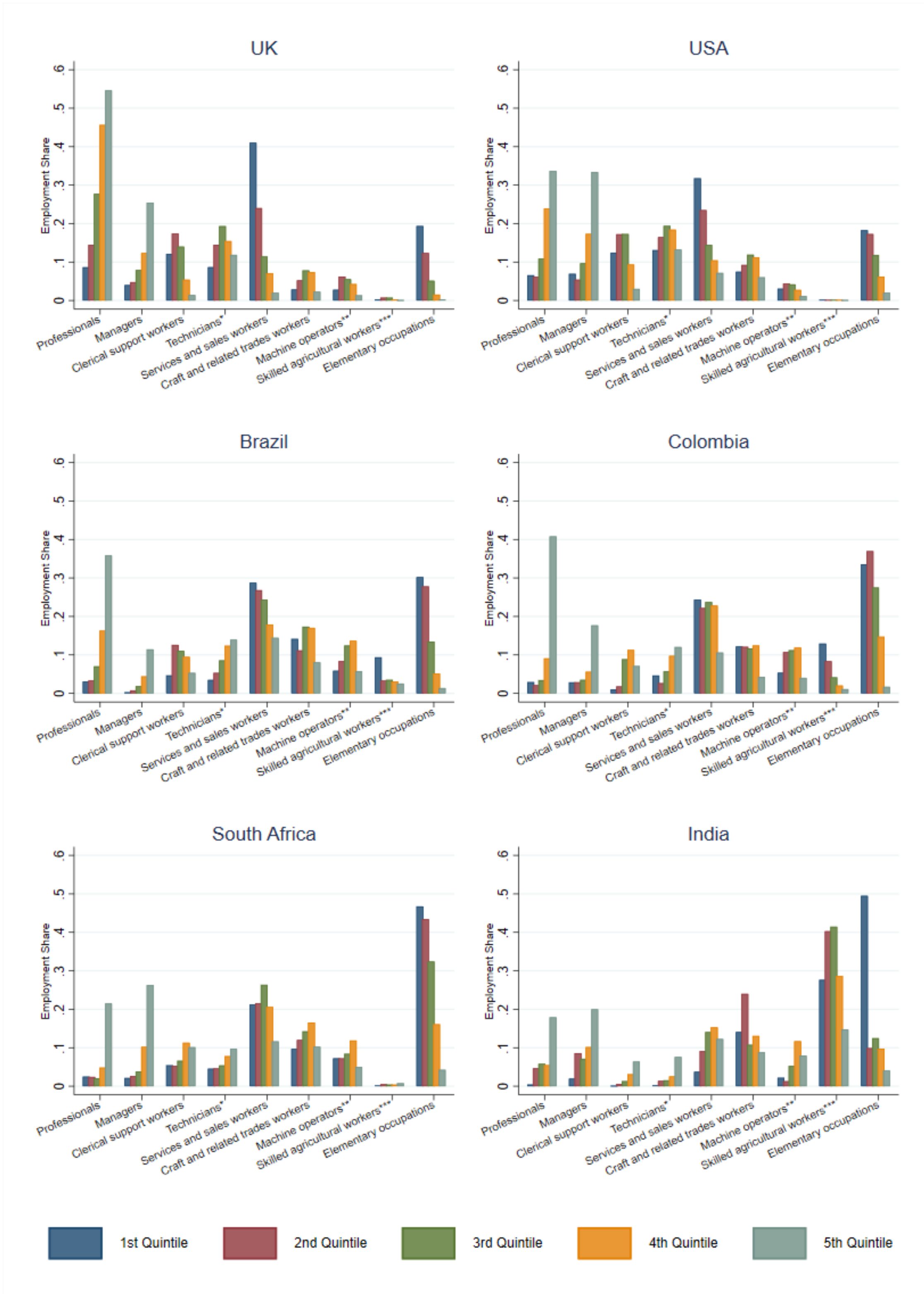
Note: The figure plots the share of employment in each quadrant of Figure 1 for each country across the 1-digit ISCO-08 occupation codes. Employment shares are conditional on age group. *: Technicians and associate professionals. **: Plant and machine operators and assemblers. ***: Skilled agricultural, forestry and fishery workers.

Figure B.4: Employment Share by Major Occupation Group and Education Level



Note: The figure plots the share of employment in each quadrant of Figure 1 for each country across the 1-digit ISCO-08 occupation codes. Employment shares are conditional on education level. For India, there is no corresponding category in the survey for "Some College or Higher Education". *: Technicians and associate professionals. **: Plant and machine operators and assemblers. ***: Skilled agricultural, forestry and fishery workers.

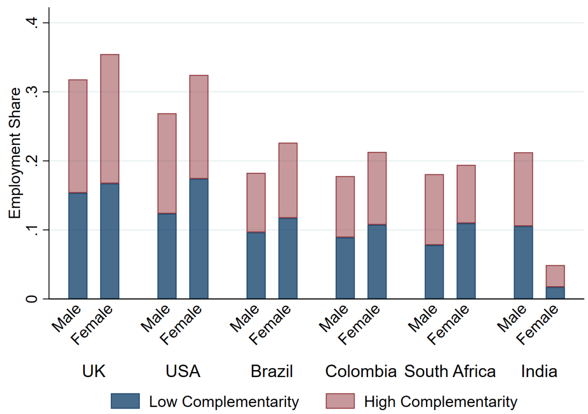
Figure B.5: Employment Share by Major Occupation Group and Earnings Quintiles



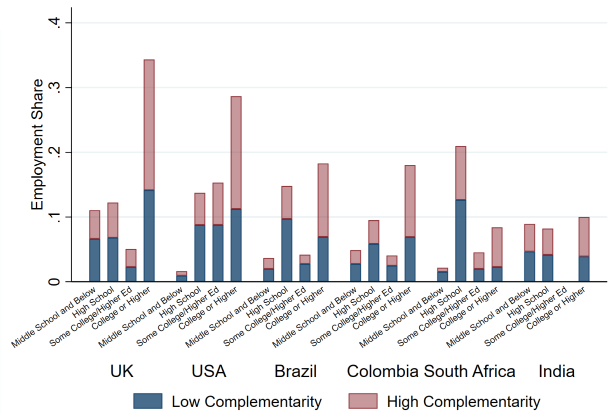
Note: The figure plots the share of employment in each quadrant of Figure 1 for each country across the 1-digit ISCO-08 occupation codes. Employment shares are conditional on earnings quintile. *: Technicians and associate professionals. **: Plant and machine operators and assemblers. ***: Skilled agricultural, forestry and fishery workers.

Figure B.6: AI Exposure and Complementarity Employment Share by Demographic Characteristics (total shares)

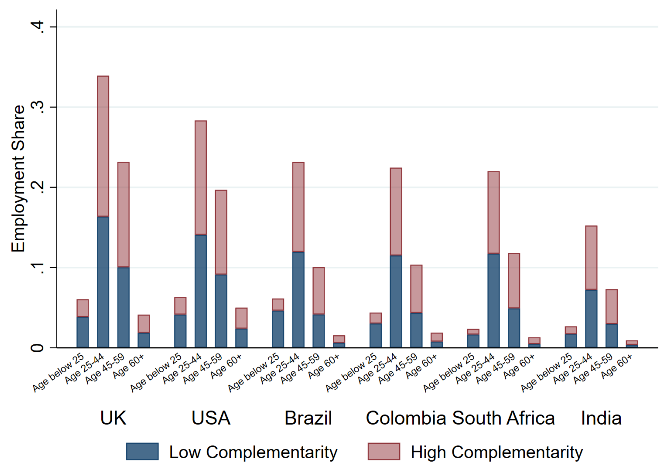
(a) Gender



(b) Education

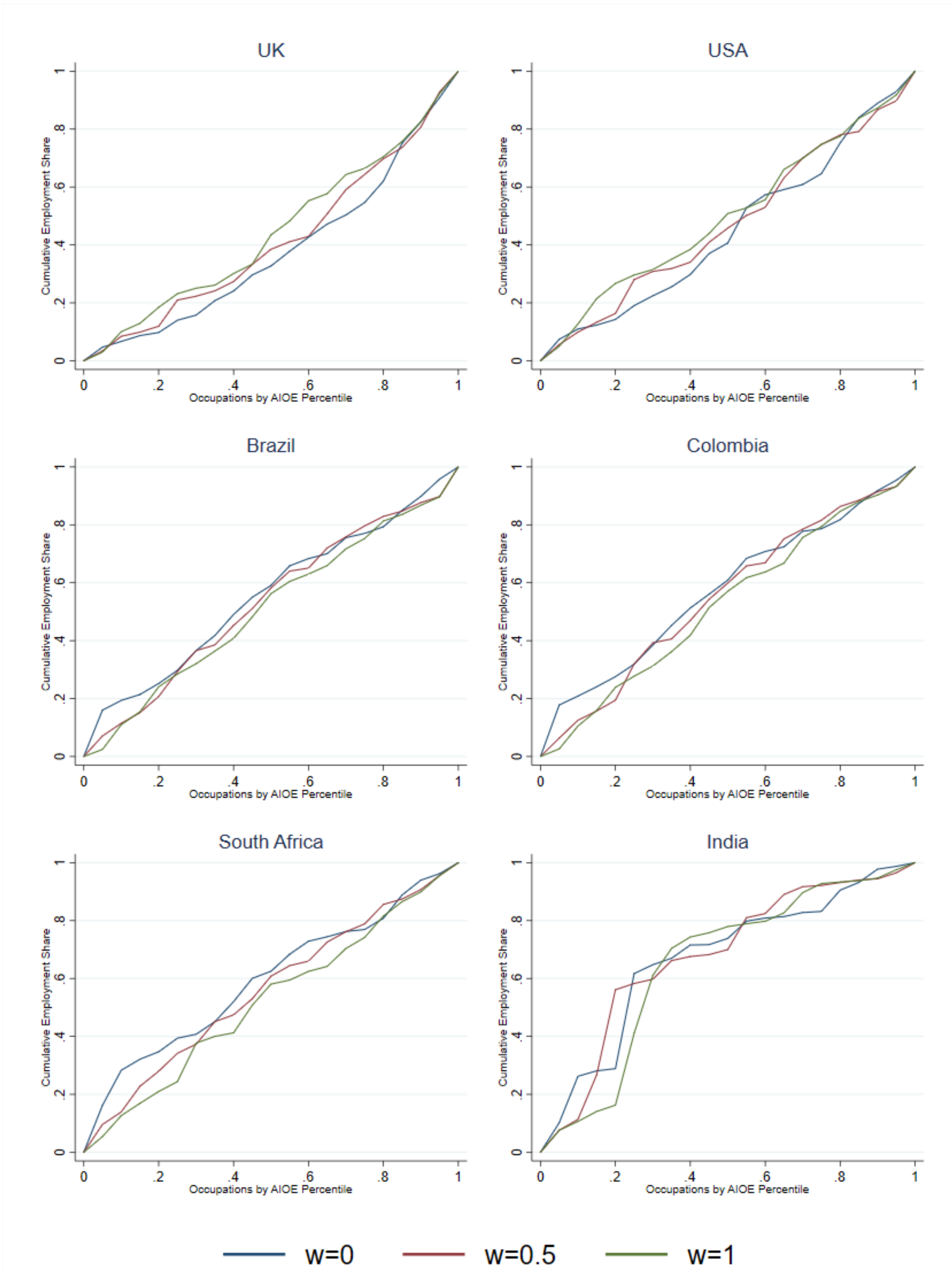


(c) Age



Note: The figures plot the share of employment in high-exposure occupations over total employment, distinguishing the share of occupations with high and low complementarity. "High" and "low" are defined as being above or below the median, respectively. For India, there is no corresponding category in the survey for "Some College or Higher Education" in the education plot (c).

Figure B.7: Cumulative Employment Distribution by Country with Different C-AIOE Specifications



Note: The figures plot the cumulative employment share with respect to different C-AIOE specifications (weight 0, weight 0.5 and weight 1) for each country. The y-axis shows the cumulative employment share in the occupations, and the x-axis the AIOE or C-AIOE normalized to be between 0 and 1, where 0 is the occupation with lowest exposure and 1 the occupation with the highest exposure.