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# The Green Future: Labor Market Implications for Men and Women

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**The Green Future: Labor Market Implications for Men and Women**

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# The Green Future: Labor Market Implications for Men and Women

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## Abstract

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# 1 Introduction

Addressing human-induced climate change stands as one of the most critical challenges of our time, demanding urgent and strategic action from policymakers worldwide. The transition towards a green economy will require steering the global workforce away from carbon-intensive and environmentally harmful jobs towards employment that contributes to reducing greenhouse gas emissions and jobs with a low carbon footprint. This reallocation may not impact all workers the same since workers in carbon-intensive jobs may have very different skills from those needed for green jobs. Moreover, the gender composition of these jobs may be different since polluting jobs are historically manual jobs dominated by men. Overall, the reallocation is a challenge but could also offer opportunities.

The effects of the green transition on the labor market are poised to differ significantly across nations, influenced by each country’s economic structure and initial emission levels. Emerging markets (EMs), in particular, may face more profound labor market shifts than advanced economies (AEs), due to their traditionally larger manufacturing base and higher carbon intensity of output.<sup>1</sup> Moreover, the characteristics and skill sets of workers in EMs are different from those in AEs; typically, emerging market labor markets are characterized by a workforce with lower educational attainment, higher levels of informality, and lower female participation rates.

The growth of green jobs has garnered considerable attention within AEs (Vona et al. (2018), Bluedorn et al. (2023), and OECD (2023a)). These studies established a foundational understanding of how the green transition influences employment dynamics and revealed the proportion of the workforce in green jobs. Typically, these jobs are occupied by individuals with higher levels of education, who often benefit from a wage premium associated with green employment. These analyses also show a pronounced gender disparity within green jobs, where women represent a minority of workers. Despite these insights, significant research gaps remain: first, the focus of the existing literature is predominantly on AEs, which leaves out the implications of the green transition for workers in emerging market economies, including the importance of and the extent of gender disparities in green jobs; second, there is a lack of exploration of the underlying causes of gender disparities in green employment; and third, there has been no examination of the contribution of the

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Shibata and seminar participants at the IMF Jobs and Growth Research Seminar for their helpful comments. **Disclaimer:** The views expressed in this study are the sole responsibility of the authors and should not be attributable to the International Monetary Fund, its Executive Board, or its management.

<sup>1</sup>See Black et al. (2023) for a discussion about carbon emission across countries and countries’ Paris Agreement pledges.

green gender gap to the broader gender wage gap; last, the implications of the rise of artificial intelligence (AI) for green jobs are still unexplored.

This study contributes to the literature on the labor market implications of the green transition in different areas. First, it delineates the prevalence and demographic distribution of green jobs within three EMs—Brazil, Colombia, and South Africa—and offers a comparative analysis with two well-studied AEs - the UK, and the US. Second, it quantifies the economic returns associated with green employment, evaluating the role of green jobs in contributing to the gender pay gap. Third, it anticipates how AI may affect the development of green jobs and on the green jobs premium.<sup>2</sup>

Our methodology employs a task-based framework to identify green jobs, categorizing occupations by their tasks into “green” or “non-green” based on the task contribution to environmental sustainability (Dierdorff et al. (2009); O\*NET Center (2021a)). We introduce two complementary measures for green jobs: an intensity measure for green tasks and a binary definition that classifies jobs as green if green tasks comprise over 5 percent of the occupations tasks. Polluting jobs are identified using Vona et al. (2018)’s approach, focusing on occupations concentrated in sectors with high emissions. To ensure comparability across countries, we map the U.S. SOC2010 to ISCO-08 codes, harmonizing occupational classifications internationally (Pizzinelli et al. (2023)). Our analysis of the green wage premium and gender pay gap employs a Mincerian regression, adjusting for variables like age, education, sector, and formality.

To assess the existence of green jobs, we perform a detailed cross-country analysis of the distribution and characteristics of green jobs. This analysis merges microdata from recent labor force surveys with green and polluting job classifications at a granular occupational level (with more than 400 ISCO-08 codes) to provide an in-depth exploration of green job importance and characteristics both across and within the five surveyed countries. By mapping green job attributes to a standardized occupational classification, this approach enables a consistent comparison of green employment patterns across vastly different economic contexts. Additionally, utilizing microdata uncovers the differing distribution of green and pollution-intensive jobs across various demographic and income segments. Consequently, it highlights both the similarities and differences in the trends of green employment between AEs and EMs.

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<sup>2</sup>Our analysis focuses on AI’s potential impact on labor markets, abstracting from other key margins through which AI could impact the green transition, including accelerating the development of green technologies or, on the negative side, increasing the energy consumption.

Our key findings reveal an interesting pattern in the distribution of green jobs: AEs and EMs show a comparable proportion of the workforce engaged in green occupations. However, the types of occupations that these green jobs encompass vary markedly between the two. In EMs, green jobs predominantly cluster among elementary occupations, plant and machine operators, and craft and related trades workers. Meanwhile in AEs, the majority of green jobs are found in managerial, professional, and technical occupations, as well as among associate professionals. This variation in the distribution of green jobs between AEs and EMs is largely attributed to differences in overall employment structure rather than disparities within the major occupational groups. In contrast, polluting jobs are found in similar occupations across AEs and EMs, mostly among craft and trade, and plant and machine operator occupations.

In studying the gender makeup of green jobs, a clear trend emerges in both AEs and EMs: women are notably underrepresented. On average, in EMs, men dominate green jobs, occupying approximately 83 percent of all green jobs. Similarly, in AEs, men account for nearly two-thirds of green jobs, echoing patterns identified in previous studies. In EMs, green jobs account for only 5 percent of women's total employment. For men, this figure is substantially higher, at almost 17 percent. In AEs similarly green jobs comprise only 6 percent of women's total employment and 19 percent of men's. Notably, this gender disparity in green jobs persists across various education levels. Further analysis into educational disparities reveals that a considerable portion of the gender gap in green jobs among college-educated workers can be attributed to the low representation of women in Science, Technology, Engineering, and Mathematics (STEM) occupations. Additionally, a smaller, yet significant, portion of the gap arises from the scarcity of women in managerial positions. Conversely, polluting jobs are also male-dominated but tend to be concentrated in manual occupations historically dominated by men.

Turning our focus to the financial benefits associated with green employment, our analysis uncovers a positive raw green wage premium across different countries, levels of college attainment, and gender. Interestingly, the green wage premium is consistently larger for women than for men, across various countries and educational achievements. Notably, the gender pay gap is narrower within green jobs compared to other sectors across all examined countries. Our empirical analysis, controlling for a range of worker characteristics including age, marital status, and formal employment status, confirms that the green wage premium for women exceeds that for men, varying from 2 to 7 percent, and that the gender pay gap is smaller in green jobs than in non-green jobs.

Looking towards the future of green jobs and their integration with AI, our analysis indicates that green jobs, on average, face similar exposure to AI than non-green jobs, where exposure is measured by the share of tasks that overlaps with AI capabilities. However, green jobs are more likely to benefit from AI advancements, whereas non-green jobs are at greater risk. In contrast, polluting jobs exhibit minimal exposure to AI, as they are predominantly manual occupations. Our analysis reveals that within green jobs, women are not only more exposed to AI but also stand in a prime position to reap its benefits. Moreover, we find a reduced gender pay gap in occupations that have high exposure and high complementarity with AI, which are precisely the roles expected to benefit and grow with AI integration. Our findings suggest that within green jobs, those more likely to be enhanced by AI also exhibit a lower gender pay gap. This correlation underscores the potential of integrating AI with green jobs, not only in advancing environmental goals but also in fostering gender equality within the workforce.

This paper is structured into five main sections. Section 2 offers a review of the existing literature. Section 3 details the data and methodology employed in our analysis. Section 4 contains the core findings concerning the demographic and occupational characteristics of workers in green, polluting, and neutral jobs. Section 5 examines the financial returns associated with green jobs, emphasizing their role in narrowing the gender pay gap. Section 6 explores the potential impacts of AI on green and polluting jobs. Section 7 concludes the paper.

## 2 Literature Review

This paper contributes to a body of literature examining the impact of the green transition on jobs focusing on the task composition of these jobs. Historically, this research has predominantly focused on green jobs within specific countries, especially in the United States, as evidenced by studies such as Hartley et al. (2015), Consoli et al. (2016), Walker (2013), Bowen et al. (2018), Vona et al. (2018), Vona et al. (2019), Upton and Han (2021), Bergant et al. (2022), and Suassay et al. (2022). Similarly, studies like Bohringer et al. (2013) have exclusively considered the German context in examining the effects of the green transition. More recently, however, the literature has expanded to encompass the impact across OECD countries, as highlighted by recent studies OECD (2023a) and Bluedorn et al. (2023). This pivot towards OECD countries largely stems from the availability of the European Union Labour Force Survey (EULFS), which offers harmonized data across occupations and countries. Our primary contribution to this literature is the analysis of the green jobs

within three emerging market economies: Brazil, Colombia, and South Africa. This focus is crucial, as the global green transition can not occur without the inclusion of EMs and can have significantly different impact on labor markets on these countries.

Furthermore, this study enriches an emerging strand of literature on the wage premium within green jobs. While recent works such as OECD (2023a) and Bluedorn et al. (2023) have identified the presence of green jobs premium in AEs, our research confirms their existence in EMs. Additionally, we explore the financial returns of green jobs for both men and women, uncovering a novel fact: the gender pay gap is narrower within green jobs compared to other jobs. Moreover, we assess the significance of green jobs in influencing the overall gender pay gap. In doing so, our investigation contributes to the broader literature on the gender pay gap across various countries and its primary drivers (OECD (2023c), Petrongolo and Ronchi (2020), and Blau and Kahn (2020)). Our study highlights how the well-documented gender gap in STEM education also contributes to the observed gender employment gap in green employment.

This paper situates itself within the rapidly expanding research domain concerning the impact of AI on labor markets. Initial studies within this field have predominantly centered around the United States, as highlighted by works such as Felten et al. (2021), Felten et al. (2023), Eloundou et al. (2023), and Webb (2020). However, the scope of inquiry has broadened in more recent contributions, encompassing a more global perspective with research covering a wide array of countries (OECD (2023b), Albanesi et al. (2023), Briggs and Kodnani (2023), Gmyrek et al. (2023), Pizzinelli et al. (2023)). Our paper extends this existent literature in two significant directions. First, we study the interplay between AI and green jobs. This intersection is critically important as both AI and the green transition are poised to be major forces reshaping economies and labor markets. Secondly, we explore the potential impact of AI on the green wage structure, unveiling that within green jobs, jobs that have the potential to be complementary to AI also have a lower gender wage gap, indicating that the use of AI can enhance gender equality within green jobs.

### **3 Data and Methodology**

Our proposed framework for assessing the impact of the green transition on the labor market investigates three attributes of occupations: whether a job is green, the green task intensity of each job, and whether a job is polluting. The first two are determined by worker's occupation (what workers do, the intensive margin), and the latter is determined by the sector in which the worker is employed (where he/she works, the extensive margin).



We employ a bottom-up approach to identify a green job. First, we identify a measure of greenness to determine whether a job is green. For this we use the taxonomy created by Dierdorff et al. (2009) and Center (2021). This taxonomy is constructed based on occupations in the United States. For this measure they view an occupation as a bundle of tasks that a job requires. The underlying set of tasks for each occupation is classified into either green or non-green tasks. A green task is one that directly improves environmental sustainability or reduces greenhouse gas emissions. Green task intensity for each occupation is then calculated as the weighted ratio of green task importance to total tasks. For occupations involving no green tasks, the green task intensity is set to zero. Following the approach by Vona et al. (2018), the original 8-digit encoding in the US SOC2010 occupational classification is aggregated to the 6-digit level (for which employment is available) by simple averaging. Similarly to OECD (2023a), we identify a green job as one where the green intensity is greater than five percent.<sup>3</sup>

Second, we utilize a binary index of pollution-intensive sectors developed by Vona et al. (2018) for the United States to identify polluting jobs because there is no similar task taxonomy for polluting jobs. This binary index operates in two steps. Initially, a sector is identified as polluting if the emissions per worker for at least three polluting substances (CO, VOC, NO<sub>x</sub>, SO<sub>2</sub>, PM<sub>10</sub>, PM<sub>2.5</sub>, lead, and CO<sub>2</sub>) fall within the top five percent. Additionally, the sector must have a share of employees at least seven times larger than the share of employees in other sectors for that given occupation, to assure that this is a relevant sector for the occupation.

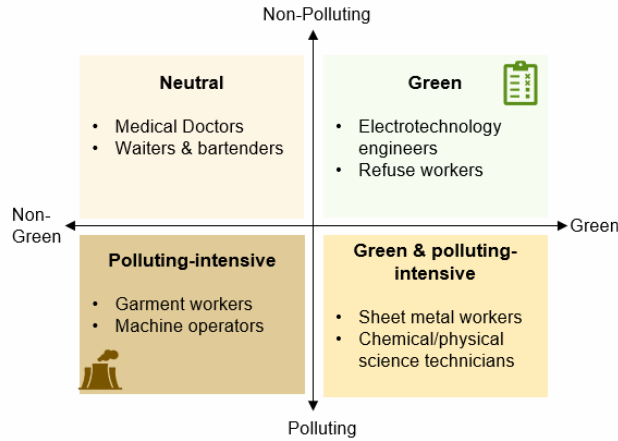
As these measures capture different aspects of the job (the task content and the sector of employed), it is possible to have green jobs in pollution-intensive sectors. As such, jobs are divided into four categories: 1. green (green job, non-polluting sector); 2. green and polluting (green job, polluting sector); 3. polluting (non-green job and polluting sector); 4. neutral (non-green job and non-polluting sector). Figure 1 represents the paper’s framework.

This methodology carries important limitations. First, it does not consider the significant role of worker reallocation and the ease with which workers can transition from certain occupations to green occupations. Additionally, it relies on the current definition of green tasks without accounting for potential changes in the demand for green tasks or the creation of new green tasks. It also assumes that occupations have the same task content

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<sup>3</sup>Annex A and Figure A.1 show the importance of threshold to determine the share of workers in green jobs. Lowering the threshold to one percent leads to an increased share of workers in green jobs, whereas raising it to ten percent results in a decrease. Nonetheless, these adjustments do not alter the overarching finding that the share of green jobs remains similar across countries.

Figure 1: Occupation Categories



Note: The figure shows the four main groups of occupations analyzed in the paper. The groups are "green," "green and polluting", "polluting," and "neutral" jobs.

across countries, which is a well-known weakness of applying findings using O\*NET to other countries. Despite these limitations, the analysis provides a valuable snapshot of the current distribution of green jobs and highlights possible barriers to the expansion of the green economy.

### 3.1 Data

We use individual-level data from labor force surveys covering five countries: Brazil, Colombia, South Africa, the UK, and the US. Using the International Standard Classification of Occupations for 2008 (ISCO), we classify jobs into 436 groups (4-digit ISCO), with 130 minor (3-digit), 43 sub-major (two-digit) and 10 major groups (1-digit), based on similarity in terms of skill level and specialization required. We restrict the sample to employed individuals aged 16 to 64 and exclude those in military professions. Table 1 summarizes the data sources.

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
South Africa	Labor Market Dynamics in South Africa Survey	2019	4
UK	Labour Force Survey	2022	4
US	American Community Survey	2019	4

To identify green and polluting jobs at the international level, we crosswalk the measures of green and polluting that use US 2010 occupation codes to international standard ISCO using US employment weights where there are non-unique matches.<sup>4</sup> We then aggregate to three-, two-, and one-digit (minor, sub-major, and major) ISCO groups by simple average of the green task intensity. We classify minor- and sub-major groups as polluting if there is at least one unit or sub-major group that is polluting. Figure 1 shows examples of occupations categorized by green and polluting measures.

To look at the distribution of green jobs among workers, we group within countries green jobs by occupation, gender, education, age, and sector, using the sample weighted average to find the shares of employment in each group. For the sectoral analysis, we use the International Standard Industrial Classification (ISIC) of economic activities broken down by: agriculture, construction, manufacturing, market services, non-market services and mining, energy and water.

## 4 Green Labor Market Characteristics

In this section we present the results on the cross-country variation in green employment. First, we compare the distribution of green and polluting employment between AEs and EMs at the aggregate national level. We then study the importance of countries' occupational structure to explain difference in the share of green and polluting jobs. We then move to look at the characteristics of workers in those jobs by gender, age, and educational attainment. Last, we assess the interaction of gender and education in the green economy by decomposing the gender employment gap in green jobs by science, technology, engineering, and mathematics (STEM) occupations and managerial roles.

To begin, we provide a snapshot of the labor market characteristics in our five survey countries in Table 2 in 2023. There are several key differences between the countries, most notable between our three EMs - Brazil, Colombia, and South Africa and our two AEs - the UK and US. In terms of the labor force participation rate among individuals aged 15-64, the AEs demonstrate higher figures, with the United Kingdom at 77.6 percent and the United States at 72.9 percent, compared to the EMs— Brazil at 70.3 percent, Colombia at 68.3 percent, and South Africa at 62.5 percent. A similar difference is observed between EMs and AEs for female labor force participation. When examining the unemployment rate, AEs exhibit lower figures, with the UK reporting 3.8 percent and the US at 3.7 percent. In

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<sup>4</sup>We use the Bureau of Labor Statistics ISCO-08 x SOC 2010 Crosswalk available at:<https://www.bls.gov/soc/ISCOSOCCrosswalk.xls>

contrast, EMs face higher levels of unemployment, as seen in Brazil (9.4 percent), Colombia (10.8 percent), and South Africa (26.0 percent). Additionally, differences in average hourly earnings underscore economic disparities, as AEs like the United States and the United Kingdom present substantially higher earnings at 28.72 and 23.06 U.S. dollars, respectively, compared to EMs, where average hourly earnings range between 1.38 and 3.12 U.S. Dollars. Brazil, Colombia and South Africa all have data on informal employment which comprises between 38 and 58 percent of the labor market. Last tertiary schooling is different between AEs and EMs with the US and the UK having higher rates of enrollment at 87.9 percent and 77 percent respectively than the EMs, where tertiary enrollment ratios range from 58.3 percent in Colombia to as low as 24 percent in South Africa. These variations underscore the large differences on labor market across countries.

Table 2: Labor Market Summary Statistics for Survey Countries

	Brazil	Colomb- ia	South Africa	United King- dom	United States
Labour force participation rate (%)	70.3	68.3	62.5	77.6	72.9
Female labour force participation rate (%)	60.9	56.3	56.9	74.2	67.6
Unemployment rate (%)	9.4	10.8	26.0	3.8*	3.7
Average hourly earnings of employees	3.12	1.88	1.38	23.06	28.72
Informal employment (%)	38.5	58.4	40.5	-	-
Tertiary school enrollment (% gross)	56.8*	58.3*	24.0	77.0*	87.9

Source: ILO (2023), UNESCO (2023)

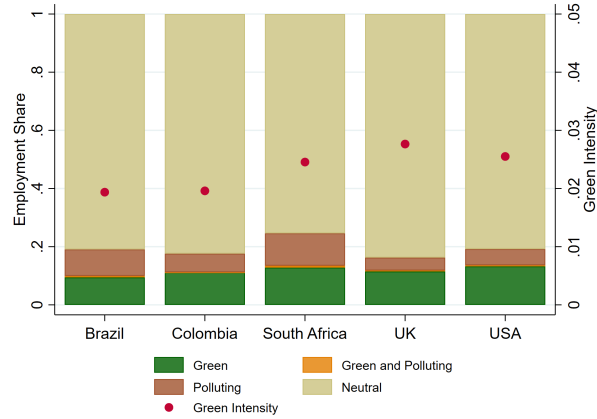
Note: The table shows summary statistics for surveyed countries during the analysis period, except for values marked with an asterisk, which represent the most recent year. The informality rate is defined only for Brazil, Colombia, and South Africa.

Note: “Labour force participation rate” and “Female labour force participation rate” use ILO modelled estimates for ages 15-64. “Unemployment rate” uses survey data processed by the ILO for ages 15-64. “Average hourly earnings of employee” uses survey data processed by the ILO in current US Dollars. “Informal employment” uses survey data processed by the ILO.

## 4.1 Aggregates

Our analysis starts by looking at the distribution of green and polluting jobs across the five sample countries: two AEs, the US and the UK, and three EMs, Brazil, Colombia and South Africa. Figure 2 plots the employment share of green, polluting, green and polluting, and neutral jobs within each of the five countries of interest. We find that green jobs are similarly present in AEs and EMs, representing between 9.4 and 13.2 percent of the employment share in each country. However, the share of polluting jobs differs – constituting a smaller proportion of employment in AEs (5 percent) than in EMs (9 percent). Moving to the green intensity, we find that the average greenness score across the working population is 0.5 percentage points higher in AEs than EMs. Although small, it suggests that while the share of green jobs is similar across different countries, the type of green jobs differs.

Figure 2: Employment Share by Green Job Type and Intensity



Note: The figure plots the share of employment in each group of occupations for each country.

## 4.2 Economic Structure

In order to analyze the characteristics of workers, we start by looking at the distribution of green, polluting, green and polluting, and neutral jobs across occupations. Within each country we group workers by their occupation, corresponding to the major ISCO group, and plot the share of workers in each group. Figure 3 presents the results for Brazil and the UK (see Figure A.3 in Annex A for the remaining countries). The nine major ISCO groups are plotted on the x-axis, with skill level in descending order – managers have the highest skill level while the lowest is associated with elementary occupations.

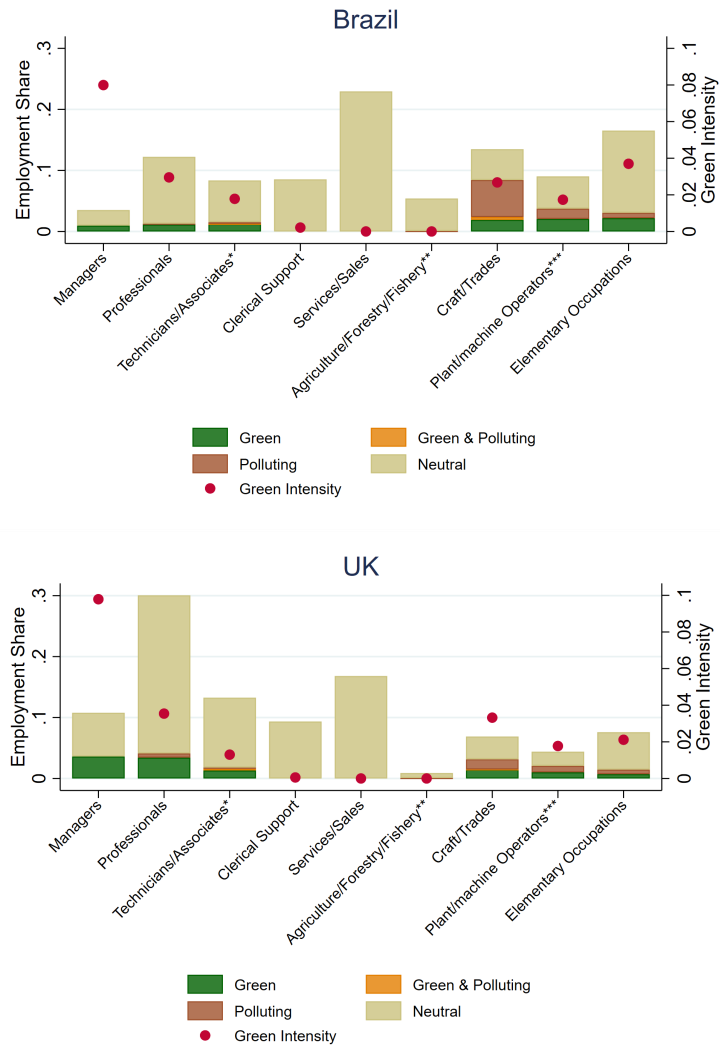
When examining the distribution of green jobs, an intriguing pattern emerges: AEs and EMs display a comparable proportion of workers in green jobs. However, the allocation of these jobs across different occupational categories diverges significantly. In EMs, green jobs predominantly cluster among elementary occupations, plant and machine operators, and craft and trade workers. For instance, in Brazil, these three categories account for 66 percent of green jobs. Within these categories, green jobs encompass refuse workers, building construction laborers, and heavy truck drivers.<sup>5</sup>

Conversely, in AEs, the bulk of green jobs are found in managerial, professional, and technical positions, as well as among associate professionals. In the UK, these three major categories account for 73 percent of green jobs. Important green jobs include engineering professionals and financial and investment advisors.<sup>6</sup>

<sup>5</sup>Heavy truck drivers’ green tasks include adjusting routes to reduce emissions, drive electric or hybrid-electric trucks or alternatives, and operate idle reduction or auxiliary power systems from alternative sources for energy and to provide power for other equipment O\*NET Center (2021b).

<sup>6</sup>These occupations are considered green because engineers can assess and reduce the environmental

Figure 3: Employment Share by Occupation Type



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. \*: Technicians and associate professionals. \*\*: Skilled agricultural, forestry and fishery workers. \*\*\*: Plant and machine operators and assemblers.

The pattern of green intensity by occupational group is similar across AEs and EMs, as managers have the highest green intensity score close to 10 percent, while professionals, technicians and associate professionals, craft and related trades workers, plant and machine operators and assemblers, and elementary occupations all have a lower green intensity score around 2 percent.

Unlike the difference in the green jobs' distribution across countries, polluting jobs are similarly concentrated across occupational categories in both AEs and EMs. Specifically, these jobs are predominantly found in craft and related trades occupations, with a secondary concentration in plant and machine operators and assemblers. In EMs, bricklayers and related workers, manufacturing laborers, agricultural and industrial mechanics and sheet-metal workers are examples of polluting sector occupations.

When one looks at the job distribution between EMs and AEs at the more granular level, some differences emerge. In Brazil, the majority (63 percent) of polluting jobs are within craft and trade occupations, followed by 18 percent in plant and machine operators. Bricklayers and related workers (e.g. refractory materials repairers)<sup>7</sup> constitute the largest share of these jobs, accounting for 32 percent of all polluting jobs in Brazil as well as driving the share of polluting jobs within the crafts and trade category, making up 47 percent. Agricultural and industrial machinery mechanics constitute 6 percent of all polluting jobs, followed by butchers and fishmongers, at 6 percent and then sheet-metal workers, at 5 percent. The latter group refers to those employed across Brazil's thirty-one steel mill factories, directly linked to Brazil's status as one of the world's leading producers of iron ore.

The contrast with the UK is stark, where labor market characteristics differ significantly due to the fact that extractive and agricultural industries are less prominent. While the largest share of polluting jobs are in craft and trade occupations, it is a much smaller share than seen in Brazil, at only 35 percent. The other notable difference is the large polluting share in professional occupations (e.g. chemical engineer) - in the UK this constitutes 14 percent, compared to just 1 percent in Brazil.<sup>8</sup> While lower-skilled polluting jobs exist

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impact of their projects and industrial accidents. They can also develop and integrate renewable energy. Financial professions can research and develop financial instruments for green investment. Financial advisors specifically can recommend environmental investments, clean tech, and tax benefits for environmental investments O\*NET Center (2021b).

<sup>7</sup>In our SOC to ISCO crosswalk, bricklayers and related workers corresponds to the SOC Code for Refractory materials repairers, except brick masons, which is in a pollution-intensive sector. For example, these sectors are responsible for highly polluting refractories, plastics, and cement production Vona et al. (2018).

<sup>8</sup>These include chemists and biologists. While biologists, botanist, and zoologist have green tasks associated with them, the green intensity falls below our threshold of 5 percent. At the same time, these

in the UK (22 percent in plant and machinery and 15 percent in elementary occupations), these jobs represent a lower share than low-skilled polluting jobs in Brazil.

We leave a discussion of green jobs' distribution within major occupation categories to Annex A.3. Within large occupation groups, we find a slight difference in the share of green jobs among managers and professionals' occupations across countries, where the difference is less than 5 p.p. The UK and the US have the largest share of green occupations among manager and professionals, with almost 35 percent, while Colombia has the lowest share, with less than 25 percent. In occupations important for EMs, like plant and machine operators, we find a larger share of green jobs in the US and South Africa, with almost 40 percent of these workers in green occupations, while in Colombia, the share is less than 15 percent. While the distribution of polluting jobs within large occupation categories is much more homogeneous across countries; the most significant difference is among crafts and trades occupations, where more than 40 percent of these workers in Brazil are in polluting occupations, while in the US, it is nearly 20 percent. Consequently, the analysis shows that most of the differences in green jobs across countries are due to differences in the employment structure of countries rather than to differences in major among occupation groups.

### 4.3 Gender

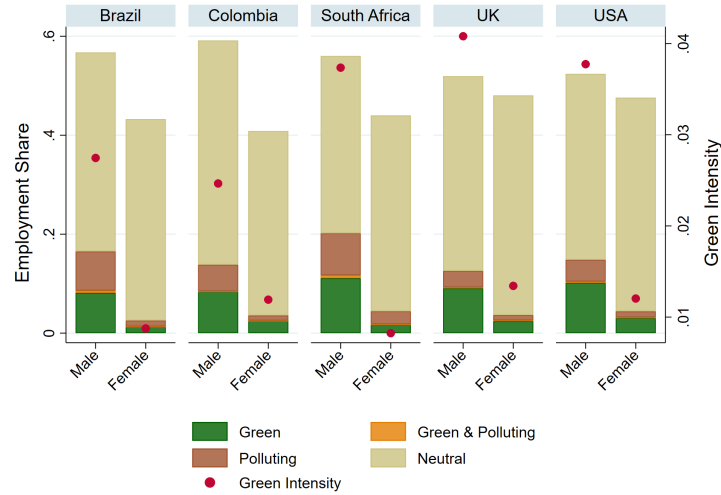
Transitioning to the analysis of worker characteristics, our investigation begins with the distribution of employment across the same four occupational categories—green, polluting, green and polluting, and neutral jobs—segmented by gender. To elucidate these patterns, Figure 5 presents the employment shares of female and male workers, detailing their distribution across each of the four sub-categories.

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professionals are in polluting sectors (e.g. biochemical engineers)



Figure 4: Employment Share by Gender



Note: The figure plots the distribution of employment in green, pollution-intensive, green and pollution-intensive, and neutral occupations conditional on gender.

Focusing on gender dynamics, Figure 5 reveals a consistent pattern across all countries, both green and polluting jobs are male-dominated. Men consistently outnumber women in both the total count of green jobs, the share of green jobs over all jobs, and the average green intensity.

In EMs, on average, men hold the majority of green jobs; men’s employment accounts for approximately 83 percent of all green jobs, and women’s employment accounts for the rest. This gender disparity in the green jobs’ distribution is similarly evident in AEs, where men hold 77 percent of all green jobs, in contrast to women, who account approximately for only 23 percent.

Expanding the analysis to consider green jobs as a share of total employment for each gender reveals additional insights. Even after accounting for the fact that women constitute a smaller portion of the overall employment pool—particularly in EMs, where labor force participation rates for women are generally lower than in AEs—on average green jobs in EMs account for only 5 percent of women’s total employment. For men, this figure is substantially higher, at almost 17 percent on average. A comparable pattern is observed in AEs, where, for individuals who are employed, green jobs comprise 6 percent of women’s total employment on average and 19 percent of men’s.

Similarly to green jobs, men hold the majority of polluting jobs. In EMs and AEs,

men hold 82 and 77 percent respectively of polluting jobs. However, the difference between the share of men and women in polluting jobs is smaller than in green jobs. Polluting jobs account for 4 percent of women’s total employment and 13 percent of men’s. In AEs this gap is even smaller - at 3 and 8 percent for women’s and men’s total employment respectively.<sup>9</sup>

Last, a closer examination of green intensity by gender in the UK, US, and South Africa underscores a significantly higher green intensity across the male-dominated population revealing a larger share of green tasks is performed by men. Comparatively, Brazil and Colombia demonstrate a slightly lower green intensity for male-held green jobs held by men (although still comparatively higher than for women-held green jobs), this is explained by the larger share of green jobs in elementary, trade and craft occupations which have lower green intensity scores than managers and professionals occupations that are more abundant in AEs, as shown in Figure 3.

#### 4.4 Age

Further analyzing job types by gender and age cohort, we don’t observe large differences between countries or gender. Despite the differences in economic structures in both AEs and EMs, the distribution of green and polluting occupations is relatively similar. In both AEs and EMs, the largest share of workers working in green jobs is among 31 to 40 years old, while polluting jobs share slightly increases with age, picking around 51 to 60 years old. The main exception is polluting jobs in South Africa, which seem to be more concentrated among young workers. We leave the discussion about the age distribution of workers working on green and polluting jobs to Annex A.5.

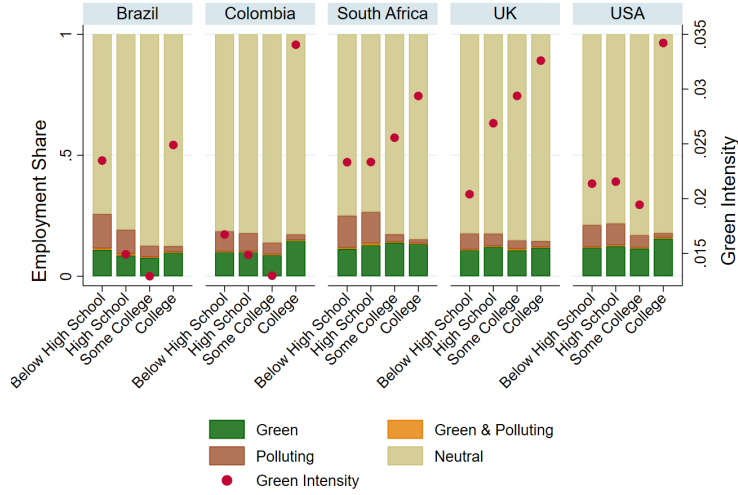
#### 4.5 Education

To understand the importance of education in green, neutral, and polluting jobs, we split individuals into four education categories: below high school, high school, some college, and those with a college degree and above. Figure 5 shows the breakdown of the employment share between green, polluting, neutral, and green and polluting jobs for each education category.

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<sup>9</sup>Figure A.5 in the Annex A.4 plots the distribution of male and female employment across each occupation category conditional on being employed.

Figure 5: Employment Share by Education



Note: The figure plots the distribution of employment in green, polluting, green and polluting, and neutral occupations conditional on workers' education.

Beginning with an examination of green jobs across workers' educational background, a noteworthy pattern emerges. Irrespective of country or educational group, the proportion of workers employed in green jobs is similar. For individuals with education levels below high school, the share engaged in green jobs ranges from 10 percent in Colombia to 12 percent in the US. On the other end of the spectrum, among those workers with at least a college education, the lowest share of workers in green jobs stands at 10 percent in Brazil, with the highest reaching 16 percent in US. This analysis reveals a consistent distribution of green jobs across varying levels of educational attainment, highlighting the broad appeal and accessibility of green jobs across different education groups.

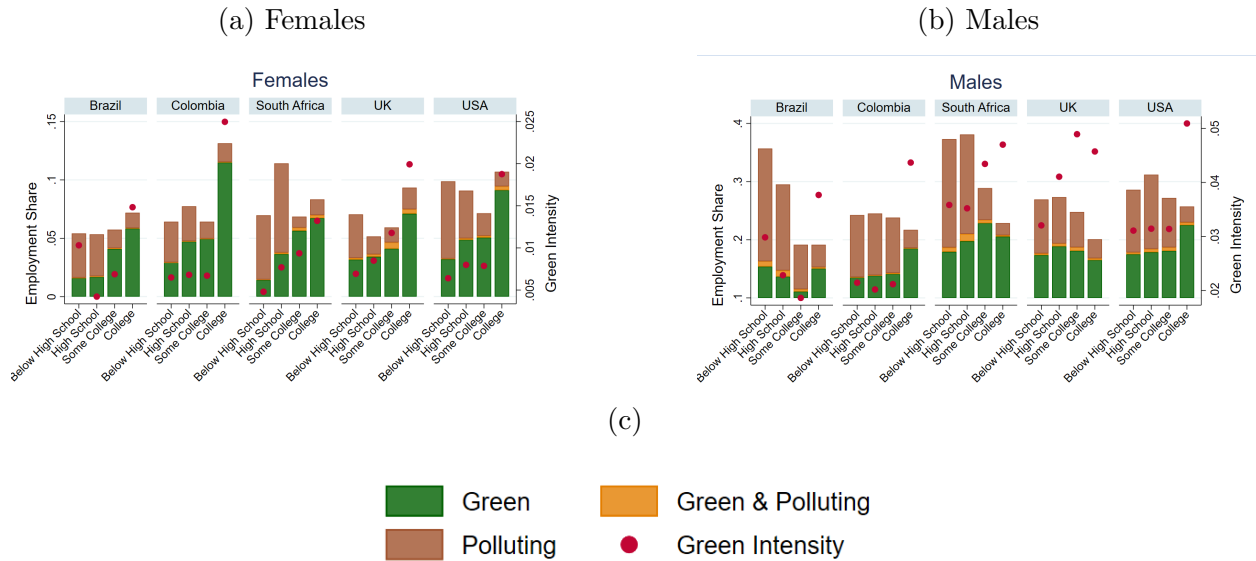
Moving to the polluting jobs, we also find a remarkably similar pattern across countries, but while green jobs were similarly distributed across education groups, polluting jobs are more concentrated at lower levels of education in all sample countries. As discussed before, Brazil and South Africa have the largest share of workers working in polluting occupations, concentrated among workers with at most high school education. In Brazil, 15 percent of workers with less than high school education work in polluting jobs, in and South Africa this number is close to 14 percent; among workers with a high-school education the figure is 11 in Brazil, and 14 in South Africa. The proportion is much lower in AEs, where the average share of polluting jobs for those with a high school education and below is 8 percent. However, among workers with college education, the share of workers in polluting

jobs varies only between 2 and 3 percent across both AEs and EMs.

## 4.6 Interaction Gender and Education

We now explore the intersection between gender, education, and green jobs, beginning with an analysis illustrated in Figure 6. This figure presents the distribution of employment across the same four categories—green, polluting, green and polluting, and neutral jobs—segmented by both gender and educational attainment.

Figure 6: Distribution of Jobs by Gender and Education



Note: The figure shows the employment share of workers in green, polluting, green and polluting, and neutral jobs by education and gender.

Figure 6 unveils significant insights into the distribution of green jobs by gender and education across our sample countries. It highlights a distinct pattern where the distribution of men in green jobs is relatively uniform across all educational levels, in stark contrast to the distribution among women. Specifically, women’s participation in green jobs tends to be skewed towards those with higher levels of education. For instance, in Colombia, only 3 percent of women with less than high-school education occupies green jobs, whereas this figure escalates to 11 percent among women with college education, nearly four times higher. Meanwhile, the discrepancy in green jobs participation between men with less than high-school education and those with college degrees is notably narrower, 14 vs. 19 percent, respectively.

Moving deeper into green occupations, we find that over 60 percent of occupations classified as green are in STEM fields. In 2018, the average STEM worker earned two-thirds more than those employed in other fields (Funk and Parker (2018)). However, women and girls are underrepresented in STEM education and careers, with the gender gap between males and females increasing as wages rise. Males are 15 to 17 percentage points more likely than females to enroll in tertiary STEM education in upper-middle-income and high-income economies compared to a 7-percentage points difference in low-income countries (Hammond et al. (2020)). Given the concentration of green jobs in STEM disciplines and the low share of female graduates in STEM fields, we examine the role of STEM education in the gender employment gap in green jobs. We decomposed the green employment gap as follows:

$$Y_m^g - Y_f^g = (Y_m^{g,S} - Y_f^{g,S}) + (Y_m^{g,M} - Y_f^{g,M}) + (Y_m^{g,S,M} - Y_f^{g,S,M}) + (Y_m^{g,O} - Y_f^{g,O}), \quad (1)$$

Within green jobs ( $g$ ), this equation describes the gap between men and women in their employment share ( $Y$ ) as a result of the gap between men ( $m$ ) and women ( $f$ ) employment ( $Y$ ) in non-managerial, stem occupations ( $S$ ), managerial, non-stem occupations ( $M$ ), managers in stem occupations ( $S, M$ ), and other green occupations ( $O$ ).

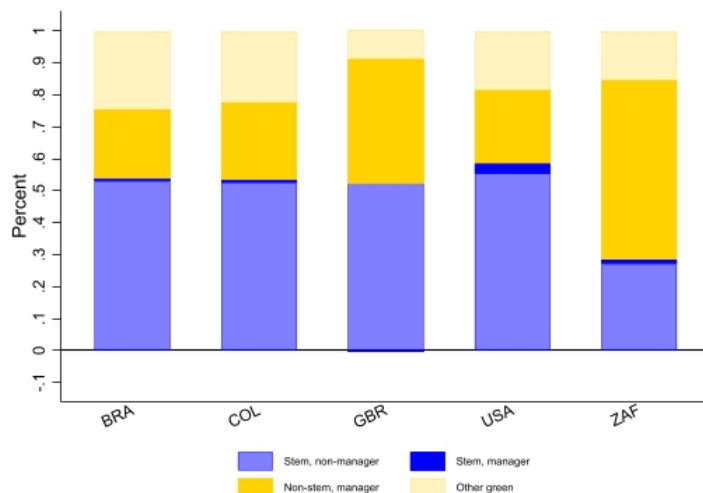
We identify STEM occupations by referencing the O\*NET (2018) list, which categorizes occupations based on work performed and, in some cases, the necessary skills, education, and/or training. STEM occupations fall into four domains: 1. life and physical science, engineering, mathematics, and information technology occupations; 2. social science occupations; 3. architecture occupations; 4. health occupations. To achieve international comparability, we crosswalk US occupational job classifications to the 4-digit ISCO codes. When duplicated matches emerge, we use US employment weights to average them out. This procedure enables the identification of STEM occupations across all labor force surveys. Out of the 44 ISCO occupations identified as green, 27 are STEM occupations, demonstrating the relevance of STEM occupations in the green economy.

Aggregating to 1-digit ISCO groups reveals that green STEM jobs comprise of one managerial occupation, 19 professional occupations, and seven technical occupations. According to the ISCO definition, managers, professionals, and technical roles necessitate higher skill levels (3 and 4). The skill level, ranging from 1 to 4, is determined based on factors such as the nature of the work, the level of formal education needed, and relevant experience. Because the green STEM occupations identified require more educational investment, in this

section we restrict the analysis to only workers with a college degree or higher.

Figure 7 plots the results of the decomposition exercise. We breakdown the employment gap in green jobs in four components: STEM, managerial, STEM managerial, and other green occupations. The employment gap is normalized across all countries.

Figure 7: Green Gender Employment Gap Deconposition



Note: The figure decomposes the employment gap between men and women in green jobs by employment in STEM, STEM and managerial, managerial, and other green occupations.

Figure 7 demonstrates the significant role of STEM education in accounting for the gender employment gap within the green jobs among college-educated workers. In nations such as Brazil, Colombia, the UK, and the US, occupations within the STEM field are responsible for approximately half of the observed disparity in green employment between men and women. In South Africa, the contribution of STEM occupations to this gender gap exceeds a quarter, underscoring the pivotal influence of STEM education on employment outcomes in green jobs.

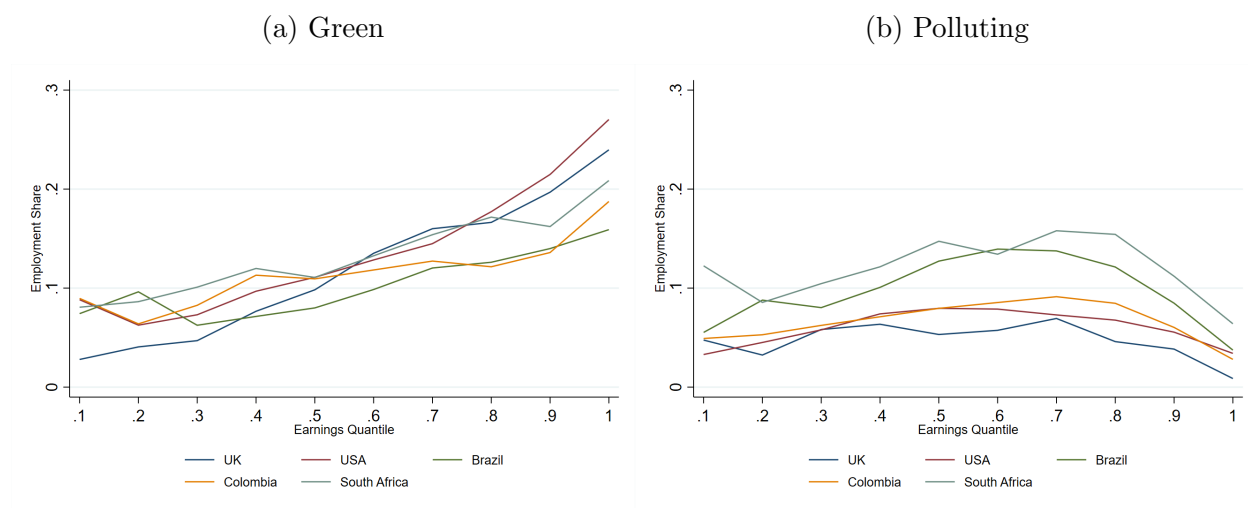
The second factor identified is the under-representation of women in managerial positions. Specifically, in South Africa, the disparity between men and women in managerial roles stands out as the most significant factor, accounting for 56 percent of the gap in green employment among those with college education. Similarly, in the UK, the gap in managerial occupations plays a crucial role, contributing to 39 percent of the overall discrepancy. This pattern is consistent across Brazil, Colombia, and the US, where the shortfall in women holding managerial positions contributes to 23 percent of the gap in green employment for

college-educated individuals.

## 4.7 Earnings

We now examine the distribution of green and polluting jobs across the earnings distribution. In Figure 8a, we plot the employment share of workers in green jobs on the y-axis and the earnings deciles on the x-axis.

Figure 8: Earnings



Note: The figure shows the employment share of workers in green (a) and polluting (b) occupations by earnings decile and country.

Focusing initially on green jobs, Figure 8a depicts a positive correlation between the proportion of workers engaged in green jobs and their earnings across all examined countries. This relationship suggests that a significant portion of individuals employed within green jobs enjoys higher earnings. Notably, in the advanced economies under study, this correlation is particularly robust; more than 20 percent of workers within the top decile of the earnings distribution are employed in green jobs. This figure is particularly striking given that green jobs constitute merely 12 percent of total employment. In EMs, South Africa and Colombia display flatter lines, but still mirror the positive trend. Brazil falls in the middle.

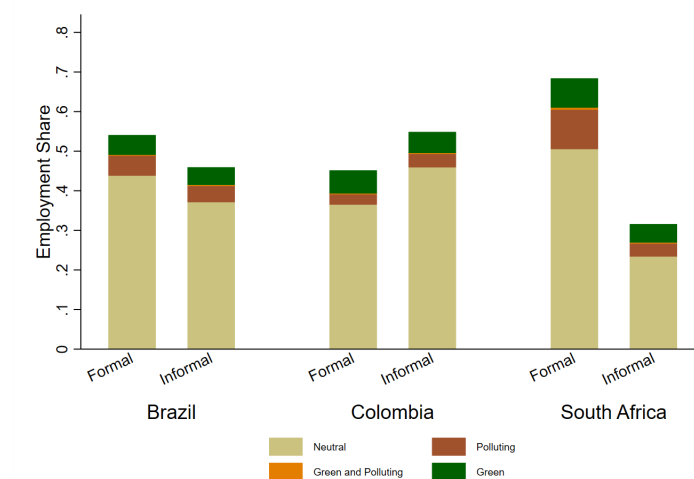
In contrast, Figure 8b, which plots the employment share of workers in polluting jobs on the y-axis and the earnings decile on the x-axis, shows that polluting jobs exhibit an inverted-U relation. This shape signifies that most polluting jobs are concentrated in middle income jobs. The pattern is more pronounced in Brazil and South Africa than in the UK,

the US, and Colombia. These findings are consistent with the fact that polluting jobs are more concentrated among low-skilled manual workers.

## 4.8 Informality

To delve into the specifics of EM labor markets, we analyze the degree of informality of green and polluting jobs across countries. Informal jobs are defined as jobs without pension benefits, self-employed or family workers without a salary in Brazil and Colombia. South Africa uses a different definition of informality. South Africa categorizes some self-employed individuals as “formal” if their employment involves professional activities. In contrast, Brazil and Colombia consider all self-employed individuals as informal. Essentially, South Africa assigns a different weight to firm characteristics, resulting in a higher shares of formal employment than the other two countries. Figure 9 illustrates employment share on the y-axis for formal and informal workers as well as green and pollution employment specific to each EM country.

Figure 9: Employment Distribution by Formality Status



Note: The figure plots the employment share of workers in green and polluting occupations by formality status in EMs. In Brazil and Colombia, individuals are deemed informal if they lack pension benefits, work as self-employed or family workers without a fixed salary. In contrast, South Africa uses a different definition of informality, designating certain self-employed individuals as formal based on specific firm characteristics.

Interestingly, green jobs are evenly distributed across both the informal and formal sector. Green jobs account for 7 percent of formal jobs in South Africa, the country with the largest proportion of green formal jobs, and 5 percent in Brazil, the country with the lowest proportion of formal green jobs. Meanwhile among informal jobs, green jobs account for at most 5 percent of informal employment in Colombia, and only 4 percent of informal employment in Brazil.



Conversely, there exists a slightly broader variation in the distribution of polluting jobs across countries. South Africa, which holds the highest percentage of polluting jobs, sees these positions making up 10 percent of its formal employment and 3 percent of informal employment. In Brazil and Colombia, a comparable trend is observed, with polluting jobs comprising approximately 4 percent of the informal job, and between 3 to 5 percent of formal employment. This diversity highlights the significant role of polluting jobs within both the formal and informal sectors.

## 5 Labor Market Returns

In this section, we study the returns to working in green jobs and assess the presence of a gender pay gap. We start the section by quantifying the main drivers of green jobs returns and the gender pay gap. We then move to a structural model to examine the main sources of the green jobs premium.<sup>10</sup>

### 5.1 Green Wage Premium

The raw green wage premium is the percentage difference between green and non-green jobs wage-per-hour remuneration. Table 3 shows the aggregate raw green wage premium across college attainment and gender. Table 3 reveals a consistent positive raw green wage premium across countries, college attainment status, and gender. In general, the green wage premium varies, being 20 percent in Brazil, 25 percent in the US, 30 percent in the UK, and 31 percent in Colombia. This result suggests that a worker holding a green job receives a higher compensation than a worker in a non-green job. We strengthen this statement later by performing a regression analysis controlling for further relevant variables.

Across various countries, our analysis reveals that women consistently enjoy a higher raw green wage premium than men when factoring in college education. For women without a college degree, the premium ranges from a 22 percent increase in Brazil to a 33 percent in the UK, compared to their male counterparts for which the premium ranges from a modest 4 percent in Colombia to a 17 percent in the UK and US. College-educated women in Brazil see a 26 percent premium, whereas in the US, the premium for similarly educated women reaches up to 35 percent. This pattern suggests that the transition to a green-based economy could benefit female workers in the short-term, with the green raw wage premium for women

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<sup>10</sup>The labor market returns analysis does not consider South Africa because of the well-known problem with the earnings data from the Labor Market Dynamics Survey documented in Köhler and Bhorat (2023)

without a college degree spanning 9 to 22 percentage points higher than for men, and 7 to 19 percentage points higher for those with a college degree.

Table 3: Raw Green Wage Premium across Education Attainment and Gender

Country	Aggregate	No College		College	
		Male	Female	Male	Female
Brazil	0.20	0.08	0.22	0.19	0.26
Colombia	0.31	0.04	0.26	0.25	0.44
United Kingdom	0.25	0.17	0.33	0.16	0.23
United States	0.30	0.17	0.26	0.24	0.35

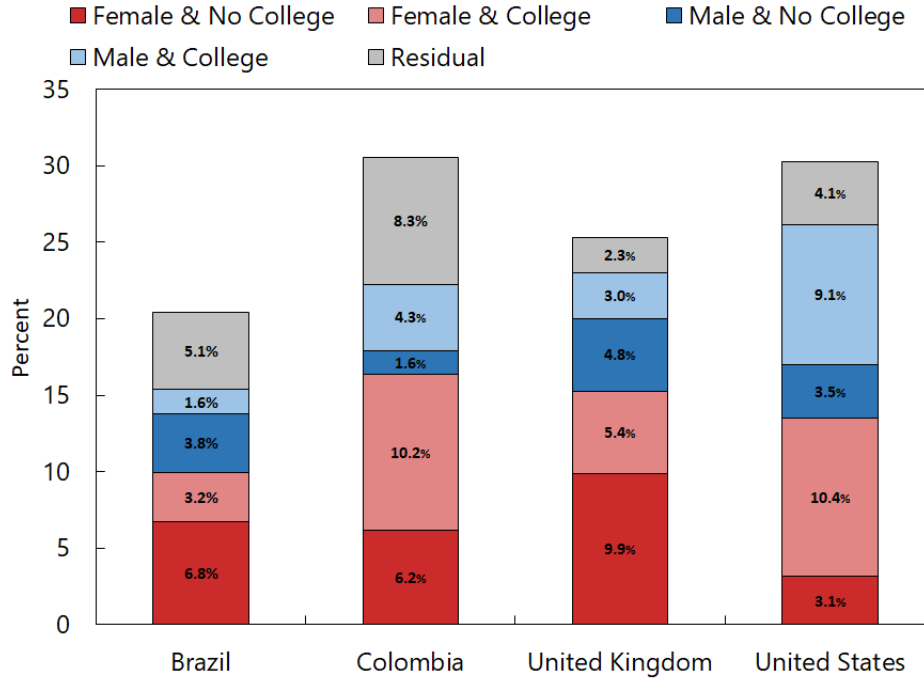
**Note:** The table presents the raw green wage premium measured as the percentage difference between green and non-green jobs wage-per-hour remuneration. Data and statistics come from Pesquisa Nacional por Amostra de Domicílios Contínua (Brazil, 2022), Gran Encuesta Integrada de Hogares (Colombia, 2022), Labor Force Survey (UK, 2022), and American Community Survey (US, 2019). College attainment is measured by at least having a college degree and gender is divided into male and female.

We continue the analysis of the raw green wage premium in each country by decomposing it into its college attainment and gender components. We use the following decomposition formula:

$$\ln(w^{\text{Green}}) - \ln(w^{\text{Non-Green}}) = \left( \sum_{\substack{g \in \{\text{Male, Female}\} \\ e \in \{\text{No College, College}\}}} \omega_{g,e} [\ln(w_{g,e}^{\text{Green}}) - \ln(w_{g,e}^{\text{Non-Green}})] \right) + \text{Residual},$$

where  $w$  is the hourly wage in green and non-green occupations,  $\omega_{g,e} \equiv (N_{g,e}^{\text{Green}} + N_{g,e}^{\text{Non-Green}}) / (N^{\text{Green}} + N^{\text{Non-Green}})$  represents the weight of each component of the green wage premium,  $g$  stands for the gender, and  $e$  education attainment. Figure 10 illustrates the raw green wage premium and how much each component contributes to it. The goal of this decomposition is to compound the raw green wage premium reported in Table 3 with their weighted relevance for each category.

Figure 10: Raw Green Wage Premium Decomposition



**Note:** Data and statistics come from Pesquisa Nacional por Amostra de Domicilios Continua (Brazil, 2022), Gran Encuesta Integrada de Hogares (Colombia, 2022), Labor Market Dynamics in South Africa Survey (South Africa, 2019), Labor Force Survey (UK, 2022), and American Community Survey (US, 2019). College attainment is measured by at least having a college degree and gender is divided into male and female.

Our findings indicate that the raw green wage premium is significantly driven by women across several countries. In Brazil, the raw premium is 20 percent, with contributions of 10 percentage points from women and 5 from men. Colombia sees a raw premium of 31 percent, with women contributing 16 percentage points compared to men’s 6 percentage points. The UK and the US present premiums of 25 percent and 30 percent, with women contributing 15 and 14 percentage points, respectively, compared to 8 and 13 from men.

## 5.2 Gender Pay Gap

We continue our analysis by studying the raw gender pay gap across countries and the contribution of green jobs. The raw gender pay gap is the percentage difference between men and women wage-per-hour remuneration. Table 4 shows the raw gender pay gap across college attainment and type of job. We first report the raw gender pay gap across countries. The raw gender pay gap varies widely being 3 percent in Colombia, 10 percent in Brazil, 17 percent in the United Kingdom, and 19 percent in the United States. These results are

qualitatively consistent with similar reports such as OECD (2023c).

Table 4: Raw Gender Pay Gaps across Jobs and Education

Country	Total	No College		College	
		Non-Green	Green	Non-Green	Green
Brazil	0.10	0.18	0.04	0.30	0.23
Colombia	0.03	0.17	-0.04	0.21	0.02
United Kingdom	0.17	0.15	-0.01	0.19	0.12
United States	0.19	0.20	0.12	0.22	0.10

**Note:** Data and statistics come from Pesquisa Nacional por Amostra de Domicílios Contínua (Brazil, 2022), Gran Encuesta Integrada de Hogares (Colombia, 2022), Labor Force Survey (UK, 2022), and American Community Survey (US, 2019). Decomposition of gender pay gap into college attainment and green/non-green jobs. College attainment is measured by at least having a college degree and green jobs are measured by using a green index above 5%. The gender wage gaps from components in columns add up to the aggregate gender pay gap for each country.

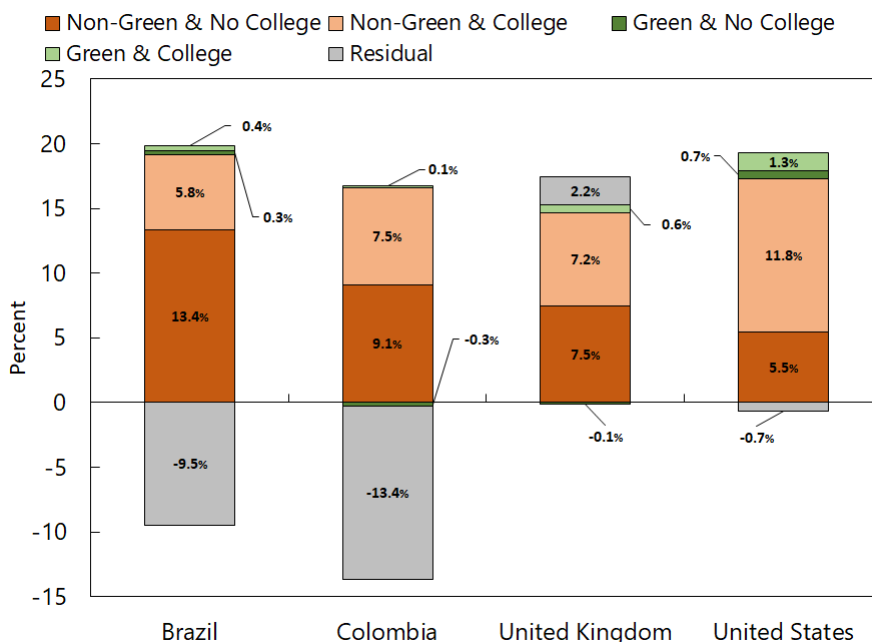
Delving into the different gender pay gaps across education attainment and job type, we find that green jobs tend to have a smaller raw gender pay gap, particularly for women without college education. In Brazil, green jobs stand out for the narrowest raw gender pay gap, the raw gender pay gap among non-college-educated workers in non-green jobs is almost 18 percent, while among workers in green is only 4 percent, similarly among college-educated workers the raw pay gap among works in non-green occupations is 30 percent while in green jobs is 23 percent. Colombia, the United Kingdom, and the United States all follow this trend, with lower raw gender pay gaps in green jobs ranging from 4 to 12 percentage points for non-college-educated workers and 2 to 23 percentage points for those with a college degree. Specifically, green jobs in Colombia show the most dramatic decrease in the gender pay gap, especially for non-college-educated workers, with a 21 percentage point reduction. This pattern indicates that currently the green-based economy may offer more equitable pay conditions, as green jobs tend to have smaller gender pay disparities compared to non-green jobs.

Similarly, to the raw green wage premium, we continue the analysis of the raw gender pay gap in each country by decomposing it into its college attainment and type of job components. We use the following decomposition formula:

$$\ln(w^{\text{Men}}) - \ln(w^{\text{Women}}) = \left( \sum_{\substack{j \in \{\text{Green, Non-Green}\} \\ e \in \{\text{No College, College}\}}} \omega_{j,e} [\ln(w_{j,e}^{\text{Men}}) - \ln(w_{j,e}^{\text{Women}})] \right) + \text{Residual},$$

where  $w$  stands for the hourly wage,  $\omega_{j,e} \equiv (N_{j,e}^{\text{Men}} + N_{j,e}^{\text{Women}})/(N^{\text{Men}} + N^{\text{Women}})$  represents the observations weight of each component of the gender pay gap,  $j$  indicates the type of jobs (whether it is green or not), and  $e$  education attainment. Figure 11 illustrates the gender pay gap and how much each component contributes to it. Following the analysis for the green wage premium, the goal of this decomposition is to compound the gender pay gap reported in Table 4 with their weighted relevance within the sample.

Figure 11: Raw Gender Pay Gap Decomposition



**Note:** Data and statistics come from Pesquisa Nacional por Amostra de Domicílios Contínua (Brazil, 2022), Gran Encuesta Integrada de Hogares (Colombia, 2022), Labor Force Survey (UK, 2022), and American Community Survey (US, 2019). Decomposition of gender pay gap into college attainment and green/non-green jobs. College attainment is measured by at least having a college degree and green jobs are measured by using a green index above 5%. Residual encompasses the differential between the aggregate gender pay gap and the gender pay gaps from the college attainment and green/non-green jobs components. The gender wage gaps from components in columns add up to the aggregate gender wage gap for each country.

Our analysis across multiple countries indicates that the raw gender pay gap is predominantly driven by disparities in college and non-college non-green jobs. In Brazil, for instance, while the overall raw gender pay gap is 10 percent, non-green jobs account for 19 percentage points of this gap, compared to a negligible 1 percentage point from green jobs. Similar trends are observed in Colombia, the UK, and the US, with non-green jobs significantly contributing to the gender pay gap—17, 15, and 17 percentage points, respec-

tively. Conversely, green jobs show minimal to slightly negative contributions, underscoring a potential for mitigating gender pay disparities. Specifically, green jobs in Colombia even exhibit a negative fifth of a percentage point contribution, suggesting a minor advantage for women.

### 5.3 Regression analysis

We formalize our previous descriptive statistics results by studying green jobs, women’s importance, and their interaction in a regression analysis. Specifically, we perform a Mincerian regression in the spirit of Bluedorn et al. (2023) described by

$$\begin{aligned} \ln(w_{i,t,c}) = & \alpha_c + \beta_c^f \cdot \mathcal{I}[\text{Female}_{i,t,c} = 1] + \beta_c^g \cdot \mathcal{I}[\text{Green}_{i,t,c} = 1] \\ & + \beta_c^{fg} \cdot \mathcal{I}[\text{Female}_{i,t,c} = 1] \cdot \mathcal{I}[\text{Green}_{i,t,c} = 1] + \gamma_c \cdot X_{i,t,c} + \varepsilon_{i,t,c} \end{aligned} \quad (2)$$

where  $w_{i,t,c}$  is the wage-per-hour remuneration,  $\mathcal{I}[\text{Female}_{i,t,c} = 1]$  is a woman indicator,  $\mathcal{I}[\text{Green}_{i,t,c} = 1]$  is a green job indicator, and  $X_{i,t,c}$  is a control vector that encompasses age, education, male and female marriage status, sectors, and informality (for emerging countries). We report in this regression the percentage change in wage-per-hour remuneration from being a woman, from working in a green job, and from the interaction of being a woman working in a green job. Table 5 shows the coefficient results of the regression (2).<sup>11</sup> We find there is a statistically significant positive interaction between green jobs and women across countries. In other words, we find evidence that green jobs disproportionately increase the wages of women, suggesting a smaller gender pay gap after controlling for several other important variables.

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<sup>11</sup>In Annex C, we perform further robustness exercises controlling for more granular sector NAICS 2-digit level, and results remain broadly unchanged.

Table 5: Mincerian Regression Analysis: Gender and Job’s Greenness

	Brazil	Colombia	United Kingdom	United States
Female ( $\beta_c^f$ )	-0.22*** (0.004)	-0.14*** (0.006)	-0.11*** (0.007)	-0.15*** (0.001)
Green ( $\beta_c^g$ )	0.04*** (0.003)	0.09*** (0.006)	0.04*** (0.010)	0.11*** (0.001)
Female×Green ( $\beta_c^{fg}$ )	0.02** (0.008)	0.07*** (0.011)	0.07*** (0.018)	0.05*** (0.002)
Age	Yes	Yes	Yes	Yes
Age-Squared	Yes	Yes	Yes	Yes
Age-Cohort	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes
Married	Yes	Yes	Yes	Yes
Married-Female	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes
Informality	Yes	Yes	No	No
Observations	565,452	119,801	30,028	5,563,305
R-squared	0.393	0.539	0.393	0.291

**Note:** Statistical significance of coefficients is described by \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Numbers in parentheses depict the standard deviation of coefficients. Data and statistics come from Pesquisa Nacional por Amostra de Domicílios Contínua (Brazil, 2022), Gran Encuesta Integrada de Hogares (Colombia, 2022), Labor Force Survey (UK, 2022), and American Community Survey (US, 2019). Sample is restricted to employed individuals. Age controls are cohorts of five years from 15 to 64 years old. Education controls are less than elementary finished, elementary finished, high school finished, and college finished or more. Sector controls are main ISIC aggregates. Green is measured by having a green job index at least of 5%.

In the first row, the coefficient  $\beta_c^f$  quantifies the percentage reduction in hourly wages that women encounter in non-green jobs. Our findings reveal a statistically significant and consistent disparity, with women earning lower hourly wages than men across all countries. This gender wage gap ranges from 11 percent in the UK to 14 percent in Colombia. Moving to the second row, the coefficient  $\beta_c^g$  measures the percentage increase in hourly wages that men experience when transitioning to green jobs. We observe a statistically significant positive premium associated with green employment for men across all countries. Specifically, the green wage ranges from 4 percent in Brazil to 11 percent in the US. Finally, the third

row presents the coefficient  $\beta_c^{fg}$ , reflecting the interaction effect on hourly wages that women experience from working in green jobs. We find a statistically significant and additional positive impact for women engaged in green employment. Specifically, this supplementary effect amounts to 2 percentage points in Brazil, 5 percentage points in the US, and 7 percentage points in Colombia and the UK, confirming our prior results that women in green job experience a lower gender pay gap.<sup>12</sup>

## 6 The Future of Work

In the concluding section of our analysis, we study the potential implications of advancements in AI on green and polluting jobs. Furthermore, we examine how AI’s proliferation could influence wage dynamics within green occupations.

### 6.1 Data and Methodology

To investigate the potential impact of AI on green jobs, we employ the methodology proposed by Felten et al. (2021) for identifying jobs with higher exposure to AI. Additionally, we utilize the approach of Pizzinelli et al. (2023) to distinguish between occupations likely to benefit from AI integration and those at risk of adverse effects. This analysis begins by briefly describing the methodologies employed.

The study by Felten et al. (2021) examines the intersection between human abilities and AI capabilities, drawing on occupational ability descriptions documented by Center (2021). The researchers developed the AI Occupational Exposure (AIOE) index by correlating 10 AI applications—including image recognition and text creation—with 52 occupational abilities, such as oral comprehension and inductive reasoning. This correlation is facilitated through a crowd-sourced matrix that assigns relevance scores to each pairing of AI application and ability. The AIOE index, normalized between zero and one, quantifies the relative exposure of occupations to AI, providing a nuanced measure of AI’s potential impact across different occupations.

Expanding the analysis to encompass the potential for complementarity with AI, Pizzinelli et al. (2023) find that such complementarity is determined by social, ethical, legal,

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<sup>12</sup>We perform a similar analysis focusing in the labor market returns from the polluting economy in Annex B. We find that overall, men receive a premium from polluting jobs, except in the United Kingdom. In addition, there is weak evidence for the polluting wage premium to be lower for women than for men. Lastly, the gender pay gap tends to be higher in polluting jobs than in their non-polluting counterparts. These statistics suggests that polluting jobs are better for men than women.



and technical factors that extend beyond occupational exposure to AI. Utilizing the O\*NET repository's classification, Pizzinelli et al. (2023) examine work contexts and job zones to deepen their analysis. Work context is defined as the physical and social factors impacting the nature of work, whereas job zones categorize occupations based on shared requirements for education, training, and experience. Through this framework, Pizzinelli et al. (2023) identify 11 out of 57 work contexts as most relevant in terms of AI's likelihood to either replace human activities or to be implemented under supervision. These are aggregated into 5 groups following O\*NET's own classification. The selection of these specific contexts is based on societal choices regarding AI application modalities and the anticipated need for advanced supporting technologies (e.g., automation and robots) to fully integrate AI within specific work environments.

O\*NET defines job zones as clusters of occupations that share comparable requirements in terms of education, job training, and professional experience necessary for the role. The reasoning behind focusing on job zones lies in the idea that occupations demanding more extended periods of professional development are better positioned to incorporate AI knowledge into their training programs, thereby preparing future workers with complementary skills.

The 11 chosen contexts and the job zones are organized into six components as follows:

a. Communication: 1) Face-to-Face, 2) Public Speaking. As AI tools advance, they will significantly improve communication aspects. Yet, the nuances of in-person interactions and public speaking mainly stay within the human realm. Social norms may favor maintaining these advanced communication skills in professional settings. For instance, a trial lawyer's persuasive rhetoric or a physician's empathetic diagnosis explanation demonstrates a depth of understanding and flexibility AI cannot completely emulate.

b. Responsibility: 3) Responsibility for outcomes, 4) Responsibility for others' health. AI has the potential to revolutionize various fields by enhancing critical tasks. In healthcare, for example, AI aids in predicting patient risks and monitoring vital signs in critical conditions. However, these tasks require human supervision for accountability, ethical decisions, and compassion.

c. Physical Conditions: 5) Outdoors Exposed, 6) Physical Proximity. Roles requiring outdoor work and close physical interaction, like those of firefighters or construction workers, demand adaptability and sensory sharpness that remain crucial across various professions,

and are likely to preserve human dominance.

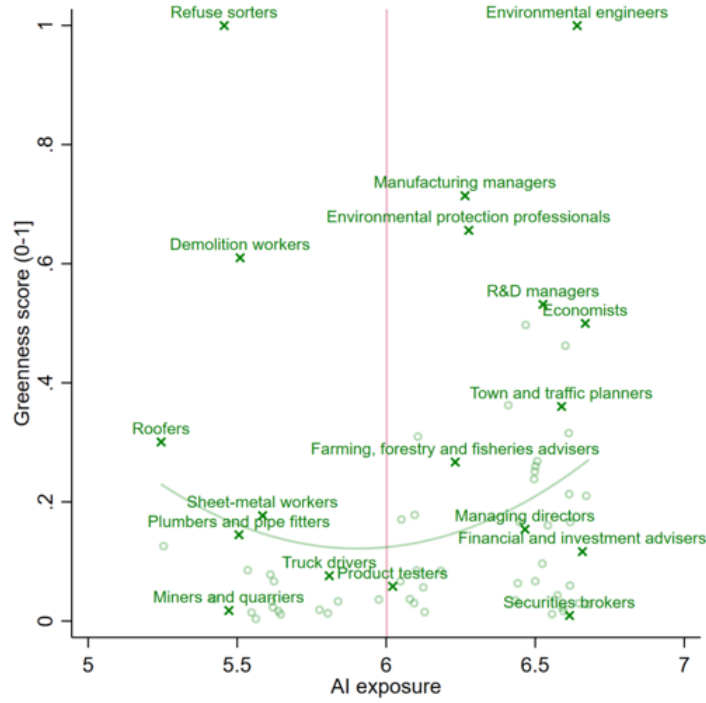
d. Criticality: 7) Consequence of Error, 8) Freedom of Decisions, 9) Frequency of Decisions. As AI automates decision-making, the need for human oversight becomes clearer, especially in roles like air traffic controllers or critical care nurses, where judgment combines data and instinct for quick, unforeseen decisions. While AI offers helpful data and advice to lower errors and quicken decision times, human insight remains indispensable.

e. Routine: 10) Degree of Automation (inverted scale), 11) Unstructured vs Structured Work. Jobs focused on routine tasks have been more susceptible to automation. While AI introduces new forms of innovation, occupations with repetitive functions remain at higher risk of being automated. Conversely, jobs requiring creativity and less structure need more sophisticated AI for independent operation. For example, customer service roles with standardized responses might be automated, whereas fashion designers, engaging in complex creative processes, might use AI for trend analysis or design assistance but remain less automatable due to their unstructured nature.

f. Skills: 12) Job Zones. AI technologies require expertise for effective operation and decision-making from AI insights. Occupations needing high education and extensive training are better positioned to incorporate AI-related skills into their programs. This approach primarily targets future workers still acquiring skills but also applies to professions with ongoing training (e.g., researchers' summer schools, managers' executive courses, practical training, conferences).

The score for each of the six groups is determined by calculating the arithmetic mean of the individual context scores. Subsequently, the complementary index is computed as the arithmetic mean of these six components, and normalized within the 0 to 1 range. Details can be found in Pizzinelli et al. (2023).

Figure 12: Occupations by AI Exposure and Greenness



Note: The figure plots greenness score and AI exposure (measured by Felten et al. (2021)’s occupation-level AI exposure (AIOE)) by ISCO-08 occupations. The red reference line shows the median of AI exposure. The green curve denotes the quadratic fitted curve.

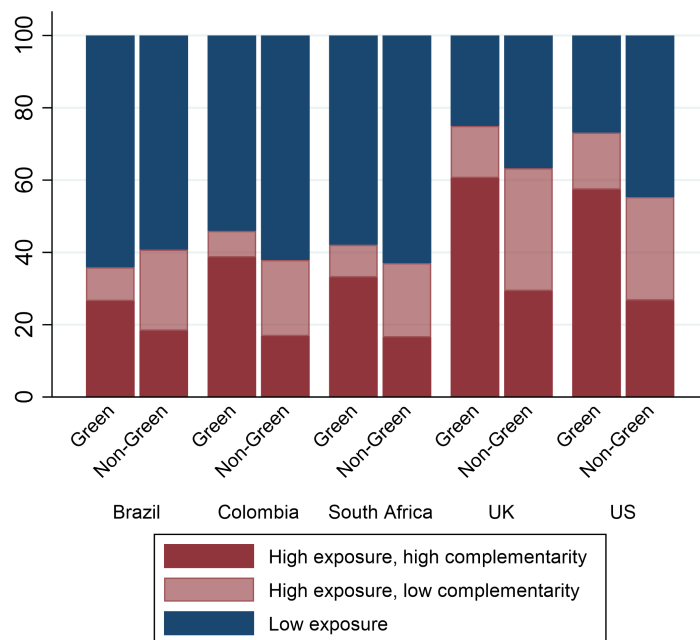
Figure 12 maps the greenness score and Felten et al. (2021)’s occupation-level AI exposure onto ISCO-08 occupations. The figure exhibits a U-shaped relationship, indicating that jobs with the lowest and highest AI exposure levels have the highest greenness scores. Environmental engineers have a green score close to one and are also highly exposed to AI. Conversely, refuse sorters also with a green score close to one have a much lower exposure score. The vast majority of jobs are clustered below the 50 percent greenness score and above median exposure.

## 6.2 AI and Greenness Results

This section commences with an examination of the relationship between green and non-green jobs in the context of AI integration, specifically focusing on the dynamics between high-exposure and high-complementarity jobs, high-exposure-low complementarity jobs, and low-exposure jobs. These classifications are established by assessing if the exposure to AI and its complementarity in an occupation are higher or lower than the median values re-

spectively. Occupations characterized by high exposure and low complementarity are the most susceptible to potential negative impacts from the broad adoption of AI. Conversely, those with high exposure and high complementarity stand to gain the most from AI integration. Figure 13 delineates the distribution of green and non-green jobs within these three AI-related categories.

Figure 13: Green jobs and AI

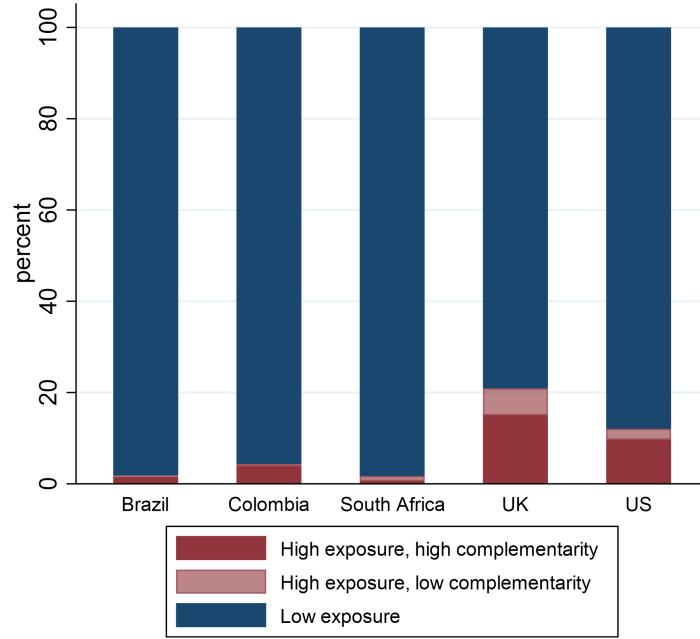


Note: The figure shows the employment distribution of workers working green and non-green jobs in high-exposure and high-complementarity occupations, high-exposure and low-complementarity occupations, and low-exposure occupations.

Upon closer examination of the employment distribution based on AI exposure and greenness in our selected countries, a notable trend emerges. In AEs, most green and non-green jobs are highly exposed to AI, with approximately 75 percent of green jobs falling into the high exposure category compared to around 60 percent for non-green jobs. In contrast, EMs show a more equal distribution, with both green and non-green jobs having lower AI exposure, each around 40 percent.

In addition, there is a common pattern in AEs and EMs, despite the difference in AI exposure across countries. In all countries, green jobs exhibit greater complementarity with AI compared to non-green jobs. This pattern is particularly evident in the UK and the US, where roughly 60 percent of green jobs have high complementarity with AI, contrasting with only 30 percent of non-green jobs. In AEs, non-green jobs, while highly exposed to AI, lack the same level of complementarity. In EMs, both types of jobs have similar AI exposure, yet

Figure 14: Polluting Jobs and AI



Note: The figure shows the employment distribution of workers working green and non-green jobs in high-exposure and high-complementarity occupations, high-exposure and low-complementarity occupations, and low-exposure occupations.

green jobs consistently demonstrate higher complementarity (around 35 percent) compared to non-green jobs (below 20 percent).

In contrast, polluting jobs across all examined countries generally show a significantly lower exposure to AI, as depicted in Figure 14. In the UK, which registers the highest AI exposure within the polluting job sector, only 21 percent of polluting job workers are exposed to AI. This is in stark comparison to 75 percent in green jobs and 66 percent in neutral jobs. In EMs, the exposure to AI among polluting jobs is notably minimal, with less than 5 percent of such jobs being AI-exposed. Both in AEs and EMs, AI exposure is primarily seen in jobs characterized by high levels of complementarity rather than substitution. The limited AI exposure in polluting jobs can be attributed to their predominantly manual and non-cognitive nature.

### 6.3 AI, Green Jobs and Gender

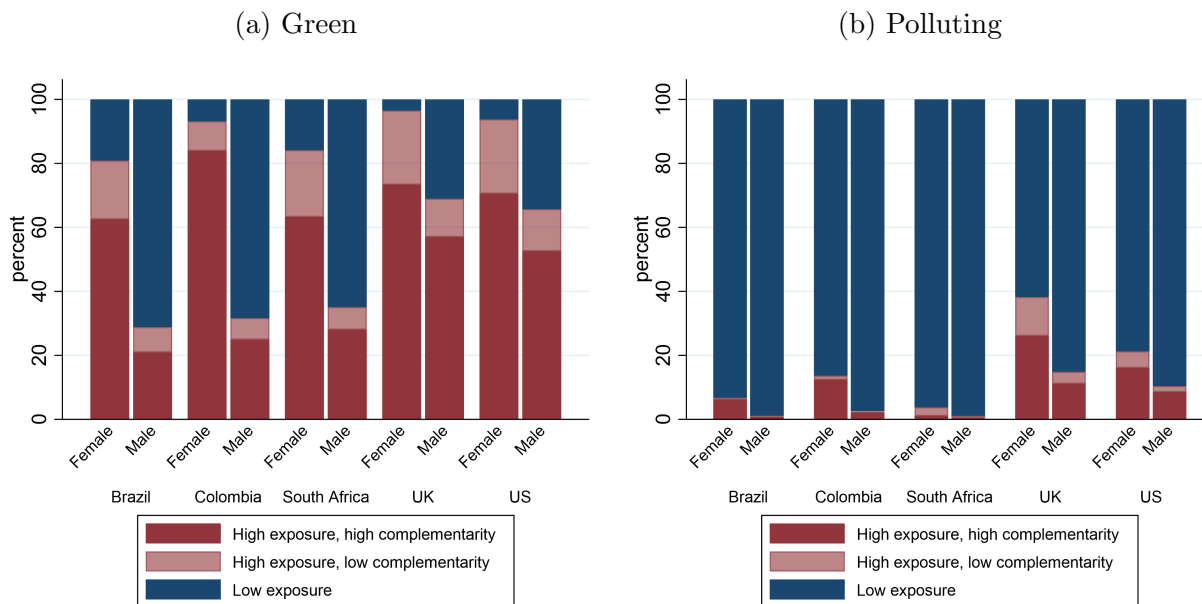
We shift our focus to exploring the nexus of green jobs, AI, gender, and education, beginning with an analysis of the gender dimension. Figure 15a presents data on AI exposure and complementarity within green jobs, distinguished by gender. The findings across our sampled countries reveal that women in green jobs face higher levels of AI exposure than their

male counterparts, a trend consistent with observations made by Pizzinelli et al. (2023) for the broader job market. This gender disparity within green jobs tends to be less pronounced in AEs compared to EMs. In EMs, the lower AI exposure among men in green jobs is attributed to the prevalence of manual occupations, whereas in AEs, green jobs are more often in professional, technical, or managerial categories, which inherently involve greater AI exposure.

Despite facing increased exposure to AI in green jobs, women might be poised to reap greater benefits from the widespread adoption of AI. Across all countries examined, women hold a larger proportion of employment in professional and technical occupations, as shown in Figure 3 and 2, which present substantial potential for complementarity with AI. While managerial positions, typically dominated by men, showcase the highest complementarity with AI, the proportion of such roles is considerably smaller compared to the abundance of professional and technical occupations.

Figure 15b reveals that, despite polluting occupations showing lower overall exposure to AI compared to green jobs, women exhibit higher exposure and greater complementarity with AI than men within polluting jobs. Similar patterns emerge across genders for both polluting and green jobs, where women holding more cognitive roles are more exposed and complementary to AI. In contrast, men are predominantly employed in manual and non-cognitive roles, particularly within polluting occupations.

Figure 15: Employment Share by AI Exposure and Gender

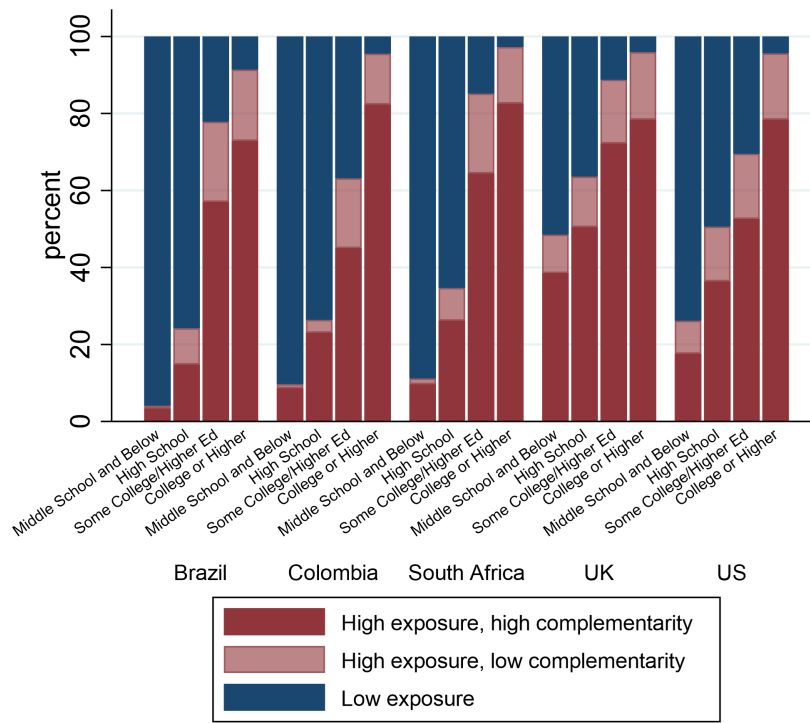


Note: The figures plot the distribution of employment by gender and AI exposure and complementarity in green and polluting jobs.

Examining education, Figure 16 indicates that individuals with a college-level education in green jobs face higher AI exposure compared to those with lower educational levels. Around 90 percent of college-educated workers, across most countries, are engaged in occupations with high AI exposure, primarily in professional roles. Conversely, those without a high school diploma are largely involved in elementary occupations, resulting in significantly lower AI exposure. In Brazil, Colombia, and the US, fewer than 20 percent of these workers find themselves in high-exposure occupations. In the UK and South Africa, over 40 and 30 percent of workers with only a middle school education or less, respectively, are in high-exposure occupations.

Analyzing the potential for complementarity in green jobs, it becomes evident that, across all countries in our sample, most green jobs exposed to AI stand to benefit, irrespective of education level. Across all countries, over 70 percent of college educated workers in green jobs could benefit from the high AI complementarity with their occupations. Workers with middle school are typically in occupations that are less exposed to AI but among those that are exposed, the majority stands to benefit from it as well.

Figure 16: Employment Share of Green Jobs by Education and AI Exposure



Note: The figure plots the distribution of employment in green occupations by AI exposure conditional on workers' education.

## 6.4 Green Jobs, AI, and Labor Market Returns

Employing a regression analysis similar to the one shown in Section 5, we examine the interaction between green jobs and the exposure to AI.<sup>13</sup> We expand regression equation (2):

$$\begin{aligned}
\ln(w_{i,t,c}) = & \alpha_c + \beta_c^f \cdot \mathcal{I}[\text{Female}_{i,t,c} = 1] + \beta_c^g \cdot \mathcal{I}[\text{Green}_{i,t,c} = 1] \\
& + \beta_c^l \cdot \mathcal{I}[\text{HELCC}_{i,t,c} = 1] + \beta_c^h \cdot \mathcal{I}[\text{HEHC}_{i,t,c} = 1] \\
& + \beta_c^{fg} \cdot \mathcal{I}[\text{Female}_{i,t,c} = 1] \cdot \mathcal{I}[\text{Green}_{i,t,c} = 1] \\
& + \beta_c^{fl} \cdot \mathcal{I}[\text{Female}_{i,t,c} = 1] \cdot \mathcal{I}[\text{HELCC}_{i,t,c} = 1] \\
& + \beta_c^{fh} \cdot \mathcal{I}[\text{Female}_{i,t,c} = 1] \cdot \mathcal{I}[\text{HEHC}_{i,t,c} = 1] \\
& + \beta_c^{gl} \cdot \mathcal{I}[\text{Green}_{i,t,c} = 1] \cdot \mathcal{I}[\text{HELCC}_{i,t,c} = 1] \\
& + \beta_c^{gh} \cdot \mathcal{I}[\text{Green}_{i,t,c} = 1] \cdot \mathcal{I}[\text{HEHC}_{i,t,c} = 1] \\
& + \beta_c^{fgl} \cdot \mathcal{I}[\text{Female}_{i,t,c} = 1] \cdot \mathcal{I}[\text{Green}_{i,t,c} = 1] \cdot \mathcal{I}[\text{HELCC}_{i,t,c} = 1] \\
& + \beta_c^{fgh} \cdot \mathcal{I}[\text{Female}_{i,t,c} = 1] \cdot \mathcal{I}[\text{Green}_{i,t,c} = 1] \cdot \mathcal{I}[\text{HEHC}_{i,t,c} = 1] \\
& + \gamma_c \cdot X_{i,t,c} + \varepsilon_{i,t,c}
\end{aligned} \tag{3}$$

where  $w_{i,t,c}$  is the wage-per-hour remuneration,  $\mathcal{I}[\text{Female}_{i,t,c} = 1]$  is a woman indicator,  $\mathcal{I}[\text{Green}_{i,t,c} = 1]$  is a green job indicator,  $\mathcal{I}[\text{HELCC}_{i,t,c} = 1]$  is a job with a high-exposure and low-complementarity (HELCC) indicator to AI,  $\mathcal{I}[\text{HEHC}_{i,t,c} = 1]$  is a job with a high-exposure and high-complementarity (HEHC) indicator to AI, and  $X_{i,t,c}$  is a control vector that encompasses age, age-squared, age-cohorts, education, male and female marriage status, sectors, and informality (for emerging countries). We report in this regression the percentage change in wage-per-hour remuneration from being a woman, from working in a green job, from working in a high-exposure and low-complementarity to AI job, from working in a high-exposure and high-complementarity to AI job, and from the double and triple cross effects among them. Table 6 shows the coefficient results of regression (3).

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<sup>13</sup>As in Section 5 the analysis does not consider South Africa



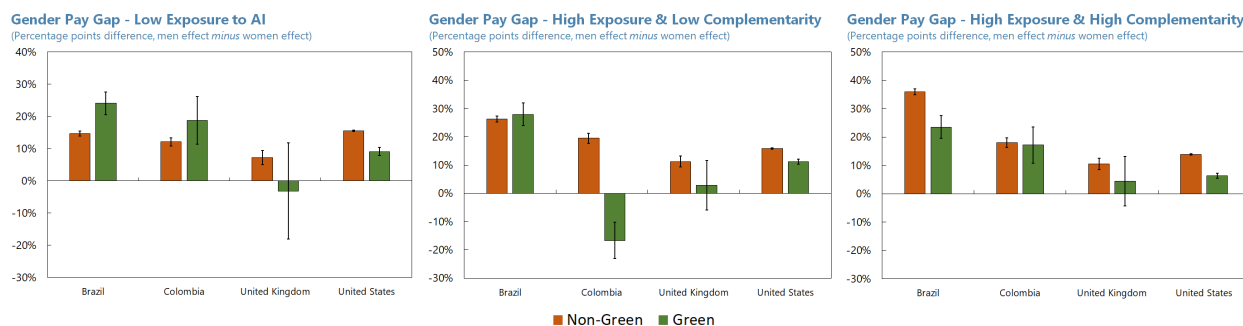
Table 6: Mincerian Regression Analysis: Gender, Greenness, and AI exposure

	Brazil	Colombia	United Kingdom	United States
Female ( $\beta_c^f$ )	-0.15*** (0.004)	-0.12*** (0.007)	-0.07*** (0.011)	-0.16*** (0.001)
Green ( $\beta_c^g$ )	0.04*** (0.004)	0.07*** (0.007)	0.06*** (0.019)	0.11*** (0.002)
HELC ( $\beta_c^l$ )	0.07*** (0.004)	0.17*** (0.007)	0.11*** (0.012)	0.11*** (0.001)
HEHC ( $\beta_c^h$ )	0.10*** (0.004)	0.16*** (0.008)	0.00 (0.013)	0.18*** (0.001)
Female×Green ( $\beta_c^{fg}$ )	-0.09*** (0.018)	-0.07* (0.037)	0.10 (0.077)	0.06*** (0.006)
Female×HELC ( $\beta_c^{fl}$ )	-0.12*** (0.005)	-0.07*** (0.009)	-0.04*** (0.014)	0.00** (0.002)
Female×HEHC ( $\beta_c^{fh}$ )	-0.21*** (0.005)	-0.06*** (0.009)	-0.03** (0.014)	0.02*** (0.002)
Green×HELC ( $\beta_c^{gl}$ )	-0.03** (0.012)	-0.29*** (0.021)	-0.02 (0.032)	-0.11*** (0.003)
Green×HEHC ( $\beta_c^{gh}$ )	0.02** (0.008)	0.11*** (0.013)	0.01 (0.023)	-0.03*** (0.002)
Female×Green×HELC ( $\beta_c^{fgl}$ )	0.08*** (0.027)	0.43*** (0.050)	-0.02 (0.089)	-0.02** (0.008)
Female×Green×HEHC ( $\beta_c^{fgh}$ )	0.22*** (0.021)	0.07* (0.041)	-0.04 (0.080)	0.01 (0.007)
Age	Yes	Yes	Yes	Yes
Age-Squared	Yes	Yes	Yes	Yes
Age-Cohort	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes
Married	Yes	Yes	Yes	Yes
Married-Female	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes
Informality	Yes	Yes	No	No
Observations	565,452 <sup>38</sup>	119,801	30,028	5,563,305
R-squared	0.395	0.543	0.399	0.296

We continue to find a statistically significant positive green jobs premium across countries for men, ranging between 4 and 11 percent for workers in low-exposure to AI jobs. For men working in jobs that are exposed to AI, we find the green premium to still be positive in most countries for men in HEHC occupations. In contrast, for men in HELC occupations, the green premium does not exist or even becomes negative in Colombia. This solidifies and provides more granularity about our first main result from Section 5 on the existence of green wage premium

Moving to women in green jobs, we plot in Figure 17 the gender pay gap for women working in green and non-green jobs and their interaction with AI.

Figure 17: Gender Pay Gap across Job’s Greenness and AI Exposure and Complementarity



**Note:** The charts show the linear combinations of the regression coefficients capturing the gender pay gap for the exposure and complementarity with AI and job’s greenness. Green bars represent the gender pay gap in green jobs and orange bars represent the gender pay gap in non-green jobs. The black interval represents the 95 percent confidence interval for the coefficient estimates from the regression analysis.

Figure 17 reveals that the gender pay gap is lower in green jobs that have more potential to complement AI. We start by analyzing the gender pay gap among women in occupations with low exposure to AI. We find that in Brazil and Colombia, the gender pay gap in green jobs is larger than in their non-green counterparts, a difference of 9 and 7 percentage points, respectively. Meanwhile, in United Kingdom and United States, the gender pay gap in low-exposed green jobs is smaller than in their non-green counterparts, a difference ranging between 7 and 10 percentage points.<sup>14</sup> Second, we analyze jobs with high exposure and low complementarity to AI. We find that only Colombia and the US have a

<sup>14</sup>It is important to note the gender pay gap difference between green and non-green jobs for Colombia and the UK are not statistically significant.

statistically significant difference between green and non-green jobs. In both countries we can assert green jobs have a lower gender pay gap than their non-green counterpart, a difference of 36 and 5 percentage points, respectively. Lastly, we study jobs with high-exposure and high-complementarity with AI. We find that overall the gender pay gap in green jobs is lower than their non-green counterpart. Brazil and the United States are the countries in which the differences in gender pay gaps are statistically significant, at 12 and 8 percentage points respectively.

## 7 Conclusion

This paper examines the features of green employment, leveraging a task-based framework to distinguish green jobs based on their contribution to environmental sustainability. By employing established methodologies that categorize jobs as “green” or “non-green” according to their tasks, we use intensity measures and binary definitions to identify green jobs, contrasting these with polluting jobs across both AEs and EMs. Our analysis of microdata from five economies reveals a similar proportion of workers in green jobs, yet it also uncovers significant disparities in occupational distribution. In AEs, green jobs are predominantly found among high-skilled workers and cognitive occupations, whereas in EMs, many green jobs are manual positions within the construction sector, reflecting differences in the structures of labor markets in AEs and EMs. Our findings indicate that green jobs are disproportionately held by men in both AEs and EMs, reflecting the underrepresentation of women in STEM fields and managerial roles, among college-educated workers. Additionally, we observe a green wage premium and narrower gender pay gaps in green jobs. In conclusion, our investigation into the effects of AI on green jobs indicates a promising synergy: many green jobs are well-positioned to harness the benefits of AI advancements. Furthermore, our study highlights the potential dynamic between the green wage premium and AI integration. Specifically, we show that green jobs with a greater capacity to leverage AI exhibit a reduced gender pay gap, which may help to attract more women to green occupations.

This study identifies significant gaps in the literature and emphasizes the need for further investigation and policy actions, especially concerning the expansion of green jobs and the promotion of gender equality within these positions. There is a pressing need for further studies that examine the resilience and expansion potential of green jobs over time, and factors that could potentially enhance or (or make disappear) the current green jobs’ wage premium, in particular for women. Additionally, the evolving impact of AI on the green economy, especially regarding wage structures and the gender gap, calls for in-depth analysis

to inform policies that promote an inclusive, equitable green job market. Addressing these areas is essential for realizing the full potential of the green economy, ensuring it benefits from diverse talents and contributes to a more sustainable economy.

## References

- Albanesi, Stefania, António Dias da Silva, Juan F Jimeno, Ana Lamo, and Alena Wabitsch**, “New Technologies and Jobs in Europe,” Technical Report DP18220, CEPR Discussion Papers 2023.
- Bergant, Katherina, Rui Mano, and Ippei Shibata**, “From polluting to green jobs: A seamless transition in the U.S.?” Working Paper 2022/129, International Monetary Fund, Washington, DC 2022.
- Black, Mr Simon, Ian WH Parry, and Karlygash Zhunussova**, *Is the paris agreement working? a stocktake of global climate mitigation*, International Monetary Fund, 2023.
- Blau, Francine D and Lawrence M Kahn**, “The gender pay gap: Have women gone as far as they can?,” in “Inequality in the United States,” Routledge, 2020, pp. 345–362.
- Bluedorn, John, Niels-Jakob Hansen, Diaa Noureldin, Ippei Shibata, and Marina M Tavares**, “Transitioning to a greener labor market: Cross-country evidence from microdata,” *Energy Economics*, 2023, p. 106836.
- Bohringer, Christoph, Andreas Keller, and Edwin van der Werf**, “Are green hopes too rosy? Employment and welfare impacts of renewable energy promotion,” *Energy Economics*, 2013, *36*, 277–285.
- Bowen, A., K. Kuralbayeva, and E.L. Tipoe**, “Characterising green employment: the impacts of ‘greening’ on workforce composition,” *Energy Economics*, 2018, *72*, 263–275.
- Briggs, Joseph and Devesh Kodnani**, “The Potentially Large Effects of Artificial Intelligence on Economic Growth,” *Global Economics Analyst*, 2023.
- Center, O\*NET**, “Green Occupations,” National Center for O\*NET Development 2021.
- Consoli, G., A. Marin, A. Marzucchi, and F. Vona**, “Do green jobs differ from non-green jobs in terms of skills and human capital?,” *Research Policy*, 2016, *45* (5), 1046–1060.
- Dierdorff, Erich C., Jennifer J. Norton, Donald W. Drewes, Christina M. Kroustalis, David Rivkin, and Phil Lewis**, “Greening of the World of Work: Implications for O\*NET-SOC and New and Emerging Occupations,” National Center for O\*NET Development 2009.
- Eloundou, Tyna, Sam Manning, Pamela Mishkin, and Daniel Rock**, “Gpts are gpts: An early look at the labor market impact potential of large language models,” 2023.

- Felten, Ed, Manav Raj, and Robert Seamans**, “How will Language Modelers like ChatGPT Affect Occupations and Industries?,” 2023.
- Felten, Edward, Manav Raj, and Robert Seamans**, “Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses,” *Strategic Management Journal*, 2021, 42 (12), 2195–2217.
- Funk, Cary and Kim Parker**, “Diversity in the STEM workforce varies widely across jobs,” Technical Report, Pew Research Center 2018.
- Gmyrek, Pawel, Janin Berg, and David Bescond**, “Generative AI and Jobs: A global analysis of potential effects on job quantity and quality,” *ILO Working Paper*, 2023, 96.
- Hammond, Alicia, Eliana Rubiano Matulevich, Kathleen Beegle, and Sai Krishna Kumaraswamy**, “The Equality Equation: Advancing the Participation of Women and Girls in STEM,” Technical Report, World Bank 2020.
- Hartley, Peter R., III Medlock Kenneth B., Ted Temzelides, and Xinya Zhang**, “Local employment impact from competing energy sources: Shale gas versus wind generation in Texas,” *Energy Economics*, 2015, 49, 610–619.
- Köhler, Timothy and Haroon Bhorat**, “Wages and wage inequality during the COVID-19 Pandemic in South Africa,” Technical Report, University of Cape Town, Development Policy Research Unit 2023.
- OECD**, *Job Creation and Local Economic Development 2023: Bridging the Great Green Divide*, Paris: OECD Publishing, 2023.
- OECD**, *OECD Employment Outlook 2023: Artificial Intelligence and the Labour Market*, OECD Publishing, Paris, 2023.
- , *Reporting Gender Pay Gaps in OECD Countries 2023*.
- O\*NET Center**, “Green Occupations,” <https://www.onetonline.org/> 2021. Accessed: [Insert date of access here].
- , “Green Task Statements,” [https://www.onetcenter.org/dictionary/22.0/excel/green\\_task\\_statements.html](https://www.onetcenter.org/dictionary/22.0/excel/green_task_statements.html) 2021.
- Petrongolo, Barbara and Maddalena Ronchi**, “Gender gaps and the structure of local labor markets,” *Labour Economics*, 2020, 64, 101819. European Association of Labour Economists, 31st annual conference, Uppsala Sweden, 19-21 September 2019.

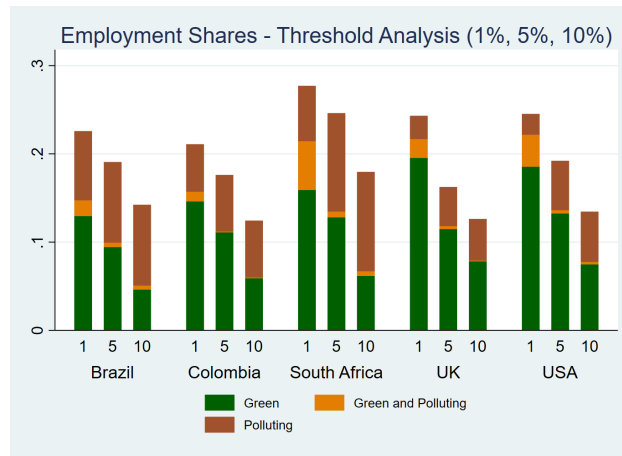
- Pizzinelli, Carlo, Augustus Panton, Marina Mendes Tavares, Mauro Cazzaniga, and Longji Li**, “Labor Market Exposure to AI: Cross-Country Differences and Distributional Implications,” 2023.
- Suassay, Aurelien, Misato Sato, Francesco Vona, and Layla O’Kane**, “Who’s fit for the low-carbon transition? Emerging skills and wage gaps in job ad data,” Technical Report, Centre for Climate Change and Economic Policy, London, UK 2022. Working Paper 406.
- Upton, Gregory B. and Yu Han**, “Labor demand shocks and earnings and employment differentials: evidence from the U.S. shale oil and gas boom,” *Energy Economics*, 2021, *102*, 105462.
- Vona, Francesco, Giovanni Marin, and Davide Consoli**, “Measures, Drivers, and Effects of Green Employment: Evidence from US Local Labor Markets, 2006–2014,” *Journal of Economic Geography*, 2019, *19* (5), 1021–1048.
- , – , – , **and David Popp**, “Environmental Regulation and Green Skills: An Empirical Exploration,” *Journal of the Association of Environmental and Resource Economists*, 2018, *5* (4), 713–753.
- Walker, Reed**, “The transitional costs of sectoral reallocation: evidence from the clean air act and the workforce,” *Quarterly Journal of Economics*, 2013, *128* (4), 1787–1835.
- Webb, Michael**, “The impact of artificial intelligence on the labor market,” 2020.

# A Additional Figures

This annex is structured into five distinct sections, each focusing on various facets of worker distribution within four primary categories: green, polluting, green and polluting, and neutral jobs. The first section, Annex A.2, presents employment distribution by 1-digit ISCO-08 occupation codes for Colombia, South Africa, and the US. The second section, Annex A.4, details employment distribution across occupation types, further segmented by gender. The third section, Annex A.5, examines the age profile of workers.

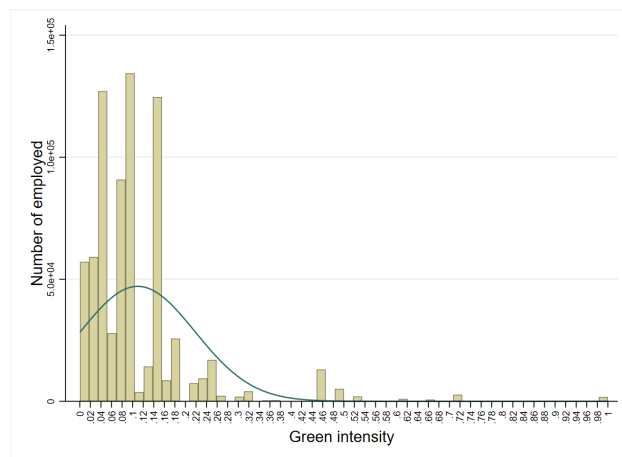
## A.1 Threshold Analysis

Figure A.1: Threshold Analysis



Note: The figure plots the employment shares of green, polluting and green and polluting jobs within each country according to the 1 percent, 5 percent and 10 percent thresholds.

Figure A.2: Threshold Analysis

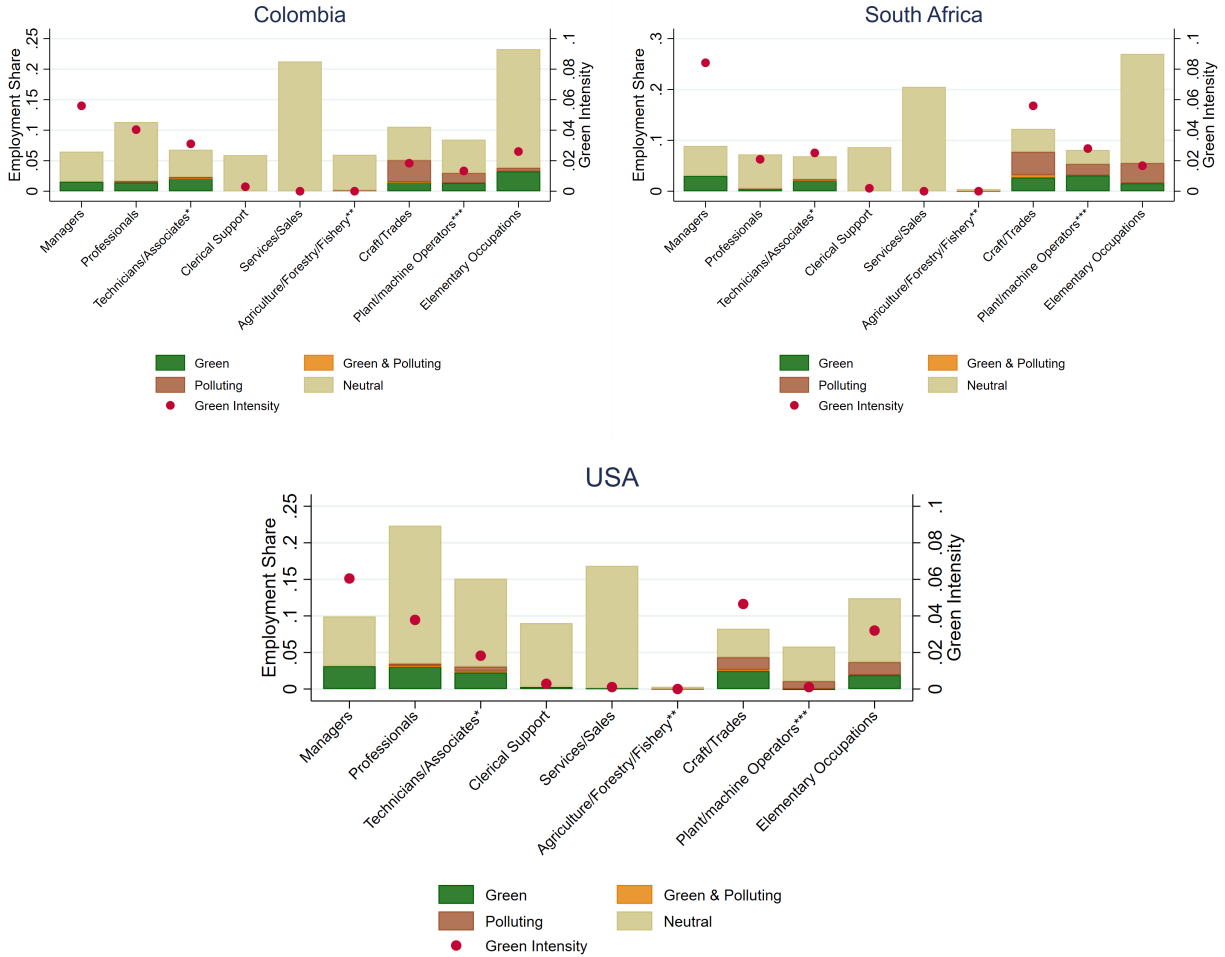




Note: The histogram plots the frequency of employment in green jobs by green intensity in the US economy.

## A.2 Green Jobs by Occupation Selected Countries

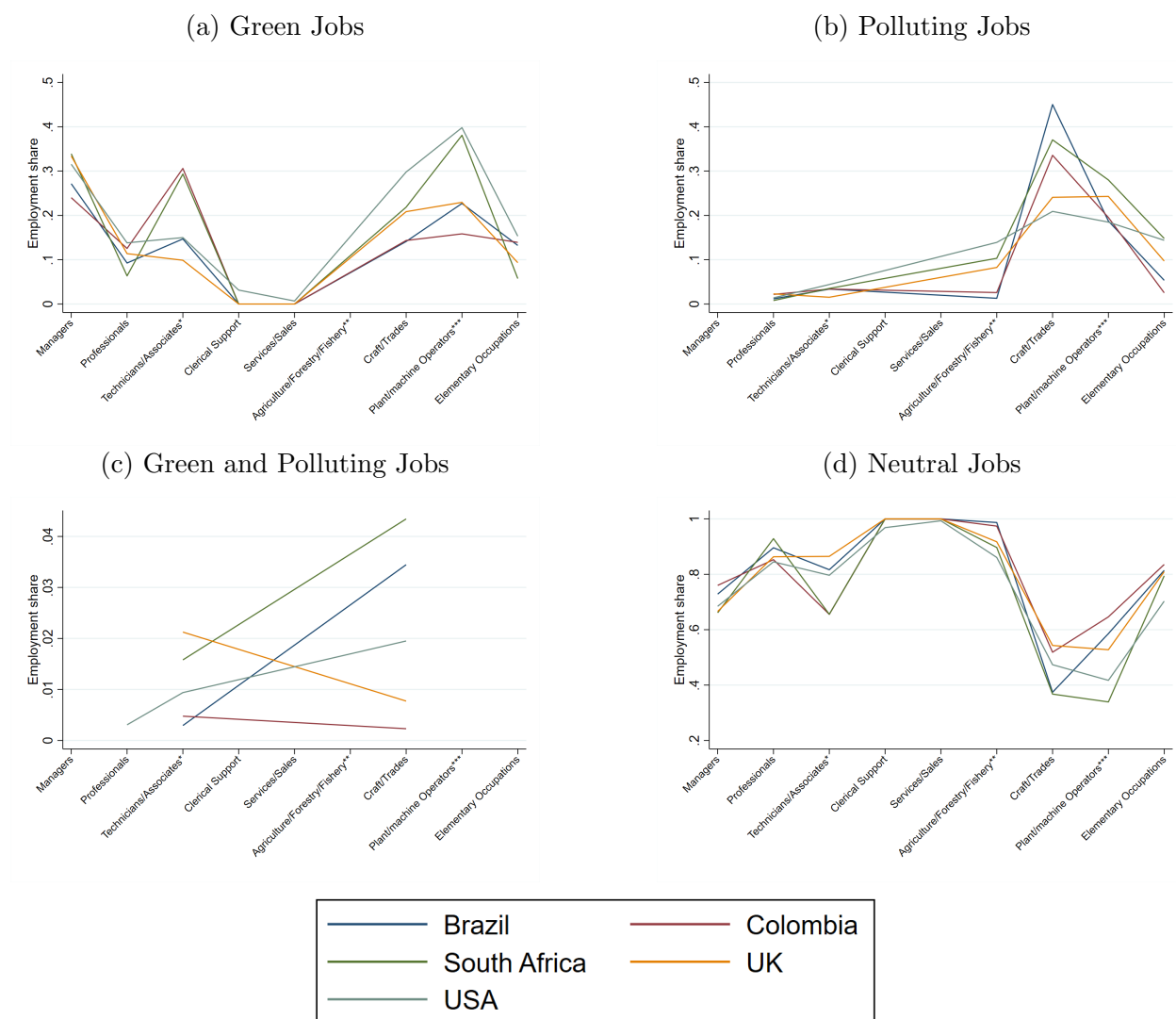
Figure A.3: Employment Share by Occupation Type



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. \*: Technicians and associate professionals. \*\*: Skilled agricultural, forestry and fishery workers. \*\*: Plant and machine operators and assemblers.

### A.3 Green Job Types by Occupation Group

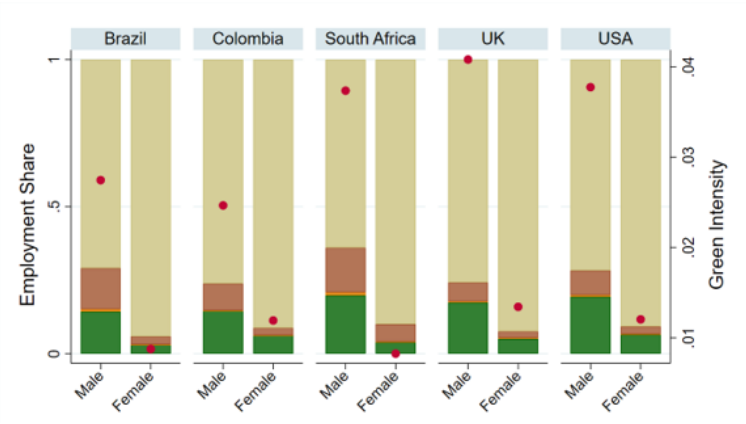
Figure A.4: Distribution of employment across occupations by Job Type



Note: The figure plots the share of employment for green, pollution-intensive, green and polluting and neutral jobs for each country across the 1-digit ISCO-08 occupation codes. \*: Technicians and associate professionals. \*\*: Skilled agricultural, forestry and fishery workers. \*\*: Plant and machine operators and assemblers.

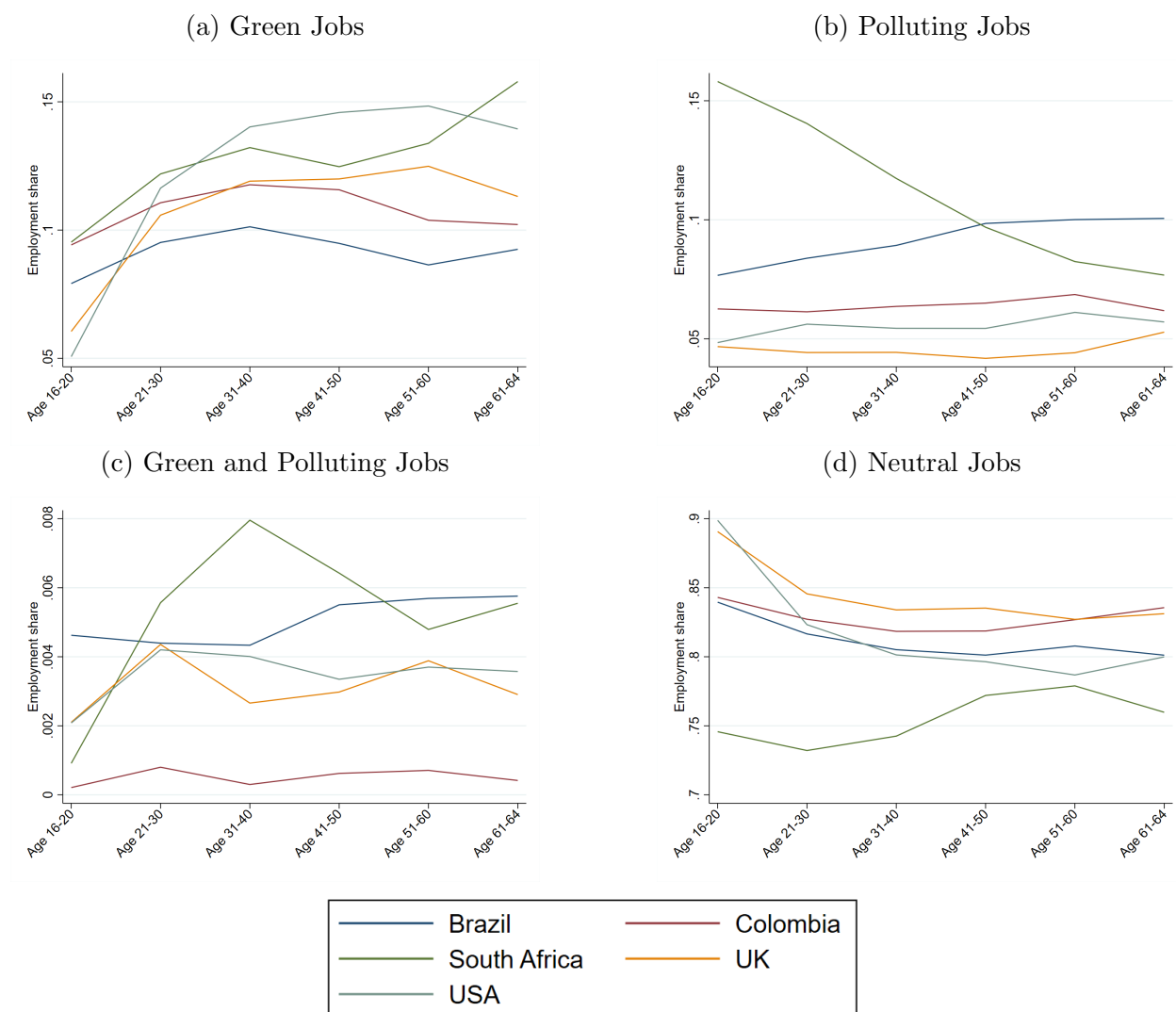
### A.4 Green Jobs by Gender

Figure A.5: Employment Share by Gender



Note: The figure plots the distribution of employment in green, pollution-intensive, green and pollution-intensive, and neutral occupations by gender.

## A.5 Employment Share of Green Job Types by Age Cohort



Note: The figure plots the share of employment for green, pollution-intensive, green and polluting and neutral jobs for each age of cohort in each country.

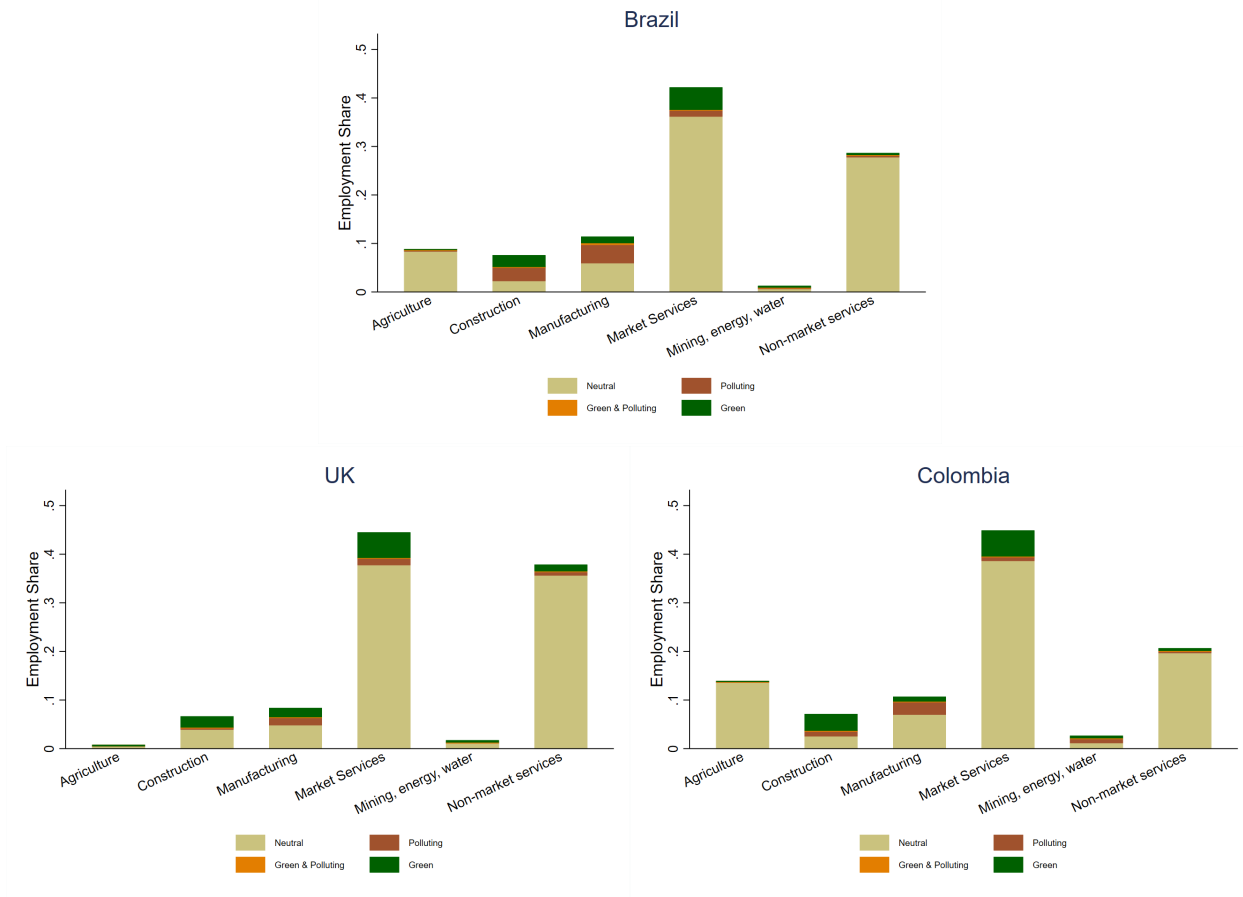
## A.6 Sector Decomposition

To further explore this finding, we break down the employment distribution of men and women across green and brown jobs, as well as by economic sectors. Figure ?? plots the employment share by the International Standard Industrial Classification of All Economic Activities (ISIC) sectors on the x-axis, and the gender distribution across green and brown jobs by color. Across all nations, female employment displays a higher concentration in market services (trade, transportation, accommodation, food, business, and administration)

and non-market services (public administration, health, social services, arts, entertainment, and household), with a majority in the latter. Male employment is more evenly dispersed across the economy. While men are also concentrated in market and non-market services, they also constitute the majority in agriculture, construction, manufacturing and mining, and energy and water sectors. Market and non-market services are largest labor market sectors across all countries, EMs have a relatively larger employment share in agriculture, which is also male dominated.

Examining the green and brown employment share distribution by ISIC sector, Figure ?? also shows that women, primarily concentrated in market services, have fewer green jobs within these sectors. Green jobs in market and non-market sectors are mostly managerial and professional roles, such as engineering professionals. In contrast, male green jobs demonstrate an equal distribution across construction, manufacturing, and market services. This pattern remains consistent across the surveyed countries. In Brazil, there is also a notable concentration of men in green jobs in brown sectors in construction and manufacturing. This is driven by the number of “Sheet metal workers” in the economy.

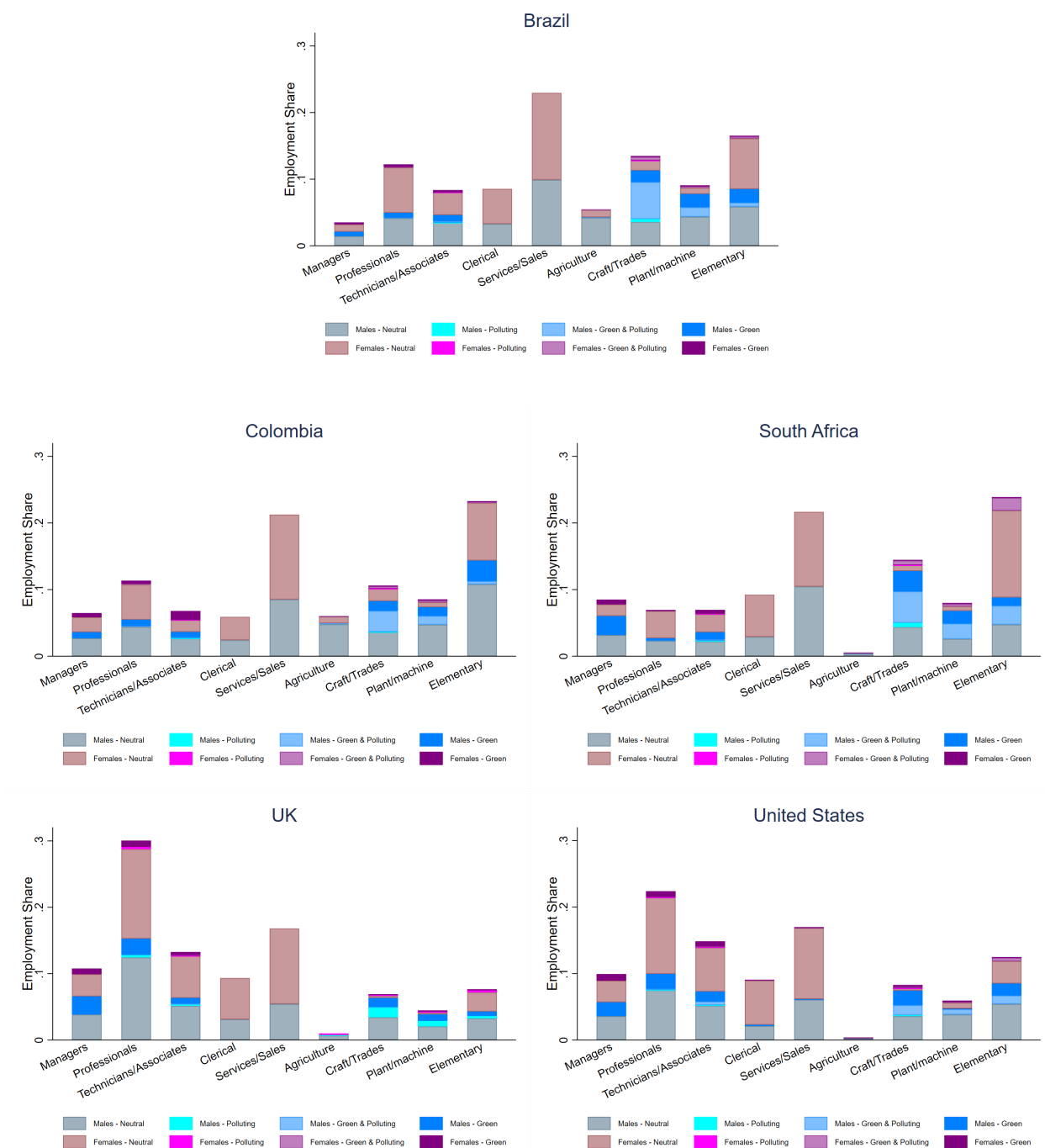
Figure A.7: Employment Share by ISIC Sector and Gender



Note: The figure plots the distribution of employment in green, pollution-intensive, green and pollution-intensive, and neutral occupations conditional on international industry sector.

## A.7 Occupational Category Decomposition

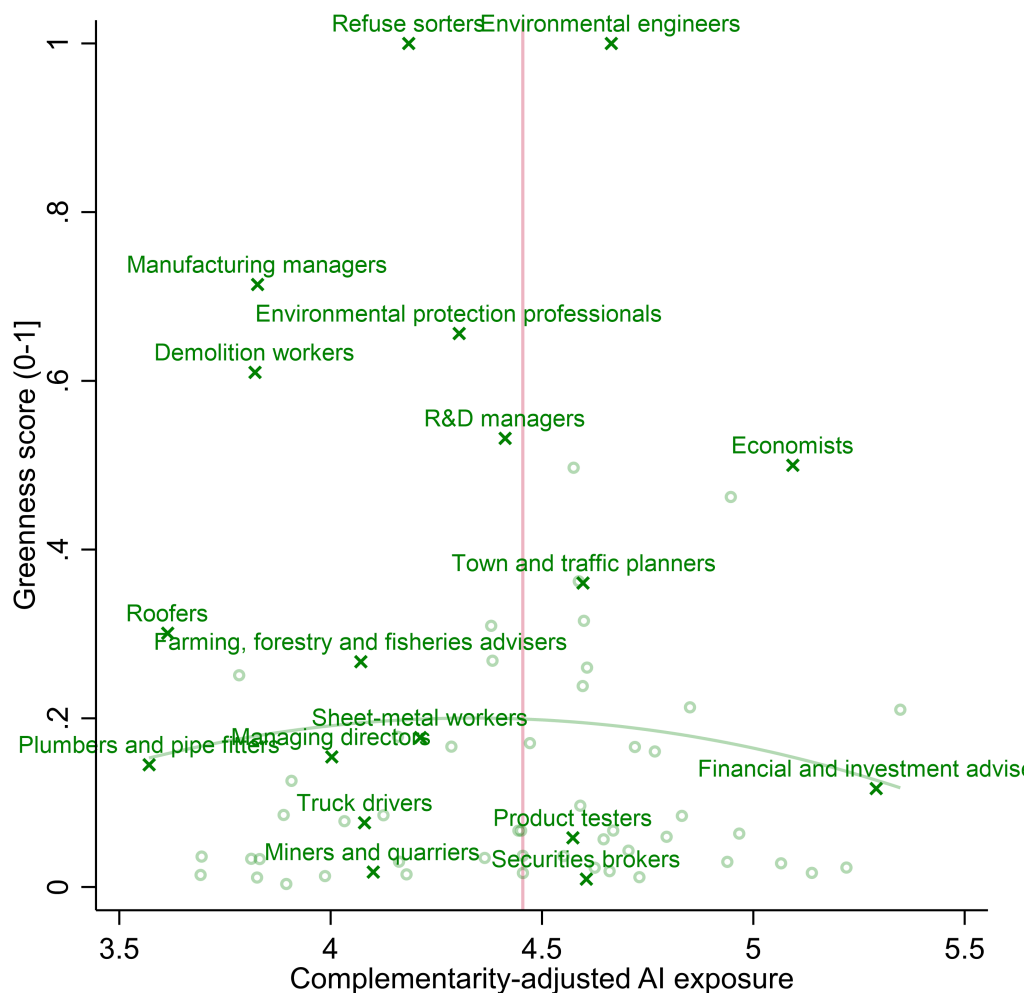
Figure A.8: Employment Share by ISCO Sector



Note: The figure plots the distribution of employment in green, pollution-intensive, green and pollution-intensive, and neutral occupations conditional on international occupation code.

## A.8 Occupations by Complementarity-Adjusted AI Exposure and Greenness

Figure A.9: Occupations by Complementarity-Adjusted AI Exposure and Greenness



Note: The figure plots greenness score and complementarity-adjusted AI exposure (C-AIOE) from Pizzinelli et al. (2023) by ISCO-08 occupations. The red reference line shows the median of C-AIOE. The green curve denotes the quadratic fitted curve.

A slightly inverted U-shaped curve is observed because some occupations, such as managerial roles, become less exposed after adjustments for complementarity, resulting in a higher number of jobs in the middle category.



## B Polluting Economy Labor Market Returns

In this section, we mirror our regression analysis in Section 5 results by focusing instead in polluting jobs. Specifically, we perform a Mincerian regression similar to (2) as

$$\begin{aligned} \ln(w_{i,t,c}) = & \alpha_c + \beta_c^f \cdot \mathcal{I}[\text{Female}_{i,t,c} = 1] + \beta_c^g \cdot \mathcal{I}[\text{Polluting}_{i,t,c} = 1] \\ & + \beta_c^{fg} \cdot \mathcal{I}[\text{Female}_{i,t,c} = 1] \cdot \mathcal{I}[\text{Polluting}_{i,t,c} = 1] + \gamma_c \cdot X_{i,t,c} + \varepsilon_{i,t,c} \end{aligned} \quad (4)$$

where  $w_{i,t,c}$  is the wage-per-hour remuneration,  $\mathcal{I}[\text{Female}_{i,t,c} = 1]$  is a woman indicator,  $\mathcal{I}[\text{Polluting}_{i,t,c} = 1]$  is a polluting job indicator, and  $X_{i,t,c}$  is a control vector that encompasses age, education, male and female marriage status, sectors, and informality (for emerging countries). We report in this regression the percentage change in wage-per-hour remuneration from being a woman, from working in a polluting job, and from the cross effect of being a woman working in a polluting job. Table C.1 shows the coefficient results of the regression (4). We find there is a statistically significant negative interaction between polluting jobs and women for Brazil and United States; for Colombia and United Kingdom the sign is not clear. In other words, we find weak evidence that polluting jobs disproportionately increase the wages of men, suggesting a larger gender pay gap after controlling for several other important variables.

Table B.1: Mincerian regression analysis over gender and job's pollution

	Brazil	Colombia	United Kingdom	United States
Female ( $\beta_c^f$ )	-0.22*** (0.004)	-0.15*** (0.006)	-0.11*** (0.007)	-0.15*** (0.001)
Pollution ( $\beta_c^g$ )	0.04*** (0.004)	0.05*** (0.008)	-0.05*** (0.015)	0.08*** (0.002)
Female×Polluting ( $\beta_c^{fg}$ )	-0.09*** (0.009)	-0.02 (0.016)	0.03 (0.029)	-0.05*** (0.003)
Age	Yes	Yes	Yes	Yes
Age-Squared	Yes	Yes	Yes	Yes
Age-Cohort	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes
Married	Yes	Yes	Yes	Yes
Married-Female	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes
Informality	Yes	Yes	No	No
Observations	565,452	119,801	30,028	5,565,956
R-squared	0.393	0.537	0.392	0.290

**Note:** Statistical significance of coefficients is described by \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Numbers in parentheses depict the standard deviation of coefficients. Data and statistics come from Pesquisa Nacional por Amostra de Domicílios Contínua (Brazil, 2022), Gran Encuesta Integrada de Hogares (Colombia, 2022), Labor Force Survey (UK, 2022), and American Community Survey (US, 2019). Sample is restricted to employed individuals. Age controls are cohorts of five years from 15 to 64 years old. Education controls are less than elementary finished, elementary finished, high school finished, and college finished or more. Sector controls are main ISIC aggregates. Polluting is measured by having a pollution index at least of 5%.

## C Robustness on Labor Market Returns

Table C.1: Mincerian regression analysis over gender and job's greenness using NAIC

	Brazil	Colombia	United Kingdom	United States
Female ( $\beta_c^f$ )	-0.25*** (0.004)	-0.16*** (0.006)	-0.08*** (0.008)	-0.13*** (0.001)
Green ( $\beta_c^g$ )	0.09*** (0.003)	0.14*** (0.006)	0.11*** (0.010)	0.12*** (0.001)
Female×Green ( $\beta_c^{fg}$ )	0.13*** (0.008)	0.18*** (0.012)	0.07*** (0.019)	0.11*** (0.002)
Age	Yes	Yes	Yes	Yes
Age-Squared	Yes	Yes	Yes	Yes
Age-Cohort	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes
Married	Yes	Yes	Yes	Yes
Married-Female	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes
Informality	Yes	Yes	No	No
Observations	565,452	119,801	30,028	5,563,305
R-squared	0.370	0.490	0.340	0.266

**Note:** Statistical significance of coefficients is described by \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Numbers in parentheses depict the standard deviation of coefficients. Data and statistics come from Pesquisa Nacional por Amostra de Domicilios Continua (Brazil, 2022), Gran Encuesta Integrada de Hogares (Colombia, 2022), Labor Force Survey (UK, 2022), and American Community Survey (US, 2019). Sample is restricted to employed individuals. Age controls are cohorts of five years from 15 to 64 years old. Education controls are less than elementary finished, elementary finished, high school finished, and college finished or more. Sector controls are standard NAICS industry classification. Green is measured by having a green job index at least of 5%.