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Measuring Green Jobs:

A New Database for Latin America and Other Regions

Hernan Winkler, Vincenzo Di Maro, Kelly Montoya, Sergio Olivieri, Emmanuel Vazquez [*]

Abstract

A growing body of literature investigates the labor market implications of scaling up "green" policies. Since most of this literature is focused on developed economies, little is known about the labor market consequences for developing countries. This paper contributes to filling this gap by providing new stylized facts on the prevalence of green occupations and sectors across countries at varying levels of economic development. Green occupations are defined using the Occupational Information Network, and green sectors are those with relatively lower greenhouse gas emissions per worker. The paper offers an initial assessment of how the implementation of green policies—aimed at expanding green sectors and strengthening the relative demand for green skills—may affect workers in developing economies. It finds that the share of green jobs is strongly correlated with the level of gross domestic product per capita across countries. When controlling for unobserved heterogeneity, a 1 percent increase in gross domestic product per capita is associated with 0.4 and 4.1 percentage point increases in the shares of new and emerging, and enhanced skills green jobs, respectively. The paper then focuses on Latin America and finds that only 9 percent of workers have a green job with respect to both occupation and sector. The findings show that within countries, workers with low levels of income and education are more likely to be employed in non-green sectors and occupations, and to lack the skills for a greener economy. This evidence suggests that complementary policies are needed to mitigate the potential role of green policies in widening income inequality between and within countries.

Keywords: Green Jobs, Green Sectors, Climate Change, Labor Markets, Structural Transformation.

JEL Codes: Q5, Q52, Q56, J01, J21,

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1. Introduction

There is a growing body of literature investigating the labor market consequences of scaling up "green" policies.[1] However, most of the evidence is focused on the labor market implications for developed economies, and little is known about the consequences of greener growth on jobs for developing countries.[2] While rich countries account for a disproportionate share of Greenhouse Gas Emissions (GHGE; see IPCC, 2022), developing economies are expected to experience a disproportionate increase in GHGE in the future (Black et al., 2022). In addition, policies to promote a greener growth strategy may induce a skill-biased shift in labor demand, potentially creating bottlenecks in developing countries with lower stocks and adaptability of skills. This shift would raise concerns about the transition path of displaced workers to new jobs in the green economy.

This paper contributes to this literature by developing a new dataset on green occupations for 120 countries. It describes new statistics on green occupations across countries at different levels of economic development. This offers an initial picture of how the availability (or scarcity) of green occupations can affect the implementation of green policies and their impact on the labor market. The paper then focuses on Latin America and Caribbean (LAC) countries to provide more granular insights into the relationship between green occupations, green sectors, and the socio-economic profile of green job holders.[3]

Green occupations are measured following the "Green Economy" program developed by the Occupational Information Network (O*NET).[4] It considers three types of occupations: new occupations that are emerging directly because of green policies ("*new and emerging*"), existing occupations that are expected to experience changes in the tasks they entail ("*enhanced skills*"), and existing occupations that will not change substantially but that will be in higher demand ("*increased demand*"). A methodological contribution of this paper is to develop a mapping of the O*NET classification of green occupations into the 4-digit International Standard Classification of Occupations (ISCO)-08 taxonomy.

Using detailed occupational tabulations (2-digit ISCO-08) from labor force surveys for 120 countries from 2011 to 2020,[5] the paper finds that, on average, 21.4 percent of employment is in green occupations, and

[1] A broad definition of green policies includes all policies to remove barriers to green, clean, and resilient growth (see Awe, 2012).
[2] Some exceptions include the 2011 UNEP ILO Green Jobs report. More recently, see the 2018 ILO Greening with Jobs report and 2021 K4D FDCO Creating Green Jobs in Developing Countries report. See also Timilsina (2022) for a discussion of related issues.
[3] See also Alfonso et al. (2022) for a recent analysis of green jobs in LAC.
[4] O*NET is a database developed by the U.S. Department of Labor on occupational information for the U.S. workforce (see https://www.onetcenter.org/overview.html).
[5] Data is available for each year in the period 2012-2019 for a set of 47 countries.

that 1.8, 10.3, and 9.3 percent are the shares of employment in “new and emerging,” “enhanced skills” and “increased demand” categories, respectively. The paper then investigates the links between green jobs and income between countries, to understand if the labor market adjustment to a greener economy is expected to be more demanding in poorer countries. When comparing countries in the latest year of available data, the results show that the share of green jobs is, in fact, lower in poorer countries, but there are substantial differences across types of green jobs. The association with income levels is very strong for “new and emerging” and “enhanced skills” occupations, but weaker for “increased demand” ones. A fixed-effects regression confirms these strong associations.

The second part of the paper asks the following question: if countries were to implement policies that penalize GHGE (such as a carbon tax, a carbon border adjustment, or banning certain forms of energy production), which jobs would be more at risk? To answer this question, the paper estimates the occupational structure of sectors of economic activity according to their GHGE levels per worker.[6] Then it classifies sectors within each country as green and non-green according to whether they are above or below the sector median GHGE level in each country. It is important to emphasize that this definition of “greenness” does not include other important dimensions such as the potential for transformation through the adoption of green technologies. Combining the green job and the sector classification, four groups of workers are defined: (i) Green occupations in green sectors (GOGS); (ii) Green occupations in non-green sectors (GONS); (iii) Non-green occupations in green sectors (NOGS), and (iv) Non-green occupations in non-green sectors (NONS). Green sectors would be less vulnerable to an increase in the cost of carbon. As a result, workers in green occupations in such sectors would face the lowest risk of displacement and highest re-employment likelihood in a greener economy in case of job loss. In contrast, workers with non-green occupations in non-green sectors would face the highest labor market vulnerability in terms of both job-loss risk and re-employment opportunities.

Using data from countries in Latin America and the Caribbean (LAC)—because of better availability of granular occupation data at the ISCO08 2-digit level—we analyze the relationship between green occupations and sectors. The first finding is that the concentration of employment in non-green occupations and non-green sectors – i.e. the most vulnerable group during a green transition – is

[6] The focus on GHGE implies that the paper focuses on mitigation, rather than adaptation, in defining green sectors. We note here that this is not the only way green sectors can be defined. For instance, an alternative definition of sectors that considers more prominently the adaptation angle would define green sectors not only based on the level of emissions, but also on the potential to create green jobs and/or foster green technologies in the longer run. Examples of sectors that would be affected by this alternative definition include water management and waste management.

significant in several LAC countries. Around 90 percent of workers in each country with available data have a job in either a non-green sector or a non-green occupation. Non-green sectors account for a large share of jobs, from 37 percent in Argentina to 59 percent in Guatemala, Bolivia, and Honduras. Most workers with green occupations are in a non-green sector (about 60 percent of them in most countries), which suggests that high-emission sectors could find some of the needed skills for the transition already in the labor force they occupy. It is important to highlight the very high concentration of non-green occupations in a high-emission sector such as agriculture—about 90 percent or more in most LAC countries.

The dynamics of green occupations and sectors also offer important insights. The share of green occupations has been remarkably constant over the last decade (i.e. between 2010 and 2019) in LAC. The share of non-green jobs in non-green sectors and occupations fell slightly from 35 to 34 percent during that period. In addition, we implement a decomposition of changes in GHGE per worker in between- and within-sector components. GHGE per worker increased between 2005 and 2018 in seven large LAC countries, mostly driven by an increase in GHGE per worker within sectors. In contrast, the reallocation of workers from relatively high GHGE sectors—i.e. agriculture and industry—to relatively low GHGE sectors—e.g. utilities, transport, and Information and Communication Technologies (ICT)—contributed to partially mitigate the increase driven by the within-sector changes. This decomposition illustrates some of the implications of the process of structural transformation on the green economy, whereby increasing energy intensity tends to make the economy less green, but the reallocation of workers away from agriculture and manufacturing towards services tends to "green" the economy (assuming everything else remains the same).

The paper also investigates the profile of green job holders. Overall, green occupations are more prevalent for males and residents of urban areas. Total employment (including green and non-green occupations) in green sectors is higher for females and more educated workers. Green occupational shares do not vary much by informality status or size of the employer firm. Still, a large share of informal workers is concentrated in the non-green occupation and sector group, which can be considered the most vulnerable during a transition. Likewise, poorer workers (those in the lowest income quintiles) are concentrated in this most vulnerable group. This is consistent with the fact that green jobs are linked to higher wages.

The rest of this paper is structured as follows. Section 2 discusses the definition of green jobs, the methodology to generate the categories of green jobs and sectors considered in this paper and describes the data. Section 3 presents cross-country patterns of green jobs, patterns of green occupations and sectors, and the profile of green job holders in LAC. Section 4 discusses some caveats of the study and presents some robustness checks. Finally, section 5 draws some conclusions.

2. Methodology and Data

Green occupations

There are different definitions of green jobs. This paper uses the Occupational Information Network (O*NET)[7] classification of occupations developed by Dierdorff et al. (2009, 2011) to define green and non-green jobs.[8] Dierdorff et al. (2009) argue that the first step to classifying jobs as green or non-green is to define the green economy, which they consider involving economic activities related to reducing the use of fossil fuels, decreasing pollution and GHGE, improving energy efficiency, increasing recycling and adopting renewable forms of energy. Considering this, the "greening" of occupations takes place when the growth of the green economy *increases the demand for existing occupations, shapes the work and worker requirements needed for occupational performance, or generates unique work and worker requirements*.

The classification is based on the US 2010 Standard Occupational Classification (SOC) System. It provides a list of 1,110 occupations, 204 of which are identified as green and divided into three mutually exclusive categories: Green Increased Demand (64 occupations), Green Enhanced Skills (62 occupations), and Green New and Emerging (78 occupations). Table 1 shows the definition of each group of occupations with examples of jobs falling into each category. The rest of the listed occupations (906) are considered non-green and represent jobs that are not affected directly by the greening of the economy.

[7] See also the Appendix for more detailed information on the data sources used in this paper.

[8] In contrast, ILO (2018) defines green jobs based on whether "they reduce the consumption of energy and raw materials, limit GHGE, minimize waste and pollution, protect, and restore ecosystems and enable enterprises and communities to adapt to climate change. In addition, green jobs have to be decent". Decent jobs are defined as "opportunities for women and men to obtain decent and productive work in conditions of freedom, equity, security and human dignity" (ILO, 1999). However, this definition combines several dimensions such as the tasks involved in the job, the "greenness" of the economic sector or firm, as well as characteristics of the job not clearly linked to the green economy (for example, social security benefits or wage levels). This paper does not follow ILO's approach because its goal is to investigate the implications of the greening of the economy (based on the "greenness" of sectors of economic activity) on workers according to their green skills or tasks. Instead of using the "decency" of a job to characterize it as green or non-green, this paper explores the characteristics of jobs related to such dimensions (e.g., wage levels, informal status, etc.) according to their vulnerability to the greening of the economy (i.e., by whether they are in sectors with a high level of emissions and/or have the green skills needed in the new economy).

Table 1 – Green occupation categories

Green job category	Definition	Examples
Increased Demand Occupations	Occupations that already exist. They may face increased demand with an expanding green economy. While their work context may change, the tasks and skills they use will not.	Carpenters and welders that will be required in the construction of new energy-efficient buildings or agricultural workers needed for more organic farming.
Enhanced Skills Occupations	Occupations that already exist. A growing green economy may or may not increase the demand for these occupations, but it would affect the type of tasks or skills required.	Construction inspectors, agricultural technicians, and architects. Workers in these jobs may need to learn how to use new materials or adhere to new energy-efficient building codes.
New and Emerging Occupations	The "purest" forms of green jobs. These occupations emerge because of the green economy creating the need for new and unique work and worker requirements. As such, these occupations emerged more recently.	Wind energy managers, climate change analysts, or water resource specialists.

Source: Own elaboration based on O*NET database and Dierdorff et al. (2009, 2011).

This paper uses the International Standard Classification of Occupations (ISCO) or its adaptations to classify occupations, instead of O*NET. Previous studies have mapped the O*NET-SOC 2010 classification of green occupations into the latest ISCO-08 taxonomy to allow for more straightforward cross-national comparisons of green occupations (Hogarth, 2011; Sofroniou and Anderson, 2021). However, their mappings are produced at the ISCO three-digit level at best. More importantly, their methodologies are based on a dichotomic definition of green jobs, in which a whole ISCO category is considered either green or non-green. This paper maps the O*NET-SOC classification of green occupations into the most detailed four-digit ISCO-08 taxonomy using a probabilistic instead of a dichotomic approach. Specifically, the paper uses data on total employment at the 2-digit level ISCO for 120 countries from circa 2001 to circa 2020 (676 country-year observations). Since each ISCO code may have several O*NET-SOC occupations associated with it (not all necessarily green), it would be misleading to consider a whole ISCO occupation as green or non-green based on whether the number of O*NET-SOC associated occupations are primarily green or non-green. Therefore, instead of constructing a binary classification, the paper estimates the share of employment within an ISCO-08 category that corresponds to O*NET-SOC occupations considered green and then considers this share as the probability that an occupation with that ISCO code is green. Since the O*NET-SOC classification is based on the US structure of employment, employment shares are based on U.S. estimates, which are obtained from the 2018 Occupational Employment and Wage Statistics (OEWS) published by the U.S. Bureau of Labor Statistics.[9]

The O*NET-SOC 2010 codes are linked to their corresponding four-digit ISCO-08 codes using the U.S. Bureau of Labor Statistics correspondence table between SOC 2010 Codes and ISCO-08 categories. This correspondence, as well as the employment estimates in the OEWS, is available at the six-digit level of the SOC. At the same time, the O*NET-SOC 2010 classification of green occupations is presented with an eight-digit level of detail. Since 12.7 percent of the 6-digit SOC occupations are associated with more than one 8-digit SOC, the total number of workers in a 6-digit SOC occupation was equally distributed among the 8-digit SOC codes associated with it.[10] As an example, Table 2 shows how the share of green occupations was constructed for a specific ISCO code, representing the probability that an individual with an occupation in this ISCO code has a green job.

Table 2 – Example of the methodology used to estimate the probability for an ISCO-08 code to represent a green occupation.

ISCO-08 Code	O*NET-SOC 2010 Code	Green Job?	2010 SOC Code	Number of US workers	"Simulated" Number of US workers	Share of Green occupations
1234	17-2061.01	Yes	17-2061	10	5	5% =5/(5+5+40+50)
1234	17-2061.02	No	17-2061		5	
1234	17-2063.00	No	17-2063	40	40	
1234	17-2064.00	No	17-2064	50	50	

Source: Own elaboration based on O*NET database (Green Occupations & O-NET-SOC 2010 Occupation List), U.S. Bureau of Labor Statistics correspondence between SOC 2010 Codes and ISCO-08 categories, and 2018 Occupational Employment and Wage Statistics.

[9] Estimates for 2018 are used since it is the most recent year in which survey data was collected using the 2010 SOC classification. After this year, estimates use a hybrid of the 2010 and 2018 SOC systems, which makes the link with the O*NET-SOC 2010 classification of green jobs less direct. While employment estimates from this program are not perfect since they exclude self-employment, they are the only source of publicly available data with information at the 6-digit level of the SOC.

[10] This assumption had to be used in other cases in which more information was not available: 1) for six SOC occupations at six-digits for which U.S. employment data was only available at five digits (in these cases employment at 5-digits was equally distributed among the SOC occupations at six-digits corresponding to the 5-digit code); 2) to estimate employment in some of the six cases in which the SOC classification from O*NET and OEWS were different: SOC 211018 in OEWS (Substance Abuse, Behavioral Disorder, and Mental Health Counselors) was equally distributed between SOC 211011 (Substance Abuse and Behavioral Disorder Counselors) and 211014 (Mental Health Counselors) from O*NET; SOC 512028 in OEWS (Electrical, Electronic, and Electromechanical Assemblers, Except Coil Winders, Tapers, and Finishers) was equally distributed between SOC 512022 and 512023 from O*NET (Electrical and Electronic Equipment Assemblers + Electromechanical Equipment Assemblers); SOC 512098 in OEWS (Assemblers and Fabricators, All Other, Including Team Assemblers) was equally distributed between SOC 512092 and 512099 from O*NET (Team Assemblers + Assemblers and Fabricators, All Other).

Green sectors

As mentioned above, this paper uses the level of GHGE per worker to classify sectors into green and non-green categories. To calculate the level of GHGE by sector, this paper follows the methodology proposed by Alcantara (2007), Alcantara et al. (2010), and Bin Su et al. (2013). This is because to account for the true 'greenness" of a sector, we should consider both the direct and indirect GHGE. For example, while the financial sector may have low levels of direct GHGE per worker, its total GHGE may be substantially higher once we consider its links with, for example, the utilities or transportation sectors. The methodology applies the Input-Output model proposed by Leontief, W. (1986) to a vector of emissions multiplier. The original Leontief model to calculate gross production has the following structure:

$$Y = [I - A]^{-1} f$$

Where Y corresponds to a column vector containing the level of gross production by economic sector, I is the identity matrix of order *n* corresponding to the *n*-sectors, A is an *n x n* matrix containing the technology coefficients for each included sector, and f is a column vector corresponding to the final demand for each economic sector.

An emission multiplier matrix is incorporated into the previous equation to calculate the level of emissions by sector. This matrix is diagonal and contains the number of emissions per production unit for each sector. The new equation for calculating emissions by sector has the following structure:

$$C = \hat{c}[I - A]^{-1} f$$

Where C corresponds to a column vector containing the level of emissions by economic sector, and $\hat{c}$ is a diagonal matrix containing the emissions multipliers for all sectors.

The level of emissions per worker by sector is estimated as the level of emissions divided by the number of workers aged 15 to 64 years in each sector. In this section, three primary sources of information are implemented to estimate GHGE per worker by sector: the Socioeconomic Database for Latin America and the Caribbean (SEDLAC),[11] the 2018 edition of the Organization for Economic Co-operation and Development (OECD) country-level Input-Output Tables (IOTs),[12] and the Climate Watch (CAIT) Historical

[11] SEDLAC is a database of harmonized socio-economic statistics constructed from the Latin American and Caribbean (LAC) household surveys. SEDLAC includes information from over 300 household surveys carried out primarily in 18 LAC countries for which a comparable income aggregate (for welfare analysis) can be created: Argentina, Bolivia, Brazil, Colombia, Costa Rica, Chile, Dominican Republic, Ecuador, El Salvador, Guatemala, Haiti, Honduras, Mexico, Nicaragua, Panama, Paraguay, Peru, and Uruguay. The SEDLAC database and project were jointly developed and are jointly maintained by CEDLAS (Universidad Nacional de La Plata) and The World Bank's LAC Team for Statistical Development (LAC TSD) in the Poverty and Equity Global Practice.

[12] Available in https://stats.oecd.org/Index.aspx?DataSetCode=IOTSI4_2018.

GHGE.[13] The OECD IOTs contain information about how each sector's gross production is distributed among all economic sectors (intermediate demand) and the final demand. The latter comprises households' domestic demand, non-profit institutions' domestic demand, government's domestic demand, capital formation, change in inventories, exports, and imports. The sector classification corresponds to 2-digits of the 4th revision of the International Standard Industrial Classification of Economic Activities (ISIC Rev. 4), with some sectors grouped according to their nature. This information generates the matrix of coefficients and the vector of final demand. The IOTs matrix has the structure described in Table 3: y_{ij} represents the demand from sector *j* for production of sector *i*, v_j represents the added value generated by sector *j*, and Y_j represents the gross production of sector *j*. Notice that the sum of the intermediate demand plus added value equals the sector's gross production. Then, the technology coefficients are calculated by dividing each sector's intermediate demand from a specific sector by that sector's gross production. In other words, each one of the technology coefficients represents the ratio y_{ij}/Y_j. In this paper, information about imports is not included in the final demand vector since they do not relate directly to the production process of each sector. Then, only domestic demand and exports are considered for the estimations.

Table 3 – Input-Output table structure

	Sector 1	***Sector 2***	...	***Sector n***	***Final demand***
Sector 1	y_{11}	y_{12}	...	y_{1n}	f_1
Sector 2	y_{21}	y_{22}	...	y_{2n}	f_2
⋮	⋮	⋮	⋮	⋮	⋮
Sector n	y_{n1}	y_{n2}	...	y_{nn}	f_n
Added Value (V)	v_1	v_2	...	v_n	
Gross product (Y)	Y_1	Y_2	...	Y_n	

Source: Own elaboration

The third source of information, the Climate Watch/CAIT series, contains information about the level of GHGE by industry and end-uses from 1990 to 2018, following the Intergovernmental Panel on Climate Change (IPCC) reporting framework. Table 4 presents the sectors included in CAIT and the activities they

[13] Available in https://www.climatewatchdata.org/ghg-emissions?end_year=2018&start_year=1990.

include according to the IPCC classification. This information builds the vector of emissions multipliers. Emissions from Land-use changes and International Bunkers are not considered since they do not clearly align with economic activities in the other classifications.

Table 4 – CAIT Sector Data

Sector / Subsector	Content	IPCC Category	Gas
Energy		1	CO_2
- Electricity & Heat	Electricity & Heat plants (fossil fuels) - Public plants (electricity, heat, CHP) - Autoproducers (electricity, heat, CHP) Other Energy industries (fossil fuels)	 1 A 1 a 1 A 1 A 1 b,c	 CO_2 CO_2 CO_2
- Manufacturing & Construction	Manufacturing & Construction (fossil fuels)	1 A 2	CO_2
- Transportation	Transportation (fossil fuels)	1 A 3	CO_2
- Other Fuel Combustion	Other sectors (fossil fuels) Biomass combustion Stationary and Mobile Sources	1 A 4 1 A 5 1 A 5	CO_2 CH_4, N_2O CH_4, N_2O
- Fugitive Emissions	Gas Venting/Flaring Oil & Natural Gas Systems Coal Mining Other Energy Sources	1 B 2c 1 B 2 1 B 1 1 B 1,2	CO_2 CH_4 CH_4 CH_4, N_2O
Industrial Processes	Cement Adipic and Nitric Acid Production Other Industrial non-Agriculture All Fluorinated Gases	2 A 1 2 B 2,3 2 2	CO_2 N_2O CH_4, N_2O HFC_5, PFC_5, SF_6
Agriculture	Enteric Fermentation Manure Management Rice Cultivation Agricultural Soils Other Agricultural Sources	4 A 4 B 4 C 4 D 4	CH_4 CH_4, N_2O CH_4 N_2O CH_4, N_2O
Land-Use Change & Forestry	Land Use Total (Forestry land, cropland, grassland, and biomass burning)	5	CO_2, CH_4, N_2O
Waste	Landfills (Solid Waste) Wastewater Treatment Human Sewage Other Non-Agricultural Sources (Waste and Other)	6 A 6 B 6 B 6 D	CH_4 CH_4 N_2O CH_4, N_2O
International Bunkers	Aviation Bunkers Marine Bunkers	1 A 3ai 1 A 3di	CO_2 CO_2

Source: CAIT-UNFCCC.

These three sources of information provide different sector classifications that cannot always be mapped to each other immediately. To properly identify sectors that can be used for the analysis, a new sector classification is created by first assigning each CAIT sector to a corresponding OECD sector and then grouping the data to match the SEDLAC's sector classification. This process produces a 14-sector classification. Table 5 presents the new cross-sector classification and the CAIT, OECD, and SEDLAC sectors included in each case.

Since the sum of the sector-level GHGE is lower than the national-level GHGE (both reported by CAIT), this paper assigns the difference to sectors without GHGE data in CAIT (e.g. financial intermediation) following these steps: (i) calculate the participation of these sectors in the national production; (ii) calculate a residue as the total country-level emissions (excluding land-use change, as explained above) minus the emissions for which the source is known (emissions from CAIT sectors); and (iii) assign each sector a level of emissions corresponding to their participation in national production times the country's residue of total emissions. We then use the sector-level GHGE from CAIT and the imputed GHGE for non-CAIT sector, as well as the IOT, to calculate the total emissions by sector (CAIT and non-CAIT).

Table 5 – Sector classification based on CAIT, OECD, and SEDLAC classifications

Sector	Included sectors CAIT	Included sectors OECD	Included sectors SEDLAC
Agriculture, hunting, forestry, and fishing	Agriculture, forestry, and fishing	Agriculture, forestry, and fishing	Agriculture, hunting and forestry Fishing
Mining and quarrying	Energy – Fugitive Emissions	Mining and extraction of energy producing products Mining and quarrying of non-energy producing products Mining support service activities	Mining and quarrying
Manufacturing, Construction & Industrial processes	Energy – Manufacturing & Construction Industrial Processes	Food products, beverages, and tobacco Textiles, wearing apparel, leather, and related products Wood and of products of wood and cork (except furniture) Paper products and printing Coke and refined petroleum products Chemicals and pharmaceutical products Rubber and plastics products Other non-metallic mineral products Manufacture of basic metals Fabricated metal products, except machinery and equipment Computer, electronic and optical products Electrical equipment Machinery and equipment n.e.c. Motor vehicles, trailers, and semi-trailers Other transport equipment Other manufacturing; repair and installation of machinery and equipment Construction	Manufacturing Construction
Electricity, gas, and water supply	Energy – Electricity & Heat Waste	Electricity, gas, water supply, sewerage, waste, and remediation services	Electricity, gas, and water supply
Wholesale and retail trade	-	Wholesale and retail trade; repair of motor vehicles	Wholesale and retail trade
Transport, storage, and communications	Energy – Transport	Transportation and storage	Transport, storage, and communications

		Publishing, audiovisual and broadcasting activities Telecommunications IT and other information services	
Hotels and restaurants	-	Accommodation and food services	Hotels and restaurants
Financial intermediation	-	Financial and insurance activities	Financial intermediation
Real estate, renting and business activities	-	Real estate activities Other business sector services	Real estate, renting and business activities
Public administration and defense	-	Public administration and defense; compulsory social security	Public administration and defense
Education	-	Education	Education
Health and social work	-	Human health and social work	Health and social work
Other community, social and personal service activities	Energy – Other Fuel Combustion	Arts, entertainment, recreation, and other service activities	Other community, social and personal service activities
Activities of private households as employers	-	Private households with employed persons	Activities of private households as employers

Source: CAIT, OECD, SEDLAC

As a quality check for our own estimations of emissions, we compare them to the corresponding emissions calculated using other sources of information. This check is necessary because there is a concern that our process of assigning emissions using IOT all sectors may result in country-level measures of emissions (when adding up the assigned GHGE of all sectors) that are very different from official measures of country-level emissions. In general, the country-level measures are very similar across sources (Table 6). Estimations are slightly higher when using our method, which is expected due to the choice of excluding imports in the calculations.

Table 6 – Comparison of estimated GHG emissions (Megatons) with other sources (2015 data)

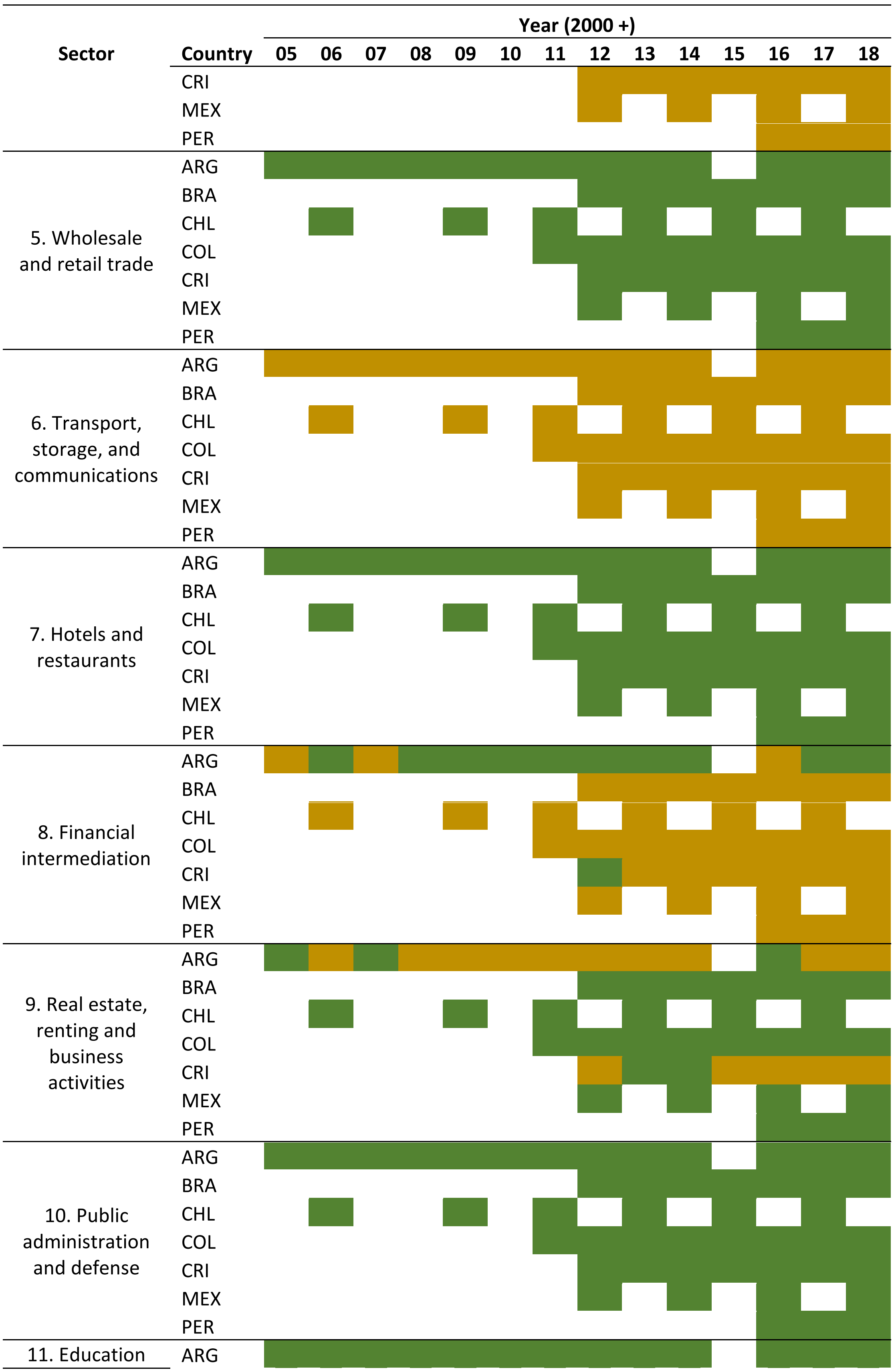
Country	Own Estimation	WDI	CAIT	OECD
ARG [a]	385.3	372.4	362.6	328.9
BRA	1228.7	1105.5	1082.7	1041.7
CHL	136.4	102.2	104.0	103.0
COL	214.9	175.0	177.0	170.6
CRI	19.2	14.3	14.6	13.6
MEX	869.9	674.3	670.1	745.8
PER	116.1	96.6	94.9	102.0

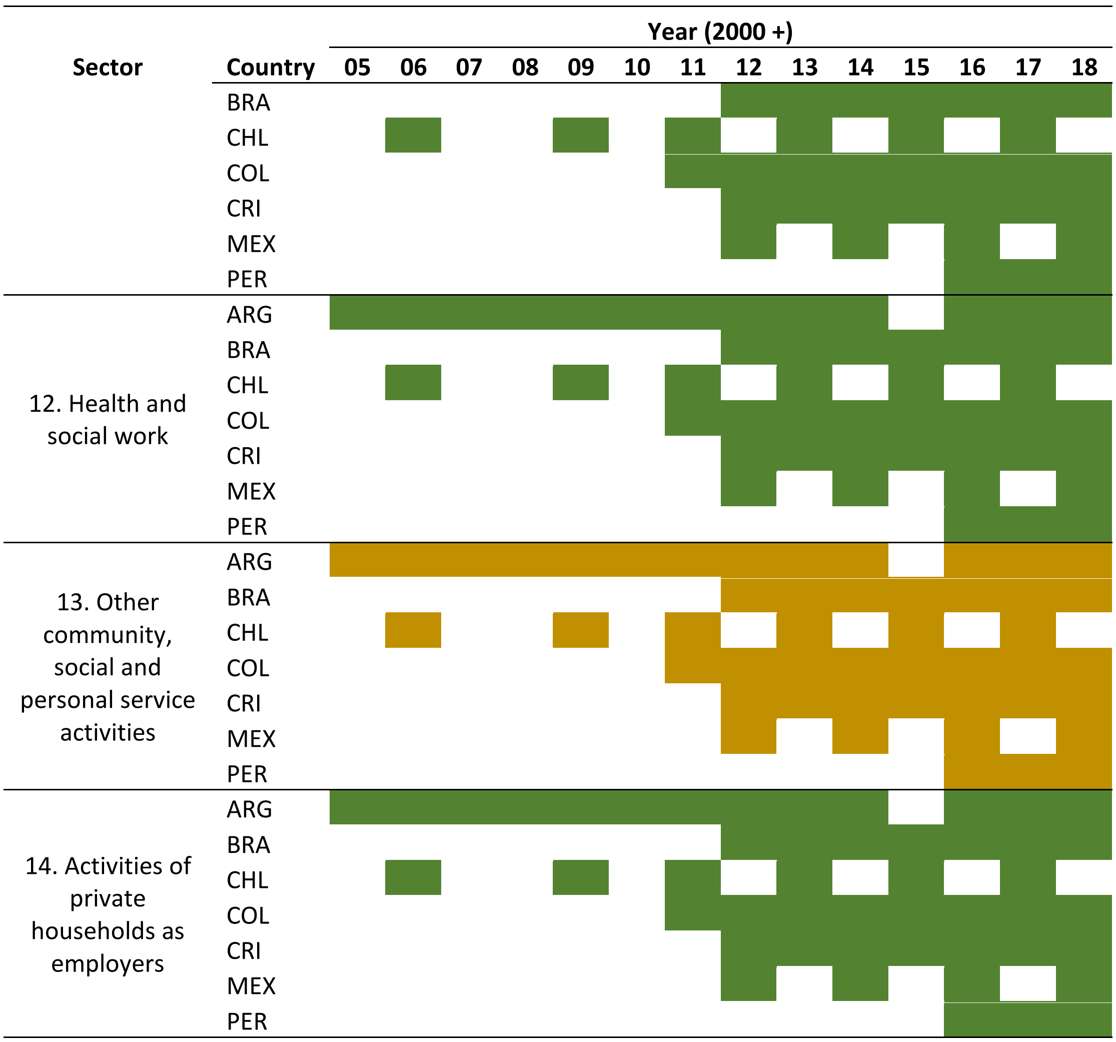
Notes:
[a] OECD data for Argentina compiles its GHGs emission data according to the IPCCC 2006 guidelines, using the Agriculture, Forestry and Other Land Use (AFOLU) category instead of Agriculture and Land Use, Land Use Change and Forestry (LULUCF) categories.

To classify the 14 sectors of economic activity into two groups (green and non-green), the paper considers whether their emissions per worker are below or above the median within each country (Table 7 reports the results for countries in LAC for which all data sources are available to calculate emissions per worker). In other words, each sector is considered green or non-green relative to the median sector emissions in each country. Since this classification is quite similar across countries (i.e., the same sector ends up as either green or non-green in most cases), the same green/non-green sectoral definition is used in every economy, including those for which it was not possible to estimate GHGE by sector. The classification to either non-green or green sector is clear from Table 7 except for Financial intermediation and Real estate (because they change status over time in Argentina, Costa Rica and Peru), which are classified as non-green and green in this paper, respectively. The paper also assumes that this sectoral classification stays the same over time.

Table 7 – Green (green color) and non-green (brown color) sectors

		Year (2000 +)													
Sector	**Country**	**05**	**06**	**07**	**08**	**09**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**
1. Agriculture, hunting, forestry, and fishing	ARG														
	BRA														
	CHL														
	COL														
	CRI														
	MEX														
	PER														
2. Mining and quarrying	ARG														
	BRA														
	CHL														
	COL														
	CRI														
	MEX														
	PER														
3. Manufacturing, Construction & Industrial processes	ARG														
	BRA														
	CHL														
	COL														
	CRI														
	MEX														
	PER														
4. Electricity, gas, and water supply	ARG														
	BRA														
	CHL														
	COL														


Year (2000 +)
Sector
Country
05 06 07 08 09 10 11 12 13 14 15 16 17 18
CRI
MEX
PER
5. Wholesale and retail trade
ARG
BRA
CHL
COL
CRI
MEX
PER
6. Transport, storage, and communications
ARG
BRA
CHL
COL
CRI
MEX
PER
7. Hotels and restaurants
ARG
BRA
CHL
COL
CRI
MEX
PER
8. Financial intermediation
ARG
BRA
CHL
COL
CRI
MEX
PER
9. Real estate, renting and business activities
ARG
BRA
CHL
COL
CRI
MEX
PER
10. Public administration and defense
ARG
BRA
CHL
COL
CRI
MEX
PER
11. Education
ARG



Source: Own elaboration based on CAIT, OECD, and SEDLAC data.

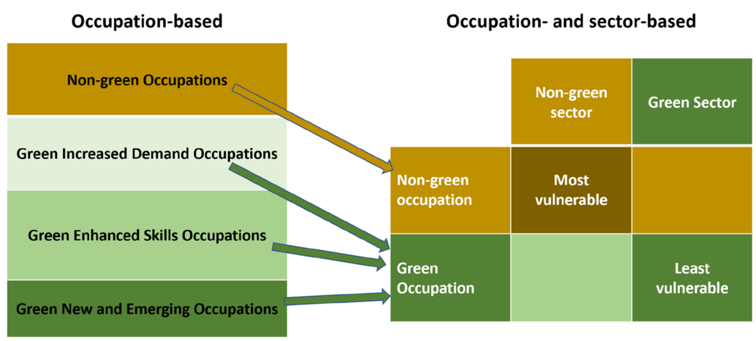
Green jobs: Occupations vs. sectors

By combining the sector and occupation classifications, four mutually exclusive job types (see Figure 1) are created. Each group faces two primary sources of vulnerabilities to green policies. First, workers in non-green sectors would be more vulnerable to policies that increase the cost of GHGE, such as a Carbon Border Adjustment Mechanism (CBAM).[14] If such a policy reduces the competitiveness of non-green sectors, they may be more likely to shrink and shed labor. Second, workers in non-green occupations would be more vulnerable in terms of lacking the skills to remain employed or find a new job if green policies create a skill-biased change in labor demand. By overlapping these two dimensions, the following four categories are created:

[14] See https://ec.europa.eu/commission/presscorner/detail/en/qanda_21_3661 the CBAM as proposed by the European Commission.

- **Jobs in green occupations and green sectors**: workers in this category are the least vulnerable as they would face a lower risk of displacement and higher chances of re-employment.
- **Jobs in non-green occupations and non-green sectors**: workers in this category are the most vulnerable as they would face a higher risk of displacement and lower chances of re-employment.
- **Jobs in non-green occupations and green sectors**: workers in this category may face lower risk of displacement from the sector, but also lower chances of re-employment.
- **Jobs in green occupations and non-green sectors**: workers in this category may face higher risks of job displacement from the sector, but higher chances of re-employment.

Figure 1 – Green jobs: occupations vs. sectors



Source: Own elaboration

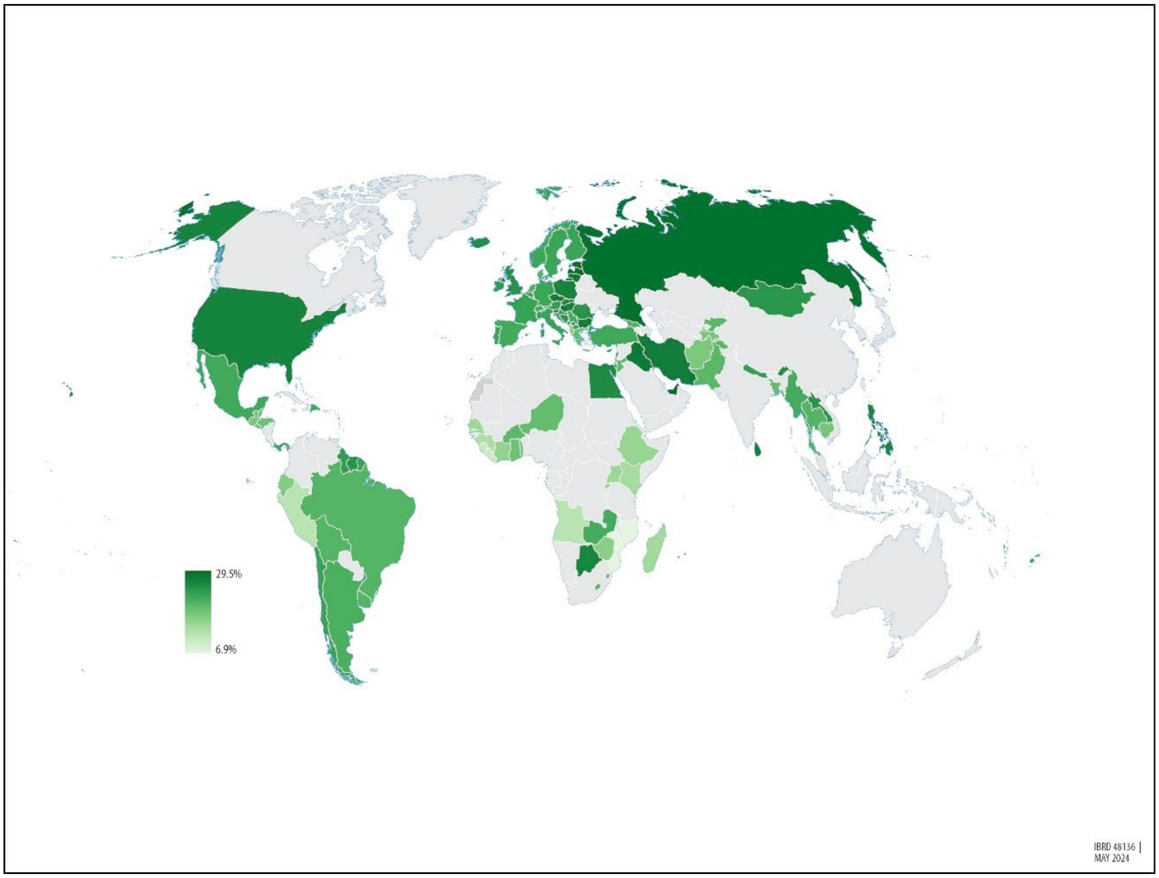
3. Results

Green occupations: Cross-country patterns

The paper finds that, on average across all countries, 21.4 percent of total employment is accounted by green occupations, and that 10.3, 9.3, and 1.8 percent are the shares of the "enhanced skills" and "increased demand", and "new and emerging" categories, respectively.[15] A broad picture of green occupations across the world is given in Figure 2, which suggests that they are more prevalent in wealthier countries. A disaggregation by job type confirms the relative scarcity of new and emerging occupations across the world (no country has more than 5 percent of green occupations of this type) (Figure 3).

[15] See appendix A1 for all the details for each country covered in the sample.

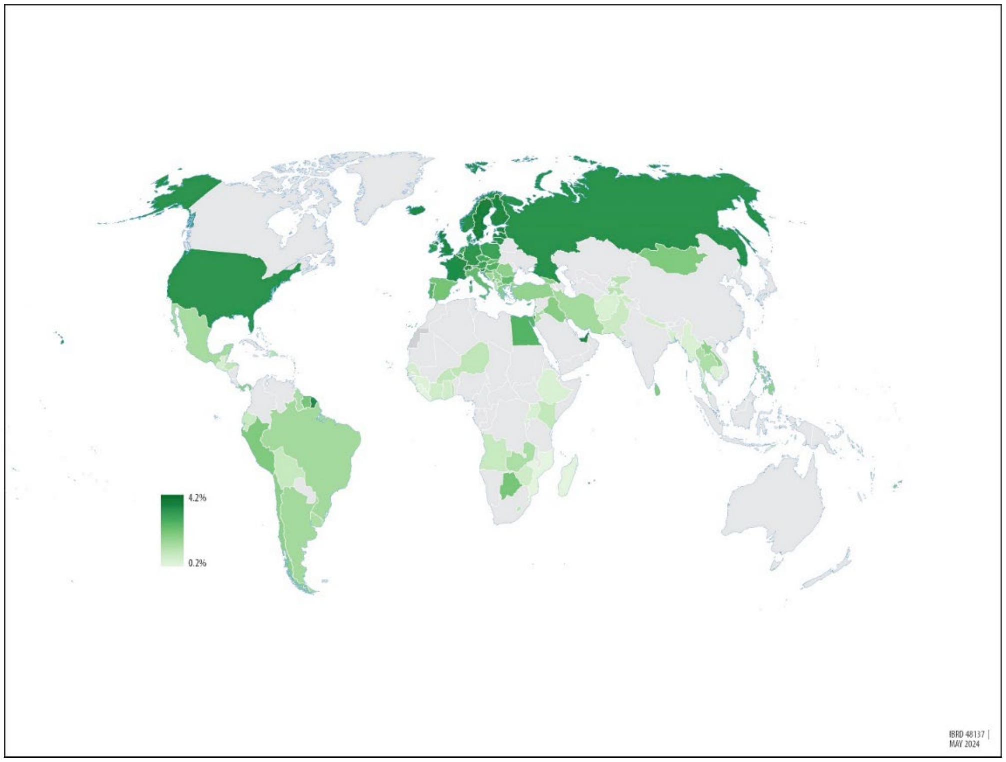
Figure 2 – Green occupations (all types) across the world



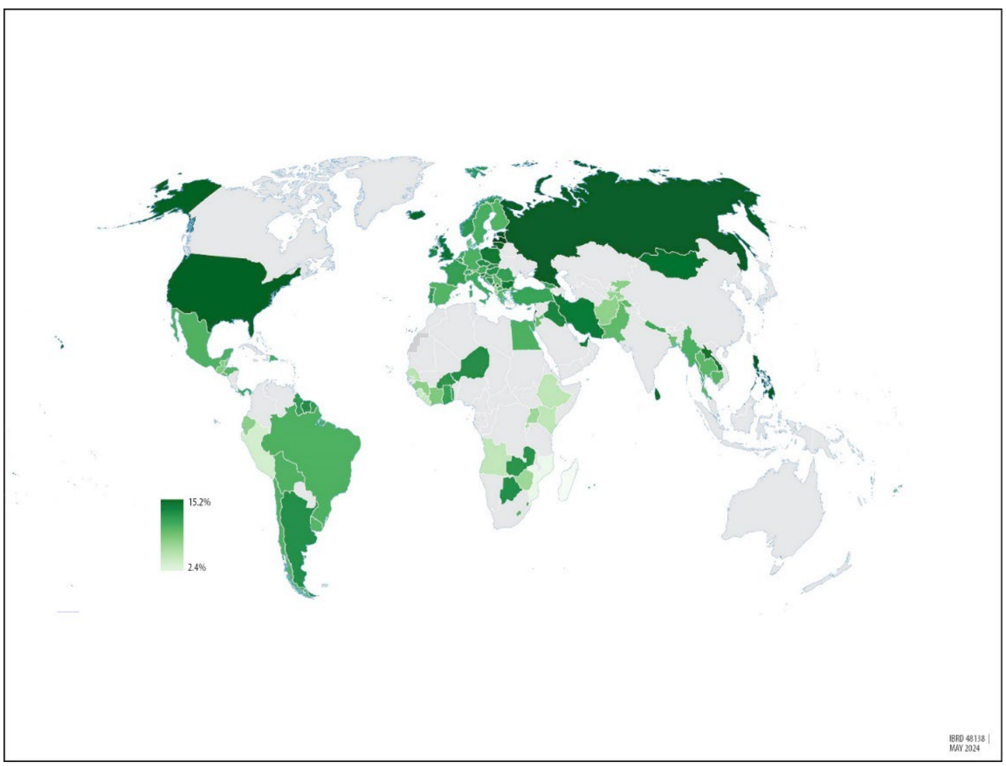
Note: share of green occupations as percentage with respect to total employment

Figure 3 – Green occupations (by types) across the world

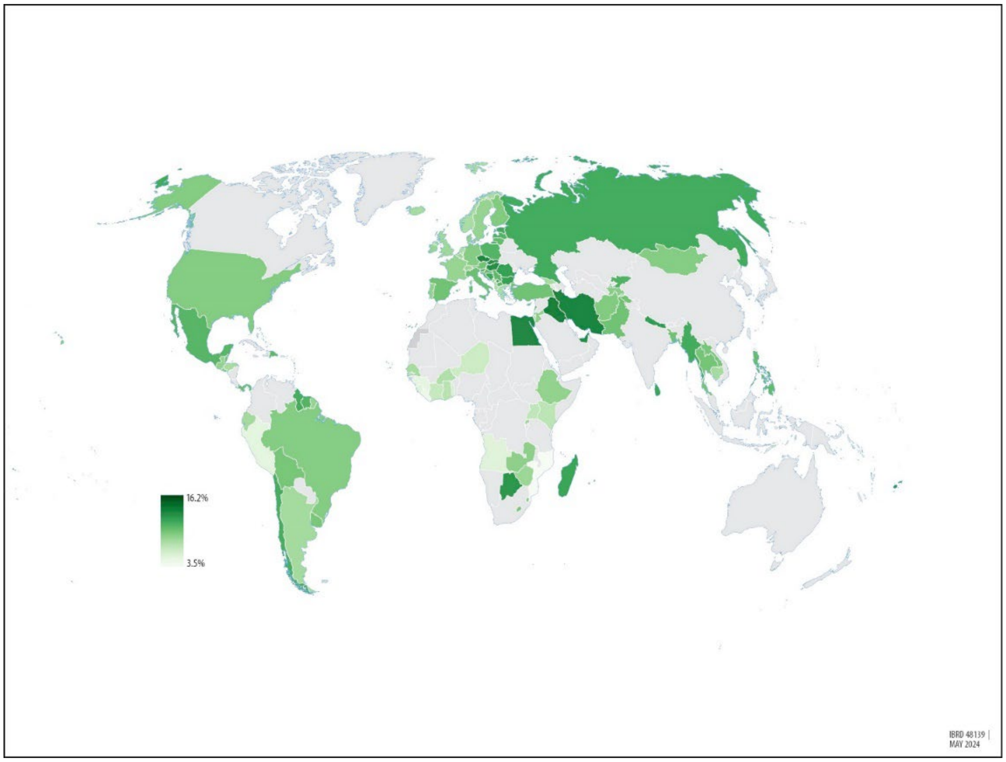
(a) New and emerging occupations



(b) Enhanced skills occupations



(c) Increased demand occupations

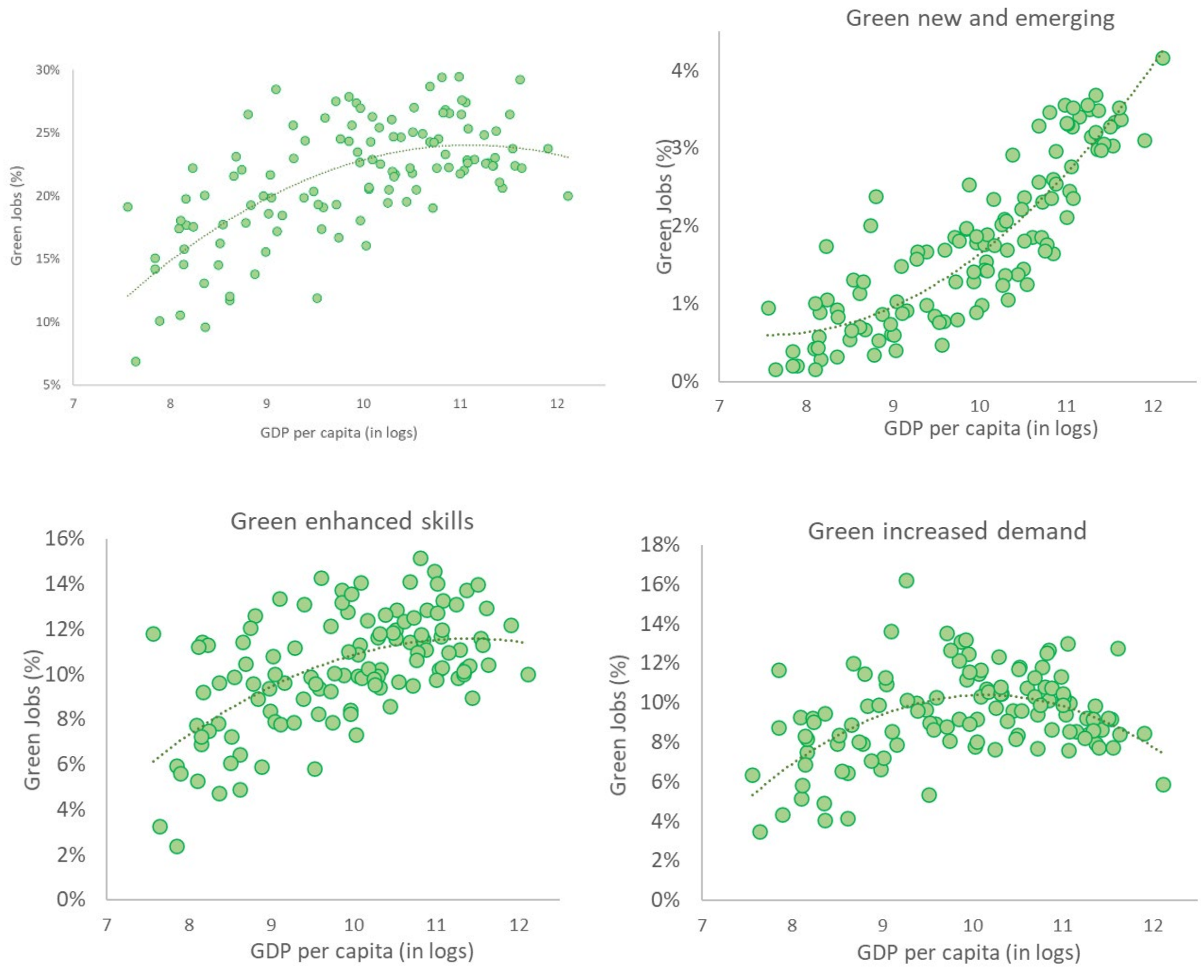


Note: share is percentage of green occupations with respect to total employment in each job type

The positive correlation between green occupations and economic development is also supported by Figure 4 in which the share of green occupations (total and by job type) is plotted against the log GDP per capita. A regression of green occupation shares on GDP per capita in Appendix A4—which controls for time-invariant unobserved heterogeneity—confirms the positive association, which is driven by "new and emerging" and "enhanced skills" occupations.[16] In particular, a 1 percent increase in GDP per capita is associated with a 0.4 and 4.1 percentage point increase in the share of new/emerging and enhanced skills green occupations, respectively. These estimates are consistent with those of Tyros et. al (2023), which finds that the green intensity of the workforce is positively correlated with countries' income levels. Given that poorer countries tend to grow at significantly higher rates, these estimates provide support to the hypothesis that there is convergence to rich countries in the share of green occupations.

[16] However, interpretation of any result that makes use of the "new and emerging occupations" classification variable has to consider that this type of green job is very scarce in developing countries. See appendix A4 for the regression results.

Figure 4 - Percentage of green occupations and GDP per capita (2017 PPP $), latest available data.

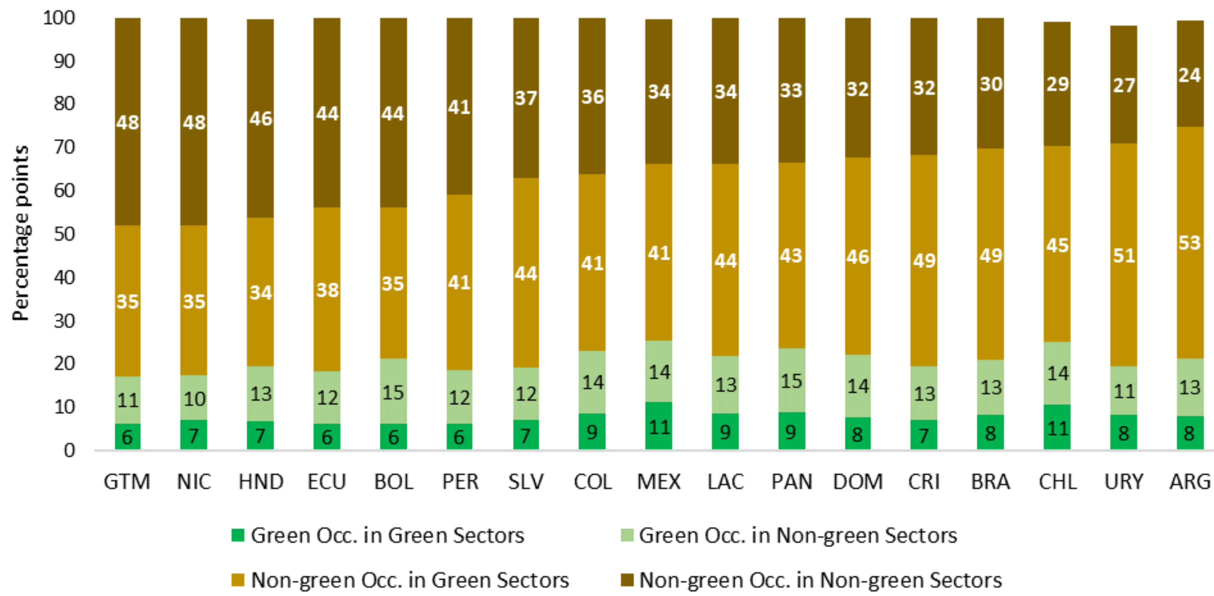


Source: Own elaboration based on ILOSTAT and SEDLAC (Employment by occupati–n - ISCO level 2 (thousands)) and WDI (GDP per capita, PPP (constant 2017 international $)). Note: Employment data from ILOSTAT are used in all cases, except for those LAC countries were data from ILOSTAT were not available (Colombia, Costa Rica, and Nicaragua) or the time series was longer on SEDLAC (Argentina, Chile, Panama, and Peru). Data for these 7 countries come from SEDLAC.

Green occupations and sectors: The case of LAC

As seen in Figure A2, the share of green occupations in LAC is lower than that of other regions except Sub-Saharan Africa. However, the availability of more granular data in LAC countries allows a deeper analysis of the relationship between green occupations and sectors. The first finding is that the concentration of employment in non-green occupations and non-green sectors is significant in several LAC countries. Figure 5 shows that non-green occupations are predominant in both green and non-green sectors in LAC. Around 90 percent of workers in each country with available data has a job in either a non-green sector or a non-green occupation. Non-green sectors account for a large share of jobs, from 37 percent in Argentina to 59 percent in Guatemala. Most workers with green occupations are in a non-green sector (about 60 percent of them in most countries), which suggests that high-emission sectors could find some of the needed skills for the transition already in the labor force they occupy.[17]

Figure 5 – Green occupations and green sectors in LAC

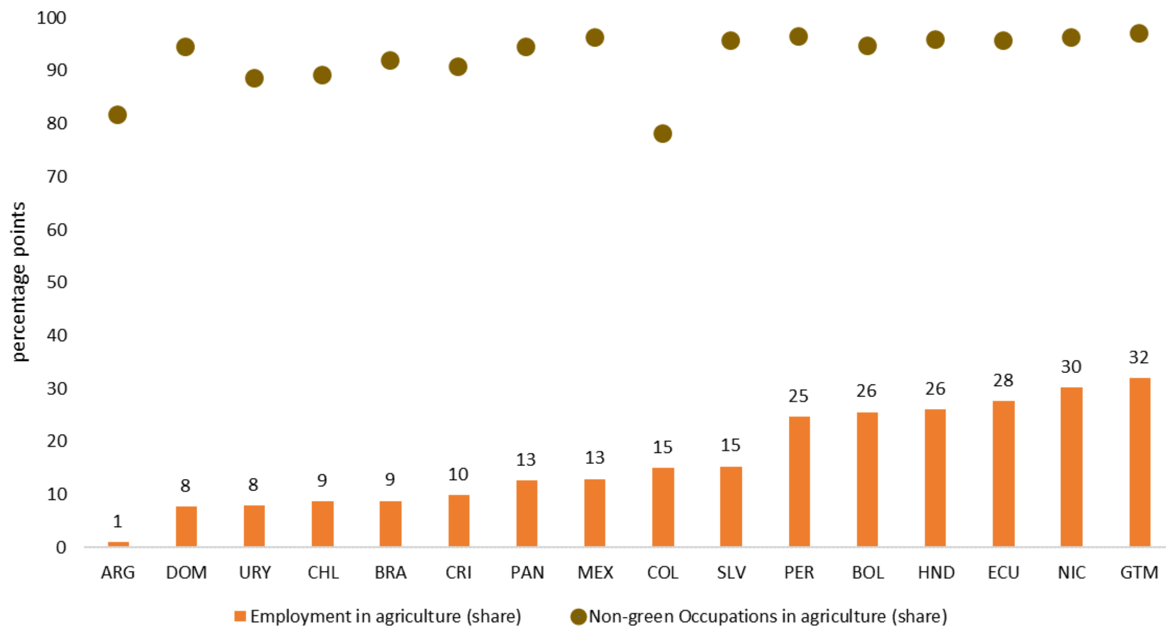


Source: Own elaboration based on SEDLAC (CEDLAS and The World Bank).

Figure 6 also highlights another important finding in terms of the very high presence of non-green occupations in the agriculture sector (included in the primary sector in the figure) —about 90 percent or more in most countries. However, it is important to keep in mind that non-green occupations are not necessarily expected to decline in size during the green transition, since they include not only "brown" ones, but also others that may be considered "neutral" from the point of view of the green transition. For example, agricultural workers are classified as non-green (see Table A8) but their jobs may not be affected at all by green policies that substitute away non-green fertilizers. In other words, the high shares of non-green occupations in agriculture does not necessarily mean that their demand will decline during the green transition.

[17] Figure A3 in the appendix provides a robustness check where green sectors include all services sectors, while non-green sectors include agriculture and manufacturing. The patterns across countries are very similar to those in Figure 5, but the share of employment in green sectors is lower in the former, since some services sectors are not green (e.g. Other community, social and personal service activities).

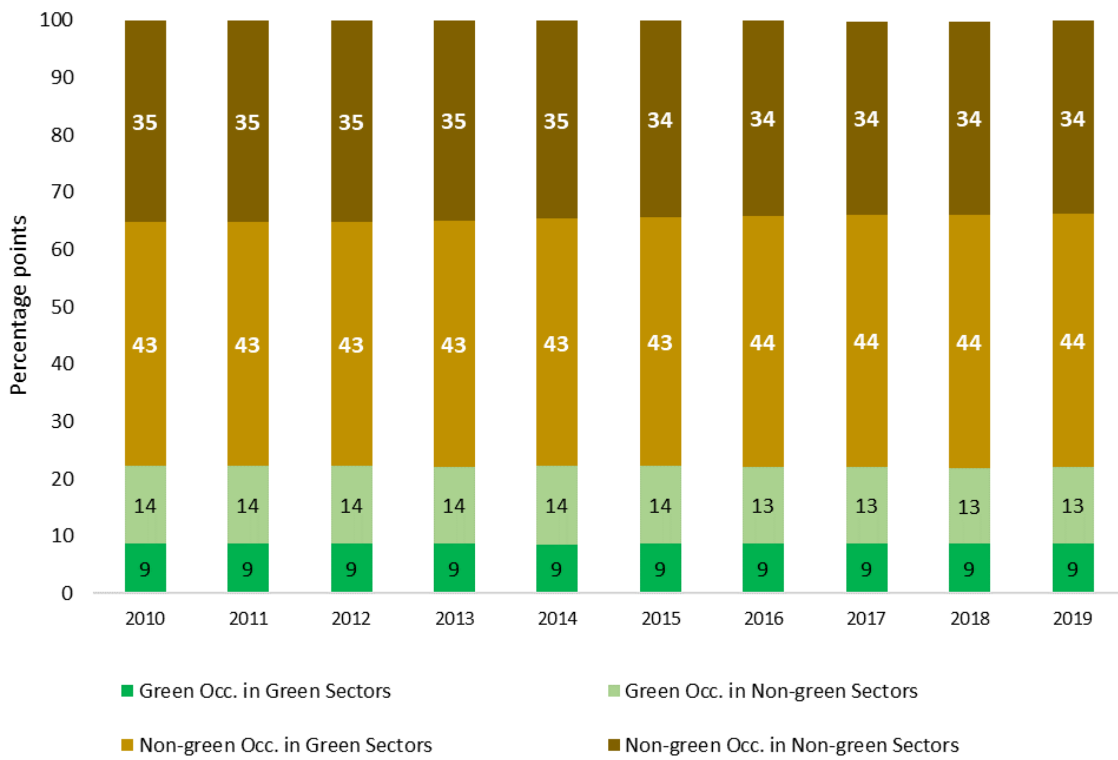
Figure 6 – Share of non-green occupations in the agriculture sector in LAC countries



Source: Own elaboration based on SEDLAC (CEDLAS and The World Bank).

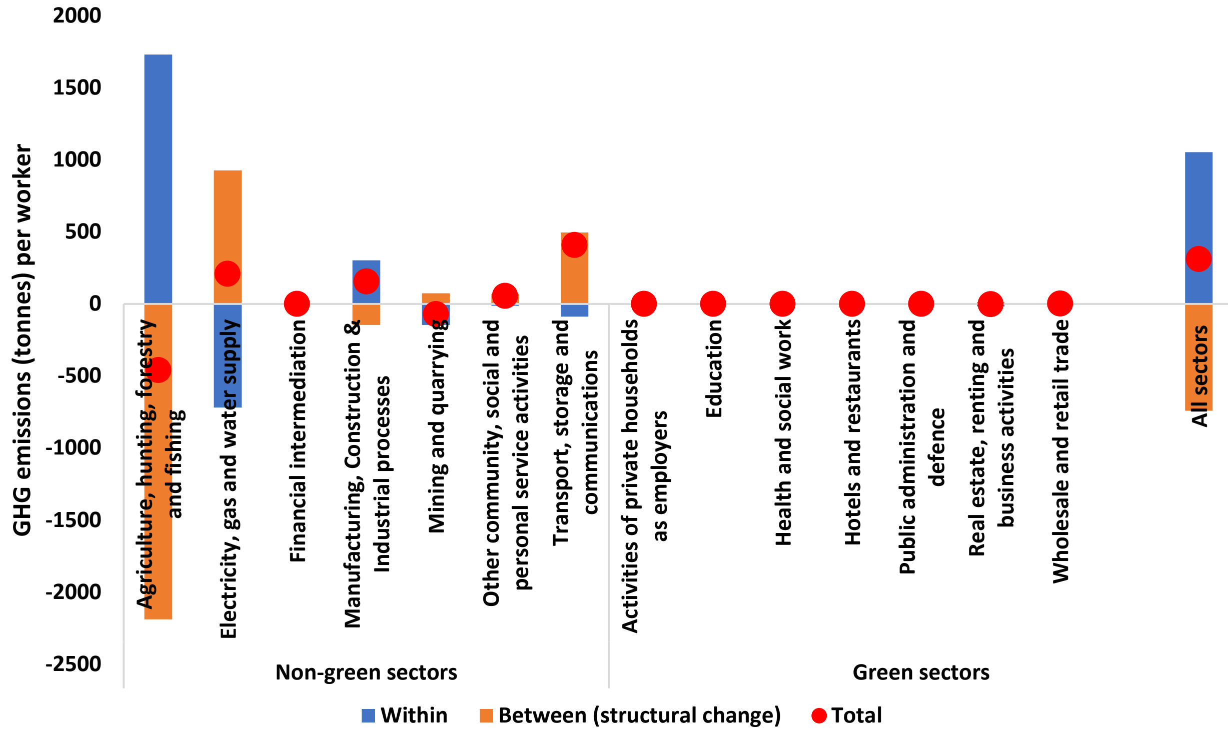
The dynamics of green occupations and sectors also offer important insights. Green occupation shares have been remarkably constant over the last decade, but the share of non-green jobs in non-green sectors fell slightly (from 35 to 34 percent), which suggests non-green employment is slowly moving towards greener sectors (see Figure 7). On the other hand, while total emissions per worker have increased only slightly between 2005 and 2018 in LAC, there were more significant changes when looking across sectors. Figure 8 provides a decomposition of GHGE per worker growth into within- and between-sector components, following the typical approach of structural change decompositions (for example, see McMillan, Rodrik and Verduzco-Gallo, 2014). From 2005 to 2018 in LAC, changes within sector contributed to increase GHGE per worker while the reallocation of workers from higher to lower GHGE sectors partially offset such increase. The main sectors contributing to these dynamics were the primary and industry sectors, because worker outflows from these high-GHGE sectors toward services contributed to lower total GHGE, while at the same time these high-GHGE sectors experienced an increase in within-sector GHGE per worker. These patterns are illustrative of the implications of structural transformation on the green economy, whereby the increasing energy intensity of sectors tends to make the economy less green, but the jobs flows from agriculture and manufacturing towards services has the opposite implication.

Figure 7 – Jobs in green and non-green occupations and sectors in LAC 2010-2019



Source: Own elaboration based on Climate watch data (GHGE in tons) and SEDLAC (Number of workers).

Figure 8 - Decomposition of the change in GHG emissions (tn.) per worker by sector in LAC, 2005-2018



Source: Own elaboration based on Climate watch data (GHG emissions in tons) and SEDLAC (Number of workers). Notes: (1) LAC region is composed of the 7 countries with emissions data: Argentina, Brazil, Chile, Colombia, Costa Rica, Mexico, and Peru. (2) In Mexico, data from 2006 were used instead of 2005 due to the lack of estimates of the number of workers. For the same reason, data from years 2006 and 2017 were used in Chile instead of 2005 and 2018. This decomposition follows the traditional shift-share approach from structural transformation studies, where changes in labor productivity are decomposed into productivity growth within the sector ("within" component) and productivity growth driven by workers moving from lower to higher productivity sectors ("between" or "structural change" component).

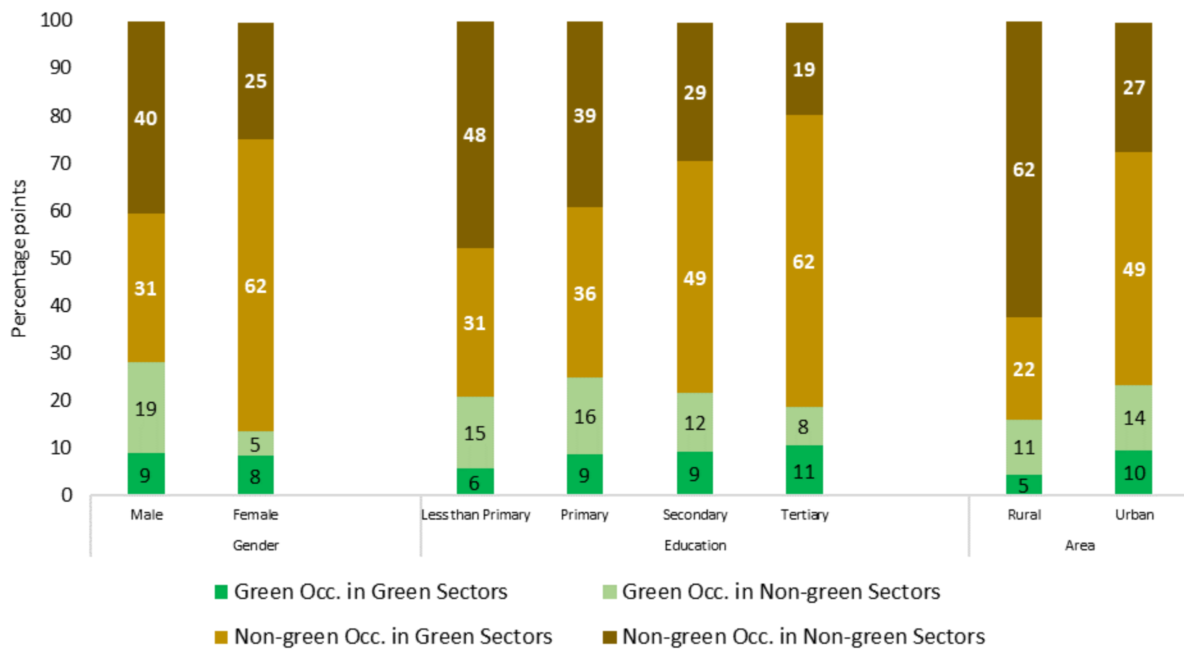
Profile of green job holders in LAC

Overall, green occupations are more prevalent among male and urban workers (see Figure 9).[18] Granata and Posadas use a different methodology to define green occupations in Indonesia, and also find that their share is higher among males than among females. However, total employment (including green and non-green occupations) in green sectors is higher for females and more educated people. A more granular picture of the gender patterns of green occupations can be grasped in Figure 10. Men are more likely to have green occupations than women (as measured by the gender gap, that is share of green occupations held by males minus share held by females), across all types of green occupations and in all LAC countries

[18] Some empirical articles find that such policies would generally benefit workers with higher levels of education and specialized in non-manual tasks (Vona, Marin, Consoli, & Popp, 2016; Marin & Vona, 2019).

except Honduras and Panama for the "New emerging" type. The opposite patterns regarding gender gaps in green occupations vs. sectors are partially driven by more general patterns of gender segregation. In particular, the fact that green occupations are biased toward men reflects the fact that those occupations are typically male-dominated (e.g. chief executives, electricians, construction workers, Table A7b). Accordingly, the higher presence of women in green sectors reflects their larger concentration of employment in the services sector (e.g. the care economy, retail, Table A7a). Finally, green occupations that require higher skills ("New emerging" and "enhanced skills") are more prevalent among those with higher levels of education (see Figure 11).[19]

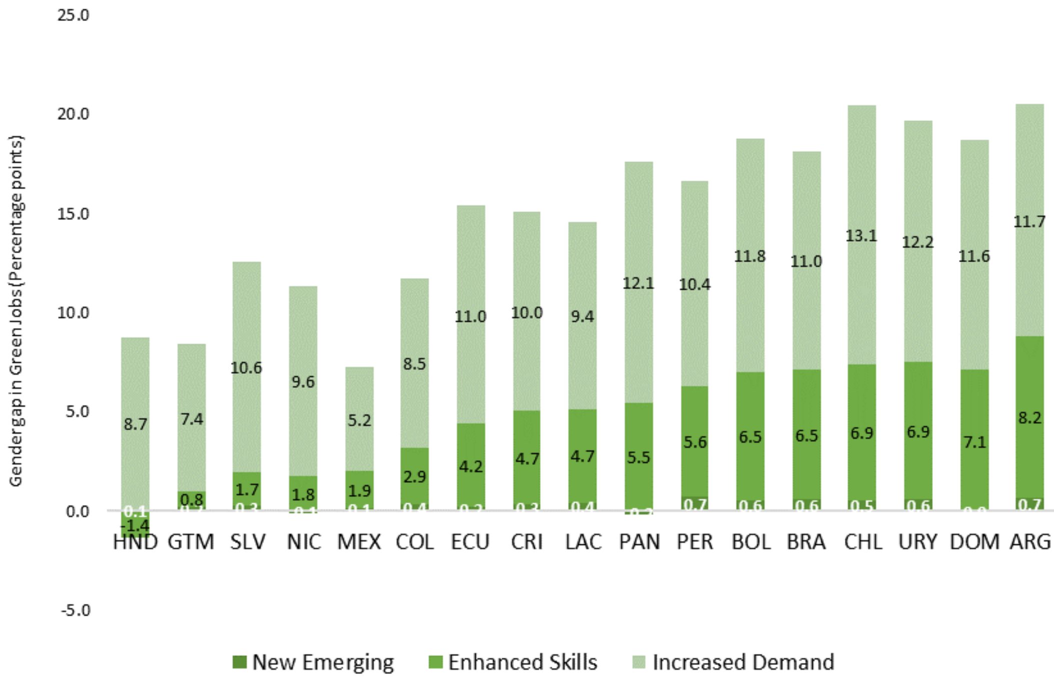
Figure 9 – Green and non-green occupations and sectors vs. job holder gender, education, and rural/urban residency in LAC, 2019



Source: Own elaboration based on Climate watch data (GHG emissions in tons) and SEDLAC (Number of workers).

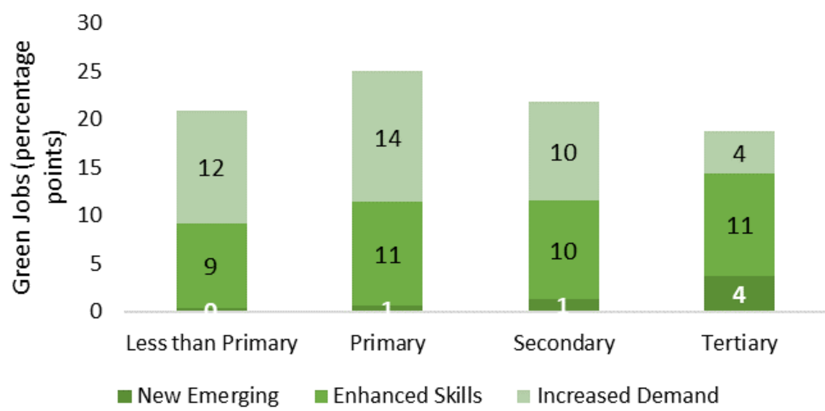
[19] IMF(2022) and Granata and Posadas (2022) also find that green jobs are linked with higher educational attainment in Europe and Indonesia, respectively.

Figure 10 – Gender Gaps in green occupations, LAC countries 2018



Source: Own elaboration based on SEDLAC data

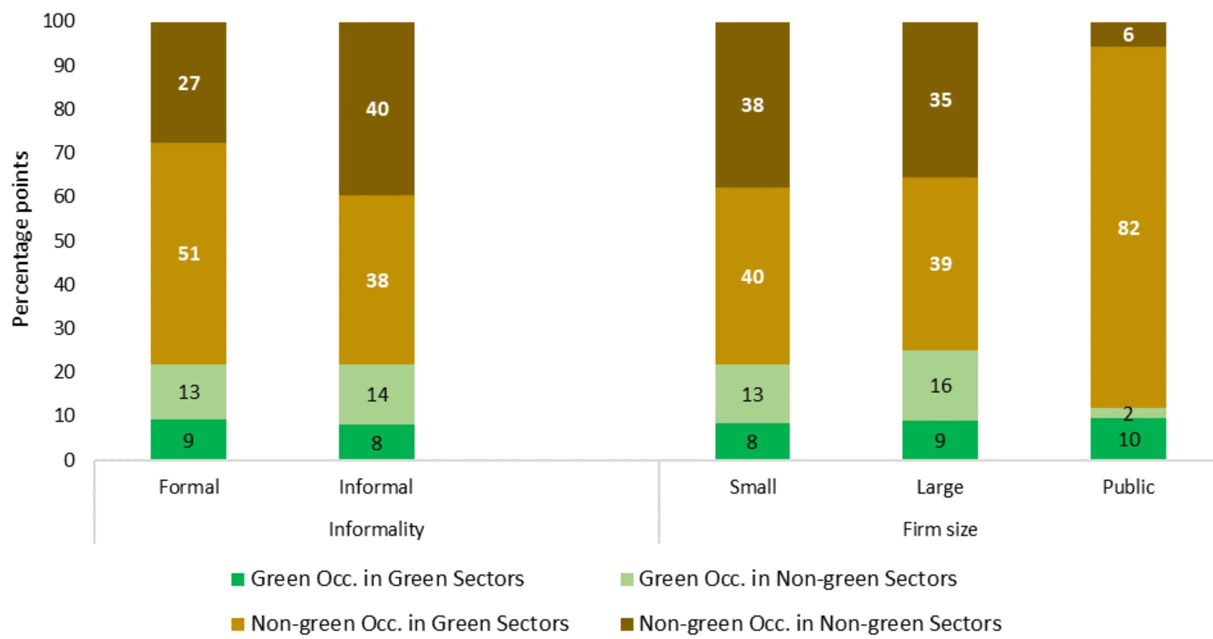
Figure 11 – Green occupations by education level, LAC 2019



Source: Own elaboration based on SEDLAC data

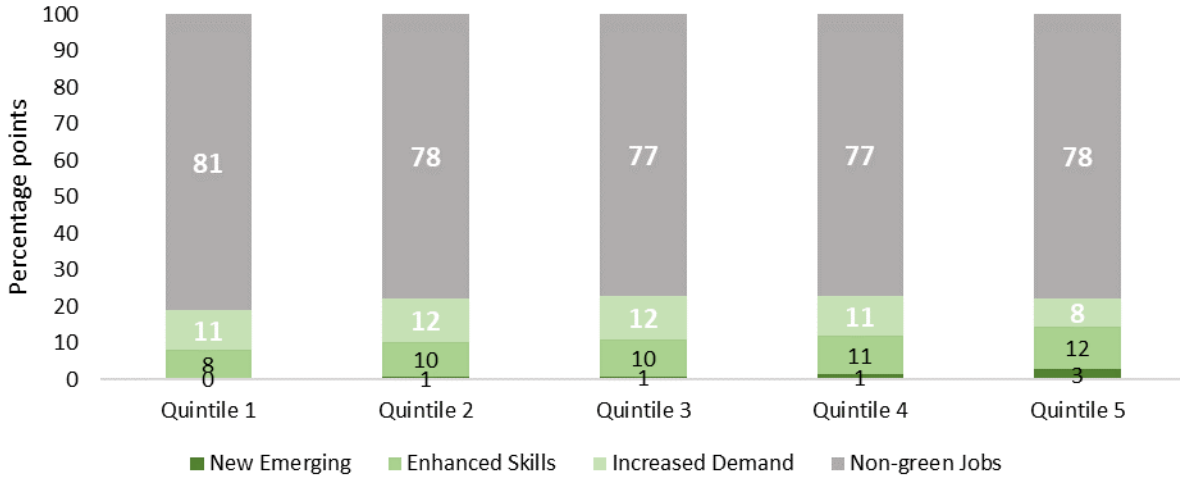
Regarding employers' characteristics, green occupation shares do not vary much across informality status and firm size (see Figure 12). However, a large share of informal workers is occupied in non-green occupations in non-green sectors (driven by the agriculture sector), which can be considered the most vulnerable group in the green transition. The gradient of green occupations by household income quintiles is not particularly large (see Figure 13), but the share of the most vulnerable workers during a green transition (i.e., non-green occupations and in non-green sectors) is significantly higher in the poorest quintiles (see Figure 14).

Figure 12 – Green and non-green occupations and sectors vs. informality and firm size in LAC, 2019



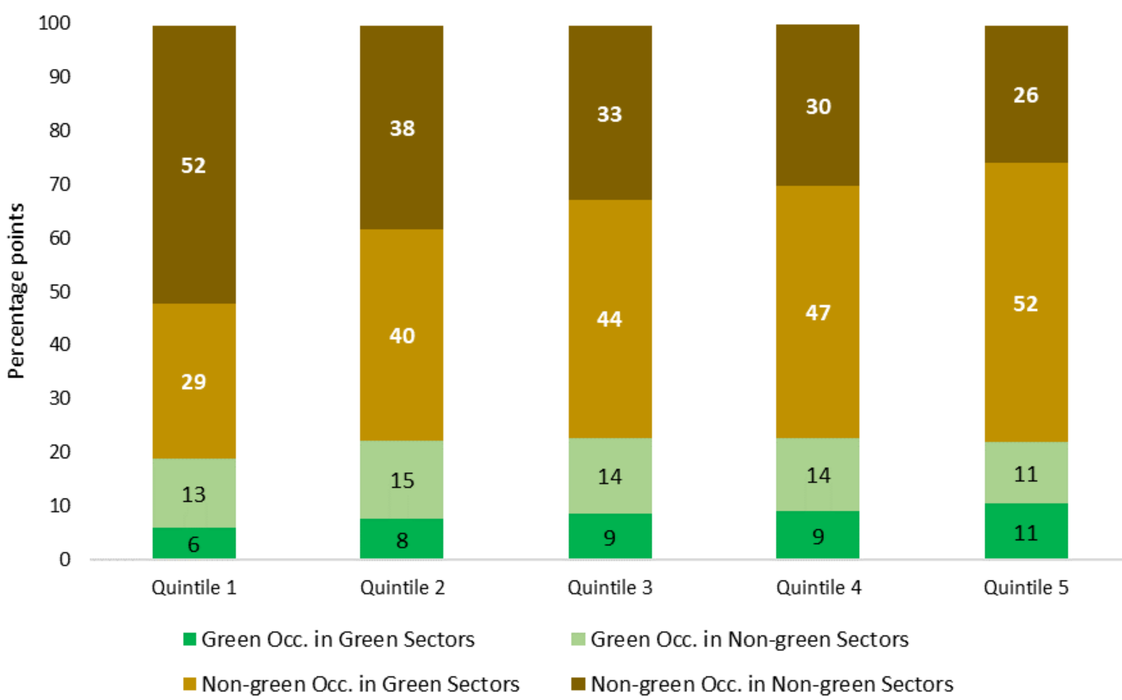
Source: Own elaboration based on SEDLAC data. Notes: “Small” are those private firms with five employees or less, “Large” are those with more than five employees, and “Public” corresponds to workers in the public/governmental sector.

Figure 13 – Green and non-green occupations by household income quintile, LAC 2019



Source: Own elaboration based on SEDLAC data

Figure 14 – Green and non-green occupations and sectors vs. household income quintiles, LAC 2019



Source: Own elaboration based on SEDLAC data

Lastly, the paper investigates how green job holders fare on the labor market in terms of labor income. Overall, green occupations are linked to significantly higher wages, even when controlling for other individual characteristics (see Table 8): green occupations are linked to hourly wages that are about 20 percent higher (as a benchmark, this magnitude is similar to the gender wage gap).[20] When disaggregated by type, the wage premium is significantly higher for new and emerging green occupations (see second column in Table 8). In line with the results above, the most vulnerable workers (i.e., those in non-green occupations and non-green sectors) display lower wages compared to the other groups (see the third column in Table 8, in which this group is entered as the omitted category). It is important to mention that the wage premium associated with green jobs may be upward-biased because workers with green jobs are significantly different from the rest in terms of observable characteristics, which raises concerns about significant differences in unobservable factors that could introduce omitted variable bias. Within these caveats, the results above suggest the green transition in general and bottlenecks in the supply of green occupations (at least in the short/medium term) could lead to higher wage and income inequality.

[20] Granata and Posadas (2022) use a different method to classify green jobs (based on text-analysis of the ISCO08 task database) and find that they are linked with higher earnings in Indonesia even when controlling for a host of other individual characteristics. IMF (2022) also finds that green jobs are associated with higher earnings.

Table 8 – Green jobs and labor income in LAC, circa 2019

	Log Hourly Labor Income PPP 2011		
	Omitted category: non-green occupation		Omitted category: non-green occupation in non-green sector
Green Occupation	0.192***		
	(0.00638)		
New Emerging		2.908***	
		(0.0509)	
Enhanced Skills		0.114***	
		(0.0133)	
Increased Demand		-0.0305***	
		(0.00943)	
Green occ. And Green Sector			0.227***
			(0.00876)
Green occ. And Green Sector			0.130***
			(0.00447)
Green occ. And Green Sector			0.349***
			(0.00887)
Constant	-0.162***	-0.114***	-0.239***
	(0.0160)	(0.0159)	(0.0162)
Observations	938,361	938,361	938,361
R-squared	0.299	0.310	0.302

Robust standard errors in parenthesis

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

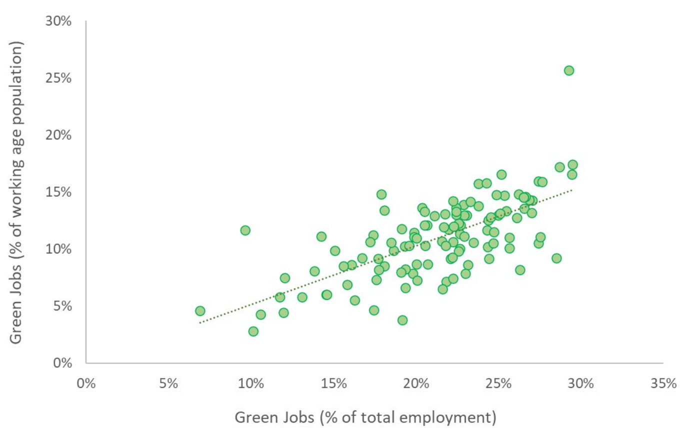
Note: pooled sample for LAC, circa 2019. Controls include dummy variables for country, educational attainment, gender, rural, as well as age and age squared.

4. Robustness Checks

This section discusses some caveats and conducts some robustness checks. First, the classification of occupations used in this study is based on O*NET, which describes the occupations that exist in the US. The main assumption when using O*NET as the source of truth to classify occupations in other countries is that the task content of each occupation in any country is the same as in the United States. Lewandowski et al. (2022) have pointed out that this is almost certain to be problematic for less-developed countries, given significant differences in workers' skills, technologies, and economic activities, which leads to large labor productivity differences across countries (Hsieh and Klenow 2010; Eden and Gaggl 2020). Similar points are made in recent papers that have compared O*NET to surveys of worker skills (see Hatayama et al., 2020 and Lo Bello et al., 2019). In addition, a recent World Bank report develops a country-specific occupational classification for Indonesia, following the O*NET methodology, and finds substantial differences in the use of skills for comparable occupations between the US and Indonesia.[21] This is a limitation of our study and an important area for future research.

Second, this paper considers the occupational characteristics ("greenness") of *employed* people. In some countries, a high share of green occupations among the employed could be accompanied by a high share of people who are inactive or unemployed. Overall, the share of green occupations is expected to be lower than those estimated in this study if taken as a share of the working-age population. This bias could be larger in economies with low employment rates. As a robustness check, Figure 15 reports the estimated green job shares as a percentage of the working-age population (to complement the shares as a percentage of employed people presented above, see Figure 5). The chart shows that both measures are highly correlated, which alleviates concerns about this bias.

Figure 15 - Green occupations as % of the working age population and as % of total employment, latest available data.



Source: Own elaboration based on ILOSTAT and SEDLAC (Employment by occupation - ISCO level 2 (thousands)) and WDI (Total population aged 15 and more). Note: Employment data from ILOSTAT are used in all cases, except for those Latin American countries were data from ILOSTAT were not available (Colombia, Costa Rica, and Nicaragua) or the time series was longer on SEDLAC (Argentina, Chile, Panama, and Peru). Data for these 7 countries come from SEDLAC.

[21] See World Bank (2020) https://pubdocs.worldbank.org/en/406191621616642876/Indotask-TR-English.pdf.

Third, the level of aggregation within occupational categories may introduce a bias. For example, in cases where the ISCO-08 code is only available at the 2-digit level (as it is the case in the analysis throughout this paper), we need to make assumptions about the distribution of workers across all the 4-digit occupations nested within a 2-digit one.[22] This paper makes the assumption that such nested distribution is identical to that of the U.S.[23] Table 9 analyzes—for the group of countries with 4-digit ISCO-08 data—the share of employment classified as green if one were to assume that such countries' highest level of disaggregation is 1, 2, 3 or 4-digits. It shows that higher levels of aggregation lead to different estimates of the share of green jobs, in total and by type. At the same time, they lead to different country rankings. For example, Peru and Panama have 22 and 18 percent of jobs in green occupations according to the 4-digit classification, respectively, but such shares are 22 and 24 percent according to the 1-digit classification. To overcome this limitation, a potential extension of our methodology is to use the occupational structure of "similar" countries (instead of that of the U.S.) with 4-digit ISCO08 data to impute the green employment shares at the 2-digit level for countries without more granular occupational data.

[22] Even though some countries in SEDLAC report the ISCO08 occupations at the 4-digit level, we decided to use the more aggregate 2-digit level since this paper is focused on cross-country comparisons. Thereby, using 4-digit classifications for some countries and 2-digit for others would introduce noise. However, the mapping of green occupations at the ISCO08 4-digit level that this paper develop is available for analyses at that level of disaggregation.

[23] As mentioned in Section 2, employment shares are based on U.S. estimates, which are obtained from the 2018 Occupational Employment and Wage Statistics (OEWS) published by the U.S. Bureau of Labor Statistics.

Table 9 - Percentage of workers in green occupations in LAC circa 2019 - by country and ISCO classification (digit level).

(a) New and Emerging

Country	ISCO classification			
	1 digit	2 digits	3 digits	4 digits
SLV	1	1	1	1
ECU	1	1	1	1
PER	1	1	1	1
DOM	1	1	1	1
HND	1	1	1	1
URY	1	1	1	1
PAN	2	2	2	2
LAC	**1**	**1**	**1**	**1**

(b) Enhanced Skills

Country	ISCO classification			
	1 digit	2 digits	3 digits	4 digits
ECU	10	8	8	8
PER	10	8	8	15
URY	10	10	10	8
SLV	11	9	9	11
DOM	11	10	10	9
HND	11	10	10	14
PAN	12	12	12	9
LAC	**10**	**9**	**9**	**12**

(c) Increased Demand

Country	ISCO classification			
	1 digit	2 digits	3 digits	4 digits
URY	10	10	10	7
PAN	10	10	10	7
ECU	11	9	9	8
SLV	11	9	9	7
PER	11	9	9	6
DOM	11	11	11	7
HND	11	8	8	8
LAC	**11**	**9**	**9**	**7**

(d) Green Jobs - Total

Country	ISCO classification			
	1 digit	2 digits	3 digits	4 digits
ECU	22	18	18	17
PER	22	19	19	22
URY	22	21	21	17
SLV	23	19	19	18
DOM	23	22	22	17
HND	24	20	20	23
PAN	24	24	24	18
LAC	**22**	**19**	**19**	**20**

Source: Own elaboration based on SEDLAC (CEDLAS and The World Bank).
Notes: LAC region restricted to the 7 countries with data at 4 digits of the ISCO: Dominican Rep., Ecuador, Honduras, Panama, Peru, El Salvador, and Uruguay.

5. Discussion

This paper contributes to the literature exploring the labor market implications of the green transition by developing a new dataset on green occupations and sectors covering several countries at varying levels of economic development. It finds a very strong association between GDP per capita and the share of green occupations. When focusing on LAC economies, it finds that poorer countries have a larger share of workers in non-green sectors (i.e., sectors with GHGE per worker below the median). Within countries, individuals with lower levels of education or in poorer income quintiles are more likely to have a non-green occupation or a non-green sector job. These findings raise the importance of complementary policies to mitigate the potential impacts of green policies on income inequality between and within countries. In fact, countries with a lower share of green occupations tend to have poorer levels of human capital and higher rates of labor market informality (see Appendix A6), two facts that raise concerns about the readiness of their workers to acquire the skills of the green economy, and to be protected against the risk of job displacement during a green transition. Thereby, policies for a just transition should consider the role of pervasive labor market informality. For example, by rolling out cash transfers for income support of displaced informal workers (IMF, 2022), by training for environmentally friendly activities in the informal economy (GIZ, 2022), by improving access to financial resources and technical capacity for local governments to facilitate the formalization of workers with green occupations—e.g., see AVINA (2013) for the case of informal recyclers in Chile—to name a few options.

This paper also provides insights on the link between the process of structural transformation and the green transition. In particular, it shows that two offsetting forces have shaped the dynamics of GHGE in Latin America for the last decade. On the one hand, the increase in the GHGE-intensity of sectors contributed to raise the overall GHGE per worker. On the other hand, the reallocation of workers from high- to low-GHGE-intensive sectors (e.g., from agriculture to services) contributed to reduce the total GHGE per worker. This is an important area of future research to better understand the extent to which the reduction in GHGE-intensity can be achieved by green policies vs broader policies aimed at facilitating economic development.

Finally, the paper has not focused on some areas that could be worth exploring in future research. This includes defining green sectors in a different way that gives more prominence to the adaptation angle, in addition to the mitigation one. To do this, future analysis could define green sectors not only based on the level of emissions, but also on the potential to create green jobs and/or foster green technologies in the longer run. Examples of sectors that would be affected by this alternative definition include water management and waste management. Another area for future research is to explore the complementarities between creation of green jobs and potential for lower-skilled labor. For example, more recyclable products could create more job opportunities for lower-skilled labor in the collection of recyclable materials, potentially mitigating the job displacement effects of greener technologies.

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Appendix

A1 - Share of green occupations, latest available data

Country	Year	Percentage of jobs in occupations:			
		Green new and emerging	Green enhanced skills	Green increased demand	Green - total
Afghanistan	2020	0.4%	7.7%	9.3%	17.4%
Albania	2019	1.0%	7.3%	7.8%	16.1%
Angola	2014	0.8%	5.8%	5.3%	11.9%
Argentina	2019	1.4%	11.7%	8.5%	21.6%
Austria	2020	3.0%	10.3%	9.8%	23.1%
Bangladesh	2017	0.5%	8.9%	9.9%	19.3%
Barbados	2019	2.4%	12.4%	10.7%	25.5%
Belgium	2020	3.2%	11.1%	8.4%	22.6%
Belize	2016	1.0%	8.9%	10.0%	19.9%
Bolivia	2020	0.8%	9.9%	9.6%	20.4%
Bosnia and Herzegovina	2020	1.5%	11.3%	11.5%	24.3%
Botswana	2019	2.1%	11.6%	12.4%	26.1%
Brazil	2020	1.4%	9.9%	9.2%	20.5%
Brunei Darussalam	2019	3.0%	11.6%	9.2%	23.8%
Bulgaria	2020	2.4%	12.8%	11.8%	27.0%
Burkina Faso	2018	0.9%	11.4%	7.5%	19.8%
Cambodia	2017	0.3%	9.6%	7.9%	17.9%
Chile	2017	2.0%	12.3%	11.0%	25.3%
Colombia	2019	1.4%	9.8%	11.7%	22.9%
Costa Rica	2019	1.4%	8.6%	9.7%	19.6%
Croatia	2020	2.6%	11.4%	10.3%	24.3%
Cyprus	2020	2.5%	10.2%	9.4%	22.1%
Czechia	2020	2.8%	11.7%	13.0%	27.4%
Côte d'Ivoire	2017	0.6%	8.4%	6.6%	15.6%
Denmark	2020	3.1%	9.0%	8.7%	20.7%
Dominican Republic	2019	1.1%	10.2%	10.5%	21.7%
Ecuador	2020	0.8%	7.9%	8.1%	16.7%
Egypt, Arab Rep.	2019	2.5%	10.0%	13.1%	25.6%
El Salvador	2019	0.8%	9.4%	9.0%	19.1%
Estonia	2020	3.6%	14.6%	11.3%	29.5%
Eswatini	2016	0.8%	9.6%	9.0%	19.3%
Ethiopia	2013	0.4%	5.9%	8.7%	15.1%
Fiji	2016	1.8%	8.4%	12.5%	22.7%

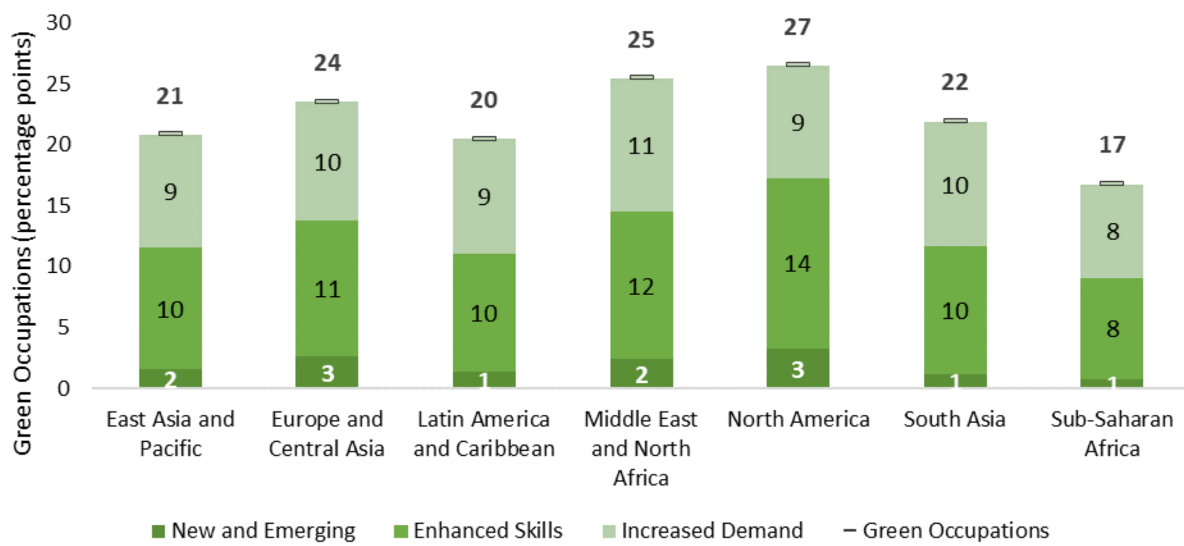
Country	Year	Percentage of jobs in occupations:			
		Green new and emerging	Green enhanced skills	Green increased demand	Green - total
Finland	2020	3.5%	9.8%	9.2%	22.6%
France	2020	3.4%	11.0%	8.5%	22.9%
Gambia, The	2012	0.3%	9.2%	8.2%	17.7%
Georgia	2020	1.8%	10.9%	8.0%	20.7%
Germany	2020	3.2%	10.0%	9.2%	22.4%
Ghana	2017	0.6%	10.8%	7.2%	18.6%
Greece	2020	1.9%	9.5%	7.7%	19.1%
Guatemala	2019	0.5%	8.3%	8.6%	17.4%
Guinea	2019	0.3%	7.8%	4.9%	13.1%
Guyana	2018	1.3%	11.0%	11.2%	23.5%
Honduras	2019	0.9%	9.6%	7.9%	18.5%
Hungary	2020	2.6%	11.6%	12.7%	26.9%
Iceland	2020	3.5%	13.7%	7.9%	25.2%
Iran, Islamic Rep.	2019	1.4%	12.8%	13.2%	27.4%
Iraq	2012	1.9%	12.1%	13.5%	27.5%
Ireland	2020	3.1%	12.2%	8.5%	23.8%
Israel	2017	3.3%	12.0%	7.6%	22.9%
Italy	2020	2.4%	10.3%	10.0%	22.7%
Jordan	2019	1.3%	9.3%	8.8%	19.3%
Kenya	2019	0.9%	5.9%	7.1%	13.8%
Kiribati	2019	1.7%	11.3%	9.2%	22.2%
Kosovo	2019	2.0%	13.8%	12.2%	27.9%
Kyrgyzstan	2018	1.0%	7.9%	10.9%	19.9%
Lao PDR	2017	1.7%	13.1%	9.6%	24.4%
Latvia	2020	3.5%	15.2%	10.8%	29.4%
Lebanon	2019	1.9%	14.1%	10.3%	26.3%
Lesotho	2019	0.9%	9.6%	9.5%	20.0%
Liberia	2014	0.2%	5.6%	4.3%	10.1%
Lithuania	2020	3.3%	14.0%	10.3%	27.6%
Luxembourg	2020	4.2%	10.0%	5.9%	20.0%
Madagascar	2015	0.2%	2.4%	11.7%	14.2%
Maldives	2019	2.9%	12.7%	9.1%	24.7%
Malta	2020	3.5%	13.3%	8.5%	25.3%
Marshall Islands	2019	2.4%	12.6%	11.5%	26.5%
Mauritius	2018	1.8%	11.6%	11.7%	25.1%
Mexico	2020	1.4%	9.9%	10.7%	22.0%
Micronesia, Federated States of	2014	1.1%	6.4%	4.2%	11.7%

Country	Year	Percentage of jobs in occupations:			
		Green new and emerging	Green enhanced skills	Green increased demand	Green - total
Mongolia	2020	2.0%	13.2%	9.2%	24.4%
Montenegro	2019	2.2%	11.8%	8.2%	22.2%
Mozambique	2015	0.2%	3.3%	3.5%	6.9%
Myanmar	2019	0.4%	10.0%	11.3%	21.7%
Nauru	2013	1.8%	10.0%	12.7%	24.5%
Nepal	2017	0.7%	10.5%	12.0%	23.1%
Netherlands	2020	3.0%	10.4%	7.7%	21.1%
Niger	2017	0.9%	11.8%	6.4%	19.2%
North Macedonia	2020	1.8%	10.2%	10.6%	22.6%
Norway	2020	3.3%	11.3%	7.7%	22.4%
West Bank and Gaza	2020	1.5%	13.4%	13.6%	28.5%
Pakistan	2018	0.7%	9.4%	9.9%	20.0%
Palau	2014	2.0%	9.8%	7.7%	19.5%
Peru	2019	0.9%	8.5%	9.1%	18.6%
Philippines	2019	1.7%	14.3%	10.3%	26.2%
Poland	2020	3.0%	12.8%	10.8%	26.6%
Portugal	2020	2.6%	11.1%	8.7%	22.3%
Romania	2020	1.8%	11.0%	11.8%	24.5%
Russian Federation	2020	3.3%	14.1%	11.3%	28.7%
Rwanda	2018	0.6%	6.9%	8.3%	15.8%
Samoa	2017	1.7%	11.2%	10.2%	23.0%
Senegal	2015	0.5%	6.1%	7.9%	14.5%
Serbia	2020	1.7%	9.4%	10.4%	21.6%
Seychelles	2019	2.3%	12.5%	9.4%	24.3%
Sierra Leone	2014	0.2%	5.3%	5.1%	10.6%
Slovak Republic	2020	2.4%	11.8%	12.5%	26.6%
Slovenia	2020	3.3%	12.7%	10.4%	26.5%
Solomon Islands	2013	0.8%	4.7%	4.1%	9.6%
Spain	2020	2.1%	9.8%	9.9%	21.8%
Sri Lanka	2018	1.9%	13.5%	11.6%	27.0%
Suriname	2016	2.1%	11.8%	10.8%	24.7%
Sweden	2020	3.7%	10.1%	8.6%	22.4%
Switzerland	2020	3.4%	10.4%	8.4%	22.2%
Tajikistan	2009	1.1%	7.5%	9.0%	17.6%
Thailand	2020	1.2%	9.6%	9.7%	20.5%
Timor-Leste	2016	0.7%	4.9%	6.4%	12.0%
Togo	2017	1.0%	11.2%	5.8%	18.1%

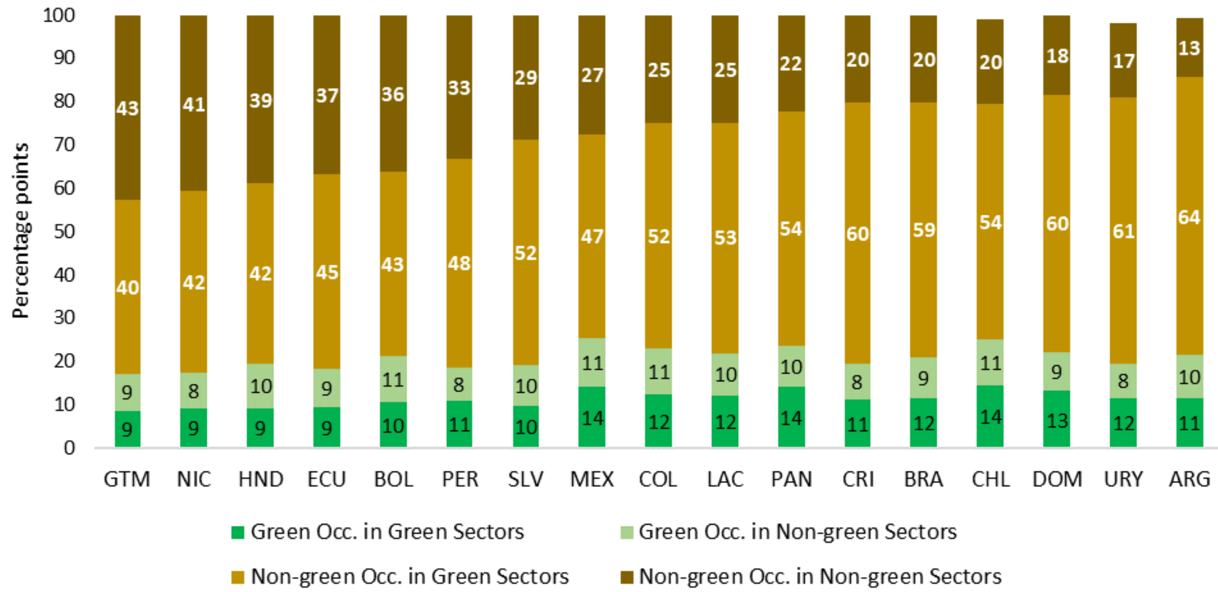
Country	Year	Percentage of jobs in occupations:			
		Green new and emerging	Green enhanced skills	Green increased demand	Green - total
Tonga	2018	1.6%	7.9%	16.2%	25.6%
Türkiye	2020	1.7%	10.6%	9.9%	22.2%
Tuvalu	2016	2.0%	12.1%	8.0%	22.1%
Uganda	2017	0.4%	7.3%	6.9%	14.6%
United Arab Emirates	2018	3.5%	12.9%	12.8%	29.2%
United Kingdom	2019	3.6%	13.1%	8.2%	24.9%
United States	2020	3.3%	14.0%	9.2%	26.5%
Uruguay	2019	1.3%	9.7%	9.6%	20.5%
Vanuatu	2019	1.3%	9.9%	6.5%	17.7%
Zambia	2019	1.3%	11.4%	8.9%	21.6%
Zimbabwe	2019	0.7%	7.3%	8.3%	16.3%

Source: Own elaboration based on ILOSTAT (Employment by occupation - ISCO level 2 (thousands))

A2 – Green occupations (all types) by region



A3 – Green occupations and green sectors in LAC. All services sectors as green, Agriculture and Industry as Non-green.



A4 – Fixed effects regressions All countries

Table A4.a. Fixed effects regression of green jobs and GHG emissions on economic development, unbalanced panel 2001-2020.

	Proportion of employment in:								log (GHG emissions)
	Green	Green new and emerging	Green enhanced skills	Green increased demand	Non-green	Green Rival	Other Non-green	Green/Non-green	
log (GDP per capita)	0.0199	0.00439***	0.0411***	-0.0256*	-0.0199	-0.0589***	0.0389***	0.0322	0.403***
	(0.0145)	(0.00107)	(0.0107)	(0.0152)	(0.0145)	(0.0215)	(0.0103)	(0.0243)	(0.0754)
Observations	663	663	663	663	663	663	663	663	2,400
R-squared	0.025	0.062	0.225	0.048	0.025	0.127	0.100	0.027	0.161
Number of countries	87	87	87	87	87	87	87	87	86

Source: Own elaboration based on ILOSTAT (series: Employment by occupation - ISCO level 2 (thousands)) and WDI (series: Total greenhouse gas emissions (kt of CO2 equivalent); GDP per capita, PPP (constant 2017 international $)).

Notes: 1) Robust standard errors in parentheses. 2) *** p<0.01, ** p<0.05, * p<0.1. 3) The unbalanced panel includes all countries with at least 2 years of complete data on green jobs and GDP per capita in the period 2001-2020.

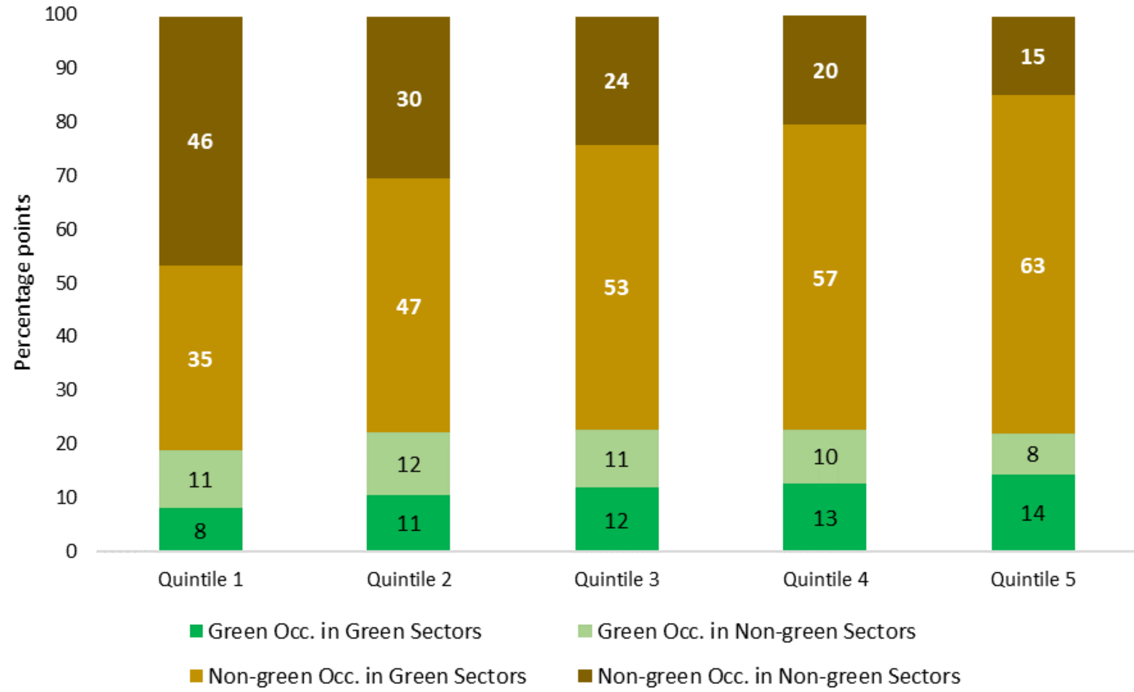
Table A4.b. Fixed effects regression of green jobs and GHG emissions on economic development, balanced panel 2011-2019.

	Proportion of employment in:								log (GHG emissions)
	Green	Green new and emerging	Green enhanced skills	Green increased demand	Non-green	Green Rival	Other Non-green	Green/Non-green	
log (GDP per capita)	0.0157**	0.00408***	0.0121**	-0.000561	-0.0157**	-0.0424***	0.0268***	0.0257**	0.0165
	(0.00644)	(0.00132)	(0.00564)	(0.00506)	(0.00644)	(0.0119)	(0.00991)	(0.0111)	(0.141)
Observations	387	387	387	387	387	387	387	387	344
R-squared	0.057	0.080	0.076	0.000	0.057	0.192	0.089	0.055	0.000
Number of countries	43	43	43	43	43	43	43	43	43

Source: Own elaboration based on ILOSTAT (series: Employment by occupation - ISCO level 2 (thousands)) and WDI (series: Total greenhouse gas emissions (kt of CO2 equivalent); GDP per capita, PPP (constant 2017 international $)).

Notes: 1) Robust standard errors in parentheses. 2) *** p<0.01, ** p<0.05, * p<0.1. 3) The balanced panel includes all countries with complete data on green jobs and GDP per capita in the period 2011-2019.

A5 – Green and non-green occupations and sectors vs. household income quintiles, LAC 2019. All services sectors as green, Agriculture and Industry as Non-green.

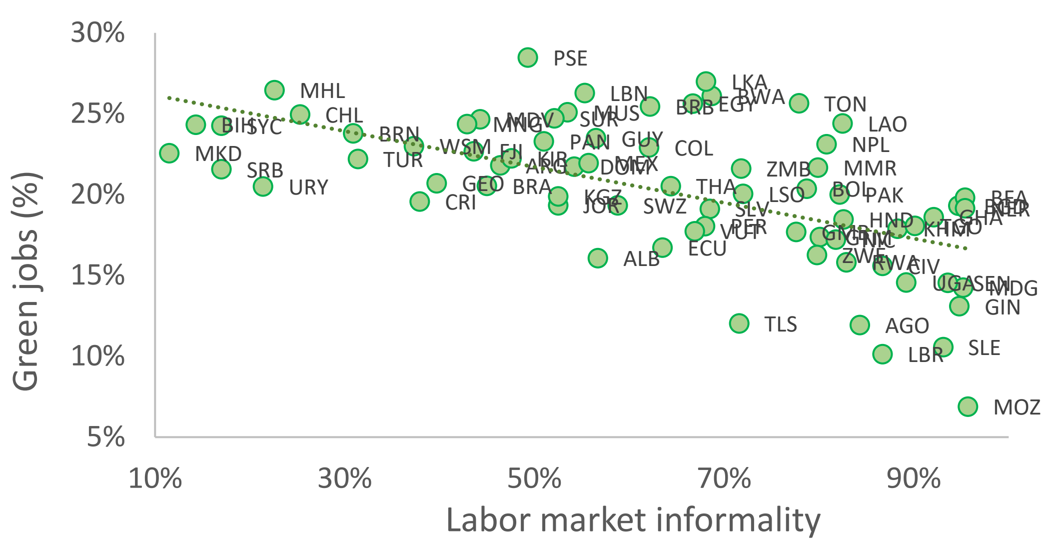


A6 – Green occupations, human capital, and informality

Figure A6.a – Green occupations and Human capital

Source: Own elaboration based on own data and the World Bank's Human Capital Index database.

Figure A6.b – Green occupations and labor market informality



Source: Own elaboration based on own data and ILO's.

A7 – Occupations with the highest shares by Green Job vs. Green Sector. LAC 2019.

Table A7.a. Females.

Green Occ. & Green Sector			Non-green Occ. & Green Sector		
2-digits ISCO	**Share**	**Classification**	**2-digits ISCO**	**Share**	**Classification**
14	28	Hospitality, Retail and Other Services Managers	53	84	Personal Care Workers
96	27	Refuse Workers and Other Elementary Workers	91	72	Cleaners and Helpers
11	19	Chief Executives, Senior Officials and Legislators	94	67	Food Preparation Assistants
Green Occ. & Non-green Sector			**Non-green Occ. & Non-green Sector**		
2-digits ISCO	**Share**	**Classification**	**2-digits ISCO**	**Share**	**Classification**
73	20	Handicraft and Printing Workers	63	45	Subsistence Farmers, Fishers, Hunters and Gatherers
82	20	Assemblers	75	28	Food Processing, Woodworking, Garment and Other Craft and Related Trades Workers
96	12	Refuse Workers and Other Elementary Workers	92	27	Agricultural, Forestry and Fishery Labourers

Table A7.b. Males.

Green Occ. & Green Sector			Non-green Occ. & Green Sector		
2-digits ISCO	**Share**	**Classification**	**2-digits ISCO**	**Share**	**Classification**
14	43	Hospitality, Retail and Other Services Managers	54	75	Protective Services Workers
11	42	Chief Executives, Senior Officials and Legislators	95	45	Street and Related Sales and Service Workers
96	26	Refuse Workers and Other Elementary Workers	35	37	Information and Communications Technicians
Green Occ. & Non-green Sector			**Non-green Occ. & Non-green Sector**		
2-digits ISCO	**Share**	**Classification**	**2-digits ISCO**	**Share**	**Classification**
71	55	Building and Related Trades Workers (excluding Electricians)	61	70	Market-oriented Skilled Agricultural Workers
74	39	Electrical and Electronics Trades Workers	92	69	Agricultural, Forestry and Fishery Labourers
83	39	Drivers and Mobile Plant Operators	62	65	Market-oriented Skilled Forestry, Fishery and Hunting Workers

A8 – Occupations with the highest Non-green Share in Agriculture. LAC 2019.

2-digits ISCO	Non-green employment in Agriculture (Share)	Classification
34	100	Legal, Social, Cultural and Related Associate Professionals
41	100	General and Keyboard Clerks
44	100	Other Clerical Support Workers
51	100	Personal Service Workers
53	100	Personal Care Workers
63	100	Subsistence Farmers, Fishers, Hunters and Gatherers
91	100	Cleaners and Helpers
94	100	Food Preparation Assistants
95	100	Street and Related Sales and Service Workers
54	100	Protective Services Workers
92	99	Agricultural, Forestry and Fishery Labourers
32	99	Health Associate Professionals
22	98	Health Professionals
26	98	Legal, Social and Cultural Professionals
23	96	Teaching Professionals
61	96	Market-oriented Skilled Agricultural Workers
35	95	Information and Communications Technicians

A9 – Data Sources

This section provides additional details on the data sources used:

- Occupational Information Network (O*NET)'s US 2010 Standard Occupational Classification (SOC) System which provides a list of 1,110 occupations, 204 of which are identified as green and divided into three mutually exclusive categories: Green Increased Demand (64 occupations), Green Enhanced Skills (62 occupations) and Green New and Emerging (78 occupations). https://www.onetcenter.org/dictionary/22.0/excel/green_occupations.html
- ILO Occupational structure data based on the International Standard Classification of Occupations (2-digit ISCO 08) for 120 countries from circa 2001 to circa 2020 (676 country-year observations). https://www.ilo.org/public/english/bureau/stat/isco/isco08/
- Climate Watch Climate Analysis Indicators Tool (CAIT) which provides data on GHG emissions by industry from 1990 to 2018, following the Intergovernmental Panel on Climate Change (IPCC) reporting framework. https://www.climatewatchdata.org/ghg-emissions?end_year=2019&start_year=1990

- OECD country-level Input-Output tables (IOTs) contain information about how each sector's gross production is distributed among all economic sectors (intermediate demand) and final demand. The latter comprises households' domestic demand, non-profit institutions' domestic demand, the government's domestic demand, capital formation, inventories, exports, and imports. The sector classification corresponds to 2-digits of the 4th revision of the International Standard Industrial Classification of Economic Activities (ISIC Rev. 4). https://stats.oecd.org/Index.aspx?DataSetCode=IOTSI4_2018
- SEDLAC Socioeconomic Database for Latin America and the Caribbean is a database of harmonized socio-economic statistics constructed from Latin American and Caribbean (LAC) household surveys. The SEDLAC database and project were jointly developed and are jointly maintained by CEDLAS (Universidad Nacional de La Plata) and the World Bank's LAC Team for Statistical Development (LAC TSD) in the Poverty and Equity Global Practice. SEDLAC includes information from over 300 household surveys carried out primarily in 18 LAC countries for which a comparable income aggregate (for welfare analysis) can be created: Argentina, Bolivia, Brazil, Colombia, Costa Rica, Chile, Dominican Republic, Ecuador, El Salvador, Guatemala, Haiti, Honduras, Mexico, Nicaragua, Panama, Paraguay, Peru, and Uruguay. The harmonized occupational variables (2-digit ISCO 08) in the SEDLAC database covers 16 countries (not available for Haiti and Paraguay) since the early 2000s (101 country-year surveys). https://www.cedlas.econo.unlp.edu.ar/wp/en/estadisticas/sedlac/
- The OECD Program for the International Assessment of Adult Competencies (PIAAC) data, and specifically the Survey of Adult Skills, measures adults' proficiency in key information-processing skills - literacy, numeracy and problem solving - and gathers information and data on how adults use their skills at home, at work and in the wider community for over 40 countries. While the data is relevant for an analysis of green jobs/skills, the paper did not eventually use the PIAAC data because countries are surveyed only every circa 10 years. This is in contrast with the SEDLAC data which offers a much higher frequency of coverage. https://www.oecd.org/skills/piaac/