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Occupational Mobility and Green Transition: A Stylized Estimation of Skill Investment Needs in South Asia*

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Abstract

This paper estimates the share of green employment in seven South Asian countries using an O*NET-based definition and finds that, on average, 24 percent of jobs in the region are currently green. The paper then assesses the potential for non-green workers to transition into green occupations. Among all non-green workers, 57 percent could transition to green jobs with limited reskilling, 16 percent with moderate upskilling, and 27 percent with full skills reconversion. These results suggest three policy priorities—promoting on-the-job training, strengthening firm-based and public–private training systems, and adopting a dual strategy that invests in reskilling and upskilling today's workforce while simultaneously advancing forward-looking education reforms that equip future cohorts for new and emerging green occupations.

Keywords: climate change, labor markets, green transitions, green skills, green jobs, occupational mobility, skills development needs.

JEL Classification: J21, J24, J62, O57, Q01, Q58.

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1. Introduction

Labor markets are undergoing profound changes driven by technological, economic, and demographic factors, with climate action also contributing to these shifts (Garrote-Sanchez and Yanez-Pagans, 2024). As the green transition accelerates, it is reshaping skill needs—creating demand for workers with "green" skills. These green skills refer to knowledge, abilities, values, and attitudes that support and promote sustainable development. However, most countries are not currently equipped to support the green transition in terms of skills development needs. Understanding skill requirements is, therefore, critical for informing how to strengthen education and training systems so that green transitions are feasible, efficient, and equitable (e.g., Sanchez-Reaza et al 2023, OECD 2023, and Fuchs 2024).

The term green transition broadly refers to the shift from an economy dependent on fossil fuels and resource-intensive industries to one that is more sustainable, low-carbon, and environmentally friendly. Several countries in South Asia, including India and Bangladesh, have committed to reducing emissions or achieving net-zero targets in the coming decades. Achieving these goals will require significant changes in their labor markets, with the demand for green skills expected to rise sharply while the need for skills used exclusively in carbon-intensive jobs is anticipated to decline—and, in some cases, disappear.

To better understand how green skills are reflected in employment, several studies have estimated the size of the green workforce and characterized workers in green occupations.[6] Existing measurement approaches help describe green employment and provide insight into the

[6] See Dercon (2014), Consoli *et al*. (2016), Moreno-Mondejar *et al*. (2021), Dell'Anna (2021), Granata and Posadas (2022; 2024), Stanef-Puică *et al*. (2022), Sulich and Soloducho-Pelc (2022), Woods *et al*. (2023), Apostel and Barslund (2024), Winkler-Seales *et al*., (2024), de la Vega *et al*. (2024), Ham *et al*. (2025), Mosomi and Cunningham (2024).

potential labor market consequences of green transitions. Most studies discuss and estimate the distributive consequences of green transitions (see Carley and Konisky, 2020; García-García *et al*., 2020; Vona, 2023; Cavallo *et al*., 2024). Yet, beyond distributional impacts, it is equally important to investigate the magnitude and type of skill investments required to enable a successful transition. Determining these needs is an important contribution to designing policies that support workers and firms during this transformation.

A central question is the scale of retraining required to enable transitions into green occupations. Some workers may require minimal training, as their existing skills can be easily upgraded to meet the demands of a green job and could be easily acquired on the job. Others, particularly those in carbon-intensive industries, may require significant upskilling or even complete retraining to transition into the green economy. This distinction—between reskilling, upskilling, and reconversion—is central for estimating the scale of investment required to meet national sustainability targets and for clarifying the respective roles of education systems and firms in providing training. Without careful planning, there is a risk that workers in declining industries will be left behind, exacerbating inequality and undermining the goal of a just transition.

In this paper, we explore three questions: (i) What is the share of green employment? (ii) What is the nature of green jobs—are they entirely new roles created by the green transition, or are they existing jobs that need to adapt? and (iii) If non-green workers were to transition into green employment, how many would require skills investment, and to what extent? While some research has started to shed light on these issues, the literature remains scarce (Bowen *et al*., 2018; Sanchez-Reaza *et al*., 2023; Urban *et al*., 2023; Popp *et al*., 2024; Owusu-Agyeman and Aryeh-Adhei, 2024; Renfors, 2024). As a result, our understanding of how labor markets are adapting to the green transition—and what is needed to support workers through skills development—remains limited.

We present estimates on the number and types of green jobs in seven South Asian countries —Bangladesh, Bhutan, India, the Maldives, Nepal, Pakistan, and Sri Lanka.[7] We then benchmark the scale of reskilling required by quantifying how many non-green workers, given their current skills, could transition to green jobs with minimal training, how many would require moderate upskilling, and how many would need comprehensive retraining. This is a benchmarking exercise rather than a scenario-based analysis as it does not model green transition pathways or future labor demand. Accordingly, it provides a stylized estimate of retraining needs if all non-green workers were to move into green occupations. In practice, not all non-green jobs will or should become green—there will remain demand for roles such as lawyers and cleaners—but many of these occupations will "green" in their processes and standards. Our stylized approach is intended to capture the economy-wide adjustment in skills that such greening implies.

Our analysis follows a three-stage methodological approach. First, we examine how green employment can be measured using nationally representative labor force surveys. We apply multiple definitions of green jobs based on occupational bottom-up approaches, highlighting the strengths and limitations of each method for quantifying the size of the green workforce. Second, we select the O*NET definition, which places a special emphasis on skills, to analyze patterns and trends in green employment and profile green workers across countries. Third, we apply the taxonomy developed by Bowen *et al.*'s (2018) notion of "green-rival" jobs and refining it using O*NET's Related Occupations Matrix, to classify all jobs into six categories:

i. Green increased demand—existing jobs requiring no change in skills

[7] Afghanistan was not included in this study due to the lack of labor force survey data to conduct the analysis.

ii. Green enhanced skills—existing jobs requiring new skills

iii. Green new and emerging—entirely new jobs created by the green transition

iv. Non-green jobs that can transition with minimal training

v. Non-green jobs that can transition with moderate training

vi. Non-green jobs that require comprehensive retraining

This approach allows us to distinguish between jobs that can be converted with short, modular on-the-job training and those that require deeper investments in certification and formal education. While short-cycle training is critical to support the reskilling of existing non-green workers, longer-cycle programs play a dual role: they enable the full reconversion of workers in occupations requiring substantial skill shifts and prepare new entrants for high-skill green jobs that are expected to expand over time. Understanding both the size of current green employment and the magnitude of skill development needed for these transitions is essential for designing education and training policies that foster inclusive and forward-looking green transitions in the region.

Our analysis of green job definitions shows that although all rely on an occupational bottom-up approach, they produce highly heterogeneous estimates of green employment and lead to different country rankings. Applying these definitions to survey data requires nontrivial assumptions—for instance, constructing crosswalks between classification systems—which can introduce measurement errors and increase the uncertainty around the estimates. Despite these challenges, the availability of multiple definitions offers important advantages. On one hand, it gives researchers and policy makers a shared framework for discussing how labor markets are adapting to the green transition. On the other hand, these definitions can be applied to regularly collected labor force surveys, making it possible to track patterns and trends in green employment and profile green workers. Thus, even if imperfect, measurement of green jobs still generates valuable policy insights.

The results from applying the O*NET definition of green jobs to household surveys in South Asia yield several stylized facts. First, green occupations account for roughly one in four jobs, and they are predominantly male-dominated and concentrated in urban areas. Second, the distribution of green employment varies systematically by age group, education level, and economic sector, though patterns differ significantly across countries. Third, the skill requirements of green jobs are not uniform: in some countries, green jobs demand relatively few additional skills, while in others they require more. Fourth, green workers are more often employers and self-employed individuals rather than paid employees. As a result, only a minority hold formal jobs with labor contracts or pay social security contributions. Fifth, the most common type of green occupation differs by country. Sixth, green jobs are associated with a significant wage premium of about 12 percent, although this premium varies across both countries and gender. Taken together, these findings highlight not only the key characteristics of green employment but also the extent to which outcomes differ across national labor markets.

While one in four jobs in South Asia is classified as green, the majority—three out of four—remain non-green. We classify these non-green jobs into three categories: i) those that can transition into green jobs easily (*reskilling*); ii) jobs that can transition with more difficulty toward green jobs with some skills investment (*upskilling*); and iii) jobs that are unable to have workers transition to green jobs without investing in new skills (*reconversion*). Our estimates suggest that about 57 percent of all jobs that are currently non-green could transition with limited reskilling, 16 percent could transition with moderate upskilling, and 27 percent could only transition with major investments in skilling (reconversion). These averages mask important country differences. For example, reskilling needs range from 38 percent in the Maldives to 68 percent in India. Jobs requiring moderate upskilling vary from 12 percent in Bangladesh to 24 percent in Nepal. Finally, jobs requiring full reconversion range from 19 percent in India to 45 percent in the Maldives. We interpret these estimates as suggestive that occupational mobility into green jobs is feasible and scalable in South Asia but achieving it will require varying levels of skills investment across countries and a gradual approach to support workers in the transition.

Our findings point to three main policy implications for supporting the green transition in South Asia. First, because most non-green jobs can transition with small to modest training, on-the-job training would serve as a central pillar to support the green transition. Short, modular programs that can be delivered directly in the workplace are particularly well-suited to support skill development efforts, complementing the role of the formal education system.

Second, the wage premium associated with green jobs provides a strong signal that both workers and firms have incentives to invest in training. However, persistent market failures—such as information asymmetries and coordination failures—can dampen these incentives. These dynamics reinforce the importance of targeted interventions to address such failures, including strengthening firm-based training systems and building robust public–private partnerships to improve information flows, mobilize resources, align training with labor market needs, and ensure scale.

Third, because the transition will unfold gradually, policy must take a dual approach: investing in reskilling and upskilling today's workforce while at the same time advancing forward-looking education reforms that equip future cohorts for new and emerging green occupations. Taken together, these implications suggest that the green transition will be most effectively supported through a combination of workplace learning, layered education systems, firm-led training, and strategic public–private collaboration. Our results serve as an entry point for policy discussions on how both formal education systems and on-the-job training mechanisms can support a green transition that is both efficient and equitable for South Asian workers.

The rest of this paper is organized as follows. Section 2 describes commonly used definitions to identify green jobs and how we apply them to the survey data. We include a description of the benefits and drawbacks of the selected definitions, and present comparative calculations of green employment for the seven countries in our sample. Section 3 presents a profile of the characteristics of green workers in South Asia, highlighting patterns and trends in green employment, as well as characterizing workers in these jobs. Section 4 disaggregates green jobs into different categories and then presents estimates of how many non-green workers would require reskilling, upskilling, or reconversion of skills to transition into a green job. In addition, this section presents the main policy implications of our results. Section 5 presents some concluding remarks.

2. Measuring green jobs: Theory and practice

The definition of a "green job" as environmentally friendly or a "carbon-intensive job" as polluting is far from universal and not easy to implement in practice (Bowen *et al*., 2018). If green jobs were defined by economic sector, for example, two administrative assistants working in a recycling center and a petroleum refinery would be classified as green and carbon-intensive, respectively. If green jobs are defined by workers' occupations, then there may be a mix of green and carbon-intensive jobs within sectors. Hence, the administrative assistants mentioned beforehand may be classified as a green occupation, regardless of whether they are employed in a green or carbon-intensive economic sector. If green jobs are defined by tasks carried out by workers, this could lead to occupations that are partly green, partly carbon-intensive, both, or neither. If the administrative assistants carry out both green and carbon-intensive tasks, defining jobs as binary — green or non-green — becomes more complicated. Accurately classifying green and carbon-intensive jobs is essential for analysis and policy making, but it is inherently challenging.

Measuring green transitions in labor markets also requires applying complex concepts to imperfect data. Theoretically, we may consider firms' output, their technology, workers' skills, or occupational task content when trying to identify green jobs (Granata and Posadas, 2022; 2024). Firm-level data that asks about output and technology is rarely available, so using the first two concepts is restricted by data availability and the level of detail when it exists (output and technology). This leaves worker skills and occupation task content to try to measure green jobs. Worker skills are multidimensional and not easy to measure (Autor and Handel, 2013; McGuinness *et al*., 2018), but most census data and labor force surveys do inquire about a worker's occupation to varying degrees of specificity. Unfortunately, census data are available at best every decade in most countries. Governments often rely on annual household surveys to monitor labor markets. Data availability thus restricts the potential definition of green jobs to the occupation task content approach, which can be applied to survey responses, making certain assumptions given that we observe occupations but not detailed tasks.

Given the accessibility of occupational data, researchers have commonly applied a bottom-up approach in household surveys (Granata and Posadas, 2022, 2024; Winkler-Seales *et al*., 2024; de la Vega *et al*., 2024; Ham *et al*., 2025). However, household surveys typically identify only workers' occupations, not the specific tasks they perform, the skills they use, or the competences they hold, as these concepts are rarely measured directly in practice. Skills refer to the cognitive and non-cognitive abilities workers bring to a job—such as problem-solving, teamwork, or technical know-how. Competences capture the formal knowledge or certifications required to perform that job, such as a license, degree, or specialized training. Tasks are the concrete activities workers carry out on a daily basis—for example, preparing reports, operating machinery, or installing solar panels. Occupations, by contrast, are standardized labels that group jobs with similar roles and responsibilities, such as "administrative assistant," "electrician," or "machine operator." Because most surveys observe occupations but not tasks, skills, or competences, empirical analyses of green jobs must rely on occupational classifications as a proxy, even though jobs within the same occupation may differ substantially in their actual environmental content.

Using an occupational bottom-up approach, there are many ways of defining green jobs in household surveys, but this paper will focus on four of them.[8] We briefly describe these approaches, discuss how they are commonly applied, and consider their benefits and drawbacks. These definitions use a worker's self-reported occupation, in which they perform certain tasks, to define whether the job is green or non-green. While some approaches speak about worker skills or competences, these are not measured in labor force surveys but are presumed to be indirectly captured through the individual's occupation. Given the scope of this paper, we refer to the original sources for an in-depth treatment of each definition. Table 1 lists the selected definitions, describes the categories used by each approach, and provides examples of occupations that are included in the definition's criteria (with some illustrations of resulting green jobs). Table A.1 in the Appendix presents a summary of the commonalities and differences across the various green job definitions.

The first definition for green jobs we review is the one proposed by the Occupational Information Network (O*NET), originally developed by Dierdorff *et al*. (2009, 2011). The classification is based on the United States 2010 Standard Occupation Classification (SCO) system and is often considered the gold standard in the field (Doan and Nguyen, 2024). Approximately

[8] For instance, Paliński *et al*. (2024) leverage natural language processing, specifically a retrieval-augmented generation model, to identify green job titles into 25 distinct sectors.

204 out of 1,110 occupations are identified as green. Those occupations are further classified into three sub-categories: i) green increased demand, which are jobs that already exist and require no changes in skills; ii) green enhanced skills, which are jobs that already exist but require new skills; and iii) green new and emerging, which are new jobs unique to the green transition. Table 1 provides specific definitions with examples.[9] In what follows, when we refer to the O*NET definition, it includes the Winkler *et al*. adjustment.[10]

[9] Tables A.2, A.3, and A.4 in the Appendix provide a list of the occupations in green increased demand, green enhanced skills, and green new and emerging categories using the O*NET definition.

[10] Hardy, Keister, and Lewandowski (2018) have also proposed a crosswalk to implement O*NET outside the United States (https://ibs.org.pl/en/resources/occupation-classifications-crosswalks-from-onet-soc-to-isco/). Specifically, Lewandowski *et al*. convert the O*NET classification to the US SOC by focusing on the first six common digits in the classification, just as we do, and then convert the US SOC codes to ISCO using the same crosswalk provided by the US Bureau of Labor Statistics (https://www.bls.gov/soc/soccrosswalks.htm). Their definition aligns exactly with the approach used in our study.

Table 1. Definitions of green jobs under different alternatives of measurement

Approach	Definition	Categories	Description	Examples (ISCO-08) with percentage of green jobs
Skills-based	O*NET	**Green increased demand**	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. The official O*NET list of occupations in this category is converted from the 8-digit O*NET-SOC code to the International Classification of Occupations (ISCO) using the methodology and crosswalks provided by Winkler et al. (2024), which employs a probabilistic rather than a dichotomous approach. Since the correspondence between the 8-digit O*NET-SOC and ISCO is not one-to-one, a worker in an ISCO occupation has a probability of belonging to this category. See Table A1 for details.	Chemical processing plant controllers (ISCO 3133); Forestry technicians (ISCO 3143); Production clerks (4322).
		Green enhanced skills	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. The official O*NET list of occupations in this category is converted from the 8-digit O*NET-SOC code to the International Classification of Occupations (ISCO) using the methodology and crosswalks provided by Winkler et al. (2024), which employs a probabilistic rather than a dichotomous approach. Since the correspondence between the 8-digit O*NET-SOC and ISCO is not one-to-one, a worker in an ISCO occupation has a probability of belonging to this category. See Table A2 for details.	Building architects (2161); Electrical engineers (2151); Construction managers (1323).
		Green new and emerging	The "purest" forms of green jobs. These are the occupations that emerge as a result of the green economy creating the need for new and unique work and worker requirements. The official O*NET list of occupations in this category is converted from the 8-digit O*NET-SOC code to the International Classification of Occupations (ISCO) using the methodology and crosswalks provided by Winkler et al. (2024), which employs a probabilistic rather than a dichotomous approach. Since the correspondence between the 8-digit O*NET-SOC and ISCO is not one-to-one, a worker in an ISCO occupation has a probability of belonging to this category. See Table A3 for details.	Chemical engineering technicians (3116) - 85% of employment in this occupation is estimated to be Green new and emerging. Manufacturing managers (1321) - 71% of employment in this occupation is estimated to be Green new and emerging. Environmental protection professionals (2133) - 59% of employment in this occupation is estimated to be Green new and emerging.

Approach	Definition	Categories	Description	Examples (ISCO-08)
Task-based	Granata & Posadas (2022)	**Non-zero Green Task Intensity (Broad definition)**	Occupations with a positive proportion of tasks that are green within it (Green Task Intensity>0), defining a task as green if it has at least one of the 347 green and green potential terms included in a broad dictionary. Each occupation has a number of tasks associated with it, created from the ILO's International Standard Classification of Occupations 2008 (ISCO-08), and the presence of a green or green potential term in the task description is sufficient to classify the task as green. The dictionary is constructed from the following sources: 1) common terms in the environmental economics literature; 2) US Bureau of Labor Statistics Green Technologies and Practices survey; 3) US Department of Labor O*NET green task statements; 4) skills/competences from the European Skills, Competences, Qualifications and Occupations taxonomy. See Table A4 for details.	Agricultural and forestry production managers (1311); Farming, forestry and fisheries advisers (2132); Forestry technicians (3143); Refuse sorters (9612). All with 100% Green Task Intensity GTI.
		Non-zero Green Task Intensity (Narrow definition)	Occupations with a positive proportion of tasks that are green within it (Green Task Intensity>0), defining a task as green if it has at least one of the 308 green terms included in a narrow dictionary. Each occupation has a number of tasks associated with it, created from the ILO's International Standard Classification of Occupations 2008 (ISCO-08), and the presence of a green term in the task description is sufficient to classify the task as green. The dictionary is constructed from the following sources: 1) common terms in the environmental economics literature; 2) US Bureau of Labor Statistics Green Technologies and Practices survey; 3) US Department of Labor O*NET green task statements; 4) skills/competences from the European Skills, Competences, Qualifications and Occupations taxonomy. See Table A5 for details.	Environmental engineers (2143) - 89% Green Task Intensity GTI; Environmental protection professionals - 86% Green Task Intensity GTI; Refuse sorters (9612) - 83% Green Task Intensity GTI; Meteorologist (2112) -78% Green Task Intensity GTI.

Approach	Definition	Categories	Description	Examples (ISCO-08)
Task-based	**India Skill Council of Green Jobs**	**Occupations with green qualifications**	Occupations with any of the 77 green qualifications defined by the Skill Council for Green Jobs: Solar PV Installer (Suryamitra); Solar PV Installer – Electrical; Rooftop Solar Grid Junior Engineer; Solar PV Installation Helper; Solar Water Pumping Junior Engineer; Solar PV Module Manufacturing Technician; Solar Lighting Assembler; Solar Photovoltaic Entrepreneur; Solar PV Cell Manufacturing Technician; Solar Domestic Product Assembler; Agrivoltaics Installer Electrical; Solar Manufacturing Junior Technician; Solar Photovoltaic Technician; Junior Technician - Solar Cold Storage; Solar Enterprise Assistant Manager; Solar Photovoltaic Site Survey Assistant; Solar Cold Storage Entrepreneur ; Junior Technician-Solar EV Charging Station; Solar EV Charging Entrepreneur; Solar PV Structural Assistant Design Engineer; Solar PV Designer;Solar PV Business Development Executive; Solar PV Installer - Civil; Solar Proposal Evaluation Specialist; Solar PV Project Manager(E&C); Solar PV Maintenance Technician - Electrical (Ground Mount); Green Hydrogen Plant Technician; Green Hydrogen Plant Entrepreneur; Green Hydrogen Plant Junior Technician- Electrolyzer; Green Hydrogen Plant Junior Technician- Power Sources; Green Hydrogen Plant Junior Technician- Storage; Green Hydrogen Plant Junior Technician-Desalination; Electrolyzer Manufacturing Plant Technician; Electrolyzer Manufacturing Plant Supervisor; Fundamentals of Financing for Green Hydrogen Project; Overview of Instrumentation and Control for Green Hydrogen Plant; Project Assistant Planner – Wind Power Plant; Wind Resource Assessor and Site Surveyor-Wind Power Plant; Construction Technician- Wind Power Plant; CMS Engineer- Wind Power Plant; O&M Mechanical Technician – Wind Power Plant; O&M Electrical & Instrumentation Technician – Wind Power Plant; Small Hydro Power Plant Technician-(Jal Urja Mitra); Biomass Depot Operator; Animal Waste Manure Aggregator; Agri-residue Aggregator; Feedstock Manager - Procurement and Composition; Technician – Operations and Maintenance (Compressed Biogas/Waste to Energy); Supervisor – Operations & Maintenance (Compressed Biogas/Waste to Energy); Plant Head- Operations (Compressed Biogas/Waste To Energy); Bio-Energy Micro Entrepreneur; Biomass Pellet Manufacturing Junior Technician; Manager- Waste Management; Improved Cookstove Installer; Portable Improved Cookstove Assembler; Clean Cookstove Sales and Maintenance Executive; Clean Cookstove Distributor; GHG Accounting and Sustainability Reporting; Green Logistics Practices; Optimize resource utilization at workplace; Adopt sustainable practices at the workplace; Plastic Recycling Operator; Safai Mitra; Biomedical Waste Management Nursing and Paramedical Staff; Waste Optimisation Professional; Material Recovery Facility (MRF) Micro – Entrepreneur ; Plastic Recycling Micro Entrepreneur; Junior Technician - Rooftop Rainwater Harvesting; Rooftop Rain Water Harvesting Entrepreneur; Sewer Entry Professional; Desludging Operator; Junior Technician- Mechanized Sewer Cleaning; Wastewater Treatment Plant Helper; Wastewater treatment Plant Technician; Nature Conservator Cum Ecotourism Guide; Apiculturist (Wild bee) – NTFP (Non-Timber Forest Produce); Micro-Entrepreneur – NTFP (Non-Timber Forest Produce) – Plant Origin. See Table A6 for details.	Electronics mechanics and servicers (7421); Technical and medical sales professionals (excluding ICT) (2433); Electrical engineers (2151); Environmental engineers (2143); Building construction labourers (9313)

Approach	Definition	Categories	Description	Examples (ISCO-08)
Task-based	**European Classification of Occupations, Skills ad Competences (ESCO)**	**Occupations with green skills**	Occupations for which at least one of the skills used is a green skill. See Table A7 for the complete list of the 591 green skills published by the ESCO and Table A8 for the list of occupations with at least one green skill used.	Garbage and recycling collectors (9611) - 60% of skills are green; Forestry and related workers (6210) - 58% of skills are green; Refuse sorters (9612) - 57% of skills are green; Mixed crop and livestock farm labourers (9213) - 43% of skills are green; Environmental engineers (2143) - 42% of skills are green.
		Occupations with essential green skills	Occupations for which at least one of the essential skills used is a green skill. See Table A7 for the complete list of the 591 green skills published by the ESCO and Table A9 for the list of occupations with at least one essential green skill used.	Forestry and related workers (6210) - 68% of skills are green; Agricultural and forestry production managers (1311) - 65% of skills are green; Hunters and trappers (6224) - 50% of skills are green; Refuse sorters (9612) - 47% of skills are green; Environmental engineers (2143) - 45% of skills are green.

Source: Authors' elaboration.

A second green jobs definition was proposed by Granata and Posadas (2022, 2024), who developed a methodology designed for emerging economies to identify green jobs using information collected in labor force surveys. They develop a dictionary of common green terms relevant to emerging economies, apply the green terms dictionary to task statements of all occupations included in the ILO's International Standard Classification of Occupations (ISCO) using text analysis, and then calculate a Green Task Intensity (GTI) index by occupation that measures the share of tasks within each occupation that directly contribute to the greening process. The higher the GTI, the larger the number of green tasks performed in an occupation. One hundred twenty-seven occupations are classified as green using a broad version of the dictionary (a GTI higher than zero is a green job), and 36 are classified as green under a narrow version of the dictionary.[11] The former 127 are considered green occupations, while the latter 36 are considered strictly green occupations. The second panel in Table 1 summarizes broad and narrow definitions, with examples.

The third green jobs definition we employ is the one proposed by the Indian Skills Council for Green Jobs (SCGJ), which proposed a taxonomy specific to India to help monitor its long-term sustainability goals. The SCGJ's national definition includes 77 occupations related to the production of renewable energy, environment, forest, climate change, and sustainable development as of September 14, 2024.[12] The third panel of Table 1 summarizes this country-specific definition and examples of the resulting green jobs. We apply this definition to other countries in the South Asia region, given India's leadership in the green transition.

The last proposed definition for measuring green jobs from occupational information uses the European Classification of Occupations, Skills, and Competences (ESCO). Within the

[11] Tables A.5 and A.6 in the Appendix list the occupations that fall under the broad and narrow categories.
[12] Table A.7 in the Appendix lists the green occupations identified by the SCGJ.

European Union, the ESCO database is a common tool to classify jobs and has labeled certain skills and knowledge concepts as green, white, or carbon-intensive (Urban *et al*., 2023). Differing from the previous approaches that use a conceptual framework to define green jobs, the ESCO approach uses machine learning methods to identify 591 out of 13,890 skills as green. Within this general identification, there are two ways of defining green occupations that depend on whether skills within that job are considered green in a broad sense or are essential green skills. On the one hand, the last panel of Table 1 shows occupations in which at least one skill is green in a broad sense. On the other hand, we also have occupations in which at least one of the essential skills to carry out that job is a green skill according to the methodology employed by ESCO.[13]

Applying these definitions in practice is not straightforward, mainly because they rely on occupational classification systems from different countries (SCO, ISCO, and ESCO), which may not always apply to the labor markets under study. For instance, the O*NET definition was based on US occupations. A perfect one-to-one mapping between the definitions and data requires that household surveys contain the same occupational codes and, most importantly, the same level of detail for these codes to accurately classify green occupations. Therefore, using these definitions requires the use of crosswalks, translating from one occupational system to another or within the same occupational system from a more detailed taxonomy to a higher level of aggregation, which requires making assumptions. We also note that occupational codes in surveys rely on potentially outdated classification systems that may not coincide with the inputs used to define green skills, tasks, or occupations. For example, the ISCO-08 classification has not been updated since 2008 and remains the most common way to categorize worker occupations in surveys. Future estimates

[13] Tables A.8 and A.9 list the occupations with green skills and essential green skills identified by the ESCO approach. The differentiation between broad green skills and essential green skills is provided by ESCO in their open database: ESCO database version 1.2.0 (downloaded on 05/27/2024 from https://esco.ec.europa.eu/en/use-esco/download).

of green employment would likely benefit from updated occupational codes that reduce the need for crosswalks and other assumptions like we require implementing in this research.

Table 2 shows the surveys we employ in this study, highlighting the year of data collection, the occupational classification system, and the level of detail for the system in the survey.

We use the most recently available labor force survey for seven countries in South Asia: Bangladesh, Bhutan, India, the Maldives, Nepal, Pakistan, and Sri Lanka. Each survey classifies occupations using its own national system, but all are adaptations of the ISCO-08 classification. A key challenge in applying green job definitions is that the level of occupational detail varies across surveys—some, such as India's and part of Sri Lanka's, report occupations at the three-digit level, while others provide more granular four-digit classifications.

Table 2. Classifications of occupations in household surveys for South Asia

Country	Survey name	Year	Classification of occupations in the survey	ISCO version	Digits
Bangladesh	Quarterly Labour Force Survey	2022	Bangladesh Standard Classification of Occupations 2020	ISCO-08	4
Bhutan	Labour Force Survey	2022	Bhutan Standard Classification of Occupations 2022	ISCO-08	4
India	Periodic Labour Force Survey	2022/23	National Classification of Occupations 2015	ISCO-08	3
Maldives	Household Income and Expenditure Survey	2019	ISCO-08	ISCO-08	4
Nepal	Living Standards Survey	2022/23	Nepal Standard Classification of Occupations (NSCO)	ISCO-08	4
Pakistan	Labour Force Survey	2020/21	Pakistan Standard Classification of Occupations 2015	ISCO-08	4
Sri Lanka	Labour Force Survey	2021	Sri Lanka Standard Classification of Occupation 2008	ISCO-08	4*

Source: Authors' elaboration from household surveys.
Notes: In India and almost a quarter of employment in Sri Lanka, estimates are at the 3-digit level and are performed assuming an equal distribution of workers in 4-digit occupations within each 3-digit occupation.

How different are the results from applying each of the definitions in these countries? Table 3 shows the results. The O*NET definition suggests the percentage of green jobs in South Asia is around 24 percent. We then include the broad and narrow definitions from Granata and Posadas (2022). The first suggests that green jobs represent 47 percent of the workforce, and the second 3 percent, which reflects that the former includes more occupations by construction (127 occupations), while the latter has fewer as it applies narrower criteria to classify jobs as green (36 occupations). The national definition from India's SCGJ provides an average estimate of green employment of 19 percent. Finally, we have the ESCO definition, in which we consider a "broad" definition in which at least one skill is green and a "narrower" definition in which at least one essential skill is green. Applying these definitions results in a regional percentage of green jobs of 74 percent for the former and 64 percent for the latter.

Table 3. Percentage of workers in green jobs under different definitions, circa 2022

Country	O*NET	Granata & Posadas (2024) - Broad	Granata & Posadas (2024) - Narrow	India Skill Council of Green Jobs	ESCO - Occupations with green skills	ESCO - Occupations with essential green skills
Bangladesh	25	55	2	36	71	60
Bhutan	26	58	3	10	75	70
India	24	62	5	22	89	87
Maldives	17	21	3	12	63	54
Nepal	28	33	2	14	70	53
Pakistan	29	54	2	26	75	65
Sri Lanka	22	45	4	16	77	59
Regional average	**24**	**47**	**3**	**19**	**74**	**64**

Source: Authors' elaboration based on microdata listed in Table 2.
Notes: (1) Green jobs definitions are presented in Table 1. (2) In India and almost a quarter of employment in Sri Lanka, estimates are at the 3-digit level and are performed assuming an equal distribution of workers in 4-digit occupations within each 3-digit occupation.

The estimates in Table 3 show heterogeneity in green employment when using different definitions. For instance, using a definition like Granata and Posadas (2024) under the narrow view indicates low levels of green employment, but using a narrow view with the ESCO approach results in over 20 times more green jobs, providing different conclusions for the same countries based on a '*similar*' empirical definition. Additionally, the variance within definitions also differs depending on which of them is employed. The standard deviation in green job estimates between countries is 15 for Granata and Posadas (2024) – broad, 12 for ESCO – essential, 9 for the India SCGJ definition, 8 for ESCO –broad, 4 for the O*NET definition, and 1 for Granata and Posadas (2024) – narrow. The variation in estimates across countries using different definitions reflects disparities in their occupational and economic structures. Such discrepancies in measurement are expected, as they stem from differences in definitions, conceptual frameworks, measurement errors from implementing crosswalks, and underlying assumptions made when applying green job definitions.

While the level of green jobs varies according to the employed definition, it is interesting to assess whether the ranking of countries remains consistent across approaches. India appears as the country with the highest percentage of green jobs under four of the definitions (Granata and Posadas (2024) and ESCO; under both broad and narrow approaches). Nepal is the country with the largest percentage of green jobs according to the O*NET definition, while it is Bangladesh according to India's SCGJ definition. The countries ranked second to sixth vary substantially across approaches. For example, while Nepal is first according to O*NET in the percentage of green jobs, it is sixth for Granata and Posadas (2024) – broad, as well as ESCO. Pakistan also fluctuates in the rankings according to the definition employed. The Maldives is the only country that consistently has the lowest percentage of green employment in all but two of the employed definitions.

This review of concepts and empirical application of different definitions of green jobs results in several takeaways. First, even though all definitions use the occupational bottom-up approach, they result in heterogeneous estimates of the prevalence of green jobs. This stems not only from differences in labor market structures—reflecting the differing contexts of the United States, India, and the European Union—but also from variation in the scope of what is considered "green". As a result, these definitions might not properly capture the specific characteristics of South Asian labor markets. Therefore, while all definitions conceptually claim to measure green jobs, they capture different dimensions because their identification of green occupations is anchored in both the labor market context and the definitional scope used for their development.

Nonetheless, the existence of operational definitions for green jobs does have benefits. On the one hand, it provides researchers and policy makers with a common language to discuss greening in labor markets. Researchers can choose the definition most suited to the context under study and the available data to measure green jobs, justifying their selection. On the other hand, these definitions can be implemented on frequently collected survey data, which allow monitoring the changes in the percentage of green employment and characterizing green workers if that is an objective of interest. This monitoring may be more relevant if definitions change over time or surveys implement more detailed occupational systems that reduce the need for crosswalks.

3. Characterizing green jobs and workers in South Asian countries

Before examining the skill requirements for supporting green transitions in South Asia, we first profile the socioeconomic and demographic characteristics of green workers in the region and estimate wage differences between green and non-green workers. For this analysis, we use the O*NET definition with the Winkler-Seales *et al*. adjustment.

Using O*NET enables wider comparisons, as similar analyses are available for other regions.[14] However, this approach comes at the cost of having to assume that South Asian countries share the same production functions (technology, capital, labor, tasks, and skills) as the US and carries potential measurement errors due to crosswalks.[15] It is likely that choosing a different definition would lead to different results in profiling green workers, so we are cautious about generalizing the results presented henceforth since they apply to only the O*NET definition of green jobs.

Table 4 presents the percentage of green jobs in South Asian countries in the first column. On average, 24 percent of jobs in the region are green.[16] Pakistan is the country with the largest percentage of green jobs, followed by Nepal, Bhutan, Bangladesh, India, Sri Lanka, and the Maldives. The second and third columns show that green jobs are mostly located in urban areas for countries for which we have information, with about 25 percent of green jobs in rural areas and 28 percent in urban areas. We also note that green jobs in South Asia are 16 percent female and 29

[14] The choice of the O*NET definition has multiple advantages. It minimizes additional variation, as O*NET-based estimates show less fluctuation across South Asian countries compared to alternative definitions. Moreover, O*NET offers a balanced approach to defining green jobs—neither too restrictive nor overly broad. By contrast, the ESCO definition tends to yield upper-bound estimates of green employment, while the Granata and Posadas–Narrow definition produces lower-bound estimates. O*NET thus provides a middle ground between these extremes.

[15] The Granata and Posadas – Broad definition is also useful, as it relies on an internationally recognized dictionary of green-related terms. However, it depends on occupational task descriptions from ISCO-08, which may be outdated or incomplete. The Indian taxonomy offers a useful perspective given the country's leadership in the region's green transition. However, the lack of publicly available documentation on its underlying assumptions makes it difficult to apply the definition in a cross-country context.

[16] Estimates of green employment in the World Bank's South Asia Development Update (World Bank, 2023) range between 2–11 percent—lower than the 24 percent estimates presented in this paper. Three factors explain this difference. First, the Development Update applies a task-based classification (Granata and Posadas, 2024), defining an occupation as green if it includes more than one green task term under ISCO-08. By contrast, our study uses a skill-based definition derived from O*NET, probabilistically mapped to ISCO-08, that classifies any occupation affected by the greening of the economy as green—even if its core skill requirements remain unchanged (Winkler et al., 2024). This broader definition yields a higher share of green workers. Second, the Development Update relies on 2015–2019 labor force data for working-age males and excludes Bhutan due to data constraints, while our analysis uses post-2022 household surveys covering all working-age workers, including Bhutan. Third, demographic sample restrictions differ: the Development Update focuses only on men, whereas our study includes both men and women. Consequently, the Development Update and our estimates can be interpreted as lower and upper bounds, respectively, of green employment in South Asia.

percent male on average. Gender gaps in green employment vary across countries, with gaps of 5 percentage points in Bhutan and Bangladesh that rise to 23 percentage points in the Maldives. In India, Nepal, Pakistan, and Sri Lanka, gender gaps range between 11-16 percentage points in favor of men.

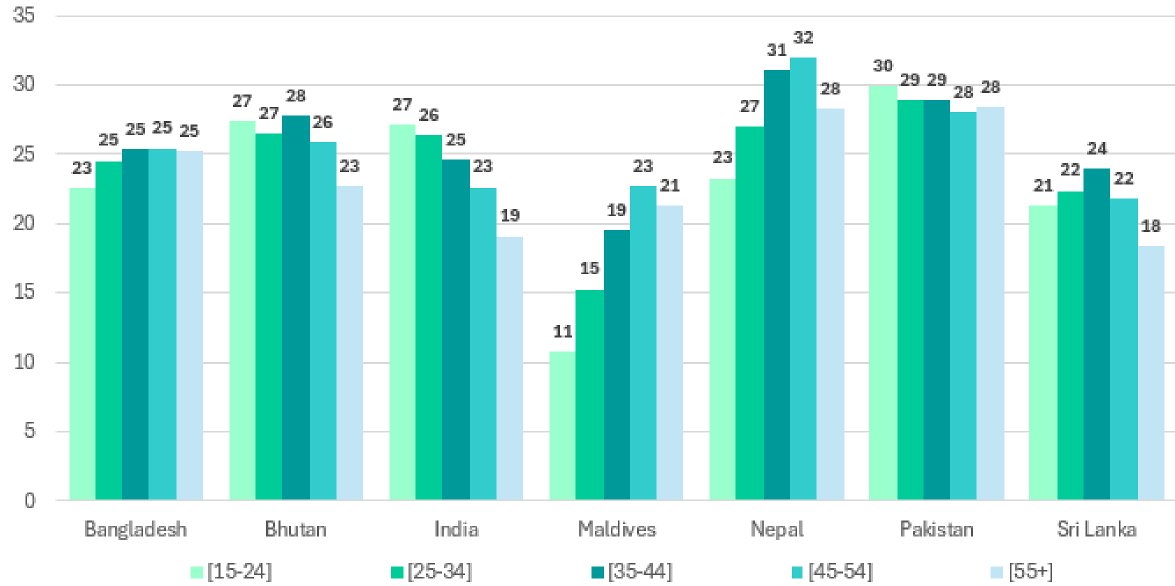
Table 4. Percentage of green jobs, circa 2022 (O*NET definition)
Overall, by area of residence, and sex

Country	Share of green jobs	Area of residence		Sex	
		Rural	Urban	Female	Male
Bangladesh	25	24	27	21	26
Bhutan	26	24	31	23	28
India	24	22	29	16	27
Maldives	17	n.a.	n.a.	4	27
Nepal	28	29	28	20	33
Pakistan	29	28	31	18	32
Sri Lanka	22	21	24	11	27
Regional average	**24**	**25**	**28**	**16**	**29**

Source: Own elaboration based on microdata listed in Table 2.
Notes: (1) The shares are computed using the O*NET definition of green jobs, converted to ISCO-08 using Winkler *et al*. (2024)'s methodology. (2) In India and almost a quarter of employment in Sri Lanka, estimates are at the 3-digit level and are performed assuming an equal distribution of workers in 4-digit occupations within each 3-digit occupation. n.a.-Not available (3) The regional average share of green jobs is calculated as a simple average across seven South Asian countries. This figure is not fully comparable with the regional averages reported separately for urban and rural areas, as data on workers' location are unavailable for Maldives. Consequently, the rural–urban averages are based on six countries, excluding Maldives.

We analyze whether the percentage of green workers varies by age groups, educational level, and economic sectors. Figure 1 shows the percentage of green jobs by age groups. The relationship is an inverted U-shape for most countries in South Asia, with heterogeneity in the age distribution of green workers across countries. For instance, older workers are more likely to be employed in green jobs in Bangladesh and the Maldives, and prime-age workers (35-44 years) are employed in green jobs in Bhutan, Nepal, and Sri Lanka. The percentage of younger green workers, aged 15-24, is larger in India and Pakistan.

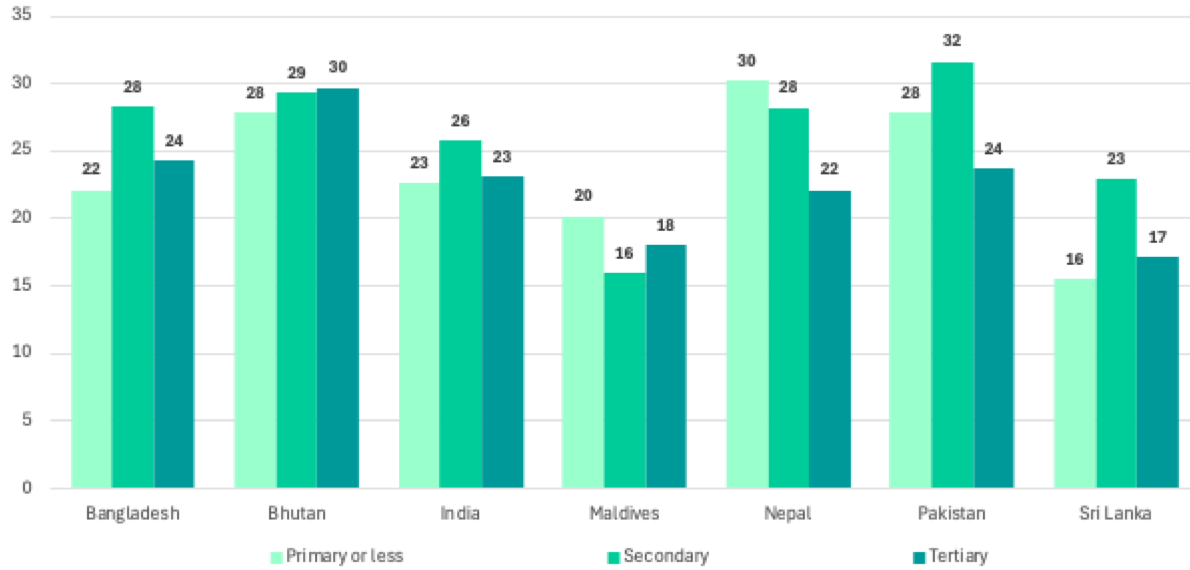
Figure 1. Percentage of green jobs by age group, circa 2022 (O*NET definition)



Source: Own elaboration based on microdata listed in Table 2.
Notes: (1) The shares are computed using the O*NET definition of green jobs, converted to ISCO-08 using Winkler *et al*. (2024)'s methodology. (2) In India and almost a quarter of employment in Sri Lanka, estimates are at the 3-digit level and are performed assuming an equal distribution of workers in 4-digit occupations within each 3-digit occupation.

In Figure 2, we plot the percentage of green jobs by educational level. On average, we find that 26 percent of workers have secondary schooling, 24 percent completed primary or less, and 23 percent have tertiary education. Again, we see heterogeneity across countries. While a larger percentage of green jobs are held by individuals with tertiary education in Bhutan, most green workers have secondary schooling in Bangladesh, India, Pakistan, and Sri Lanka, and there are more green workers with primary schooling in Nepal and the Maldives.

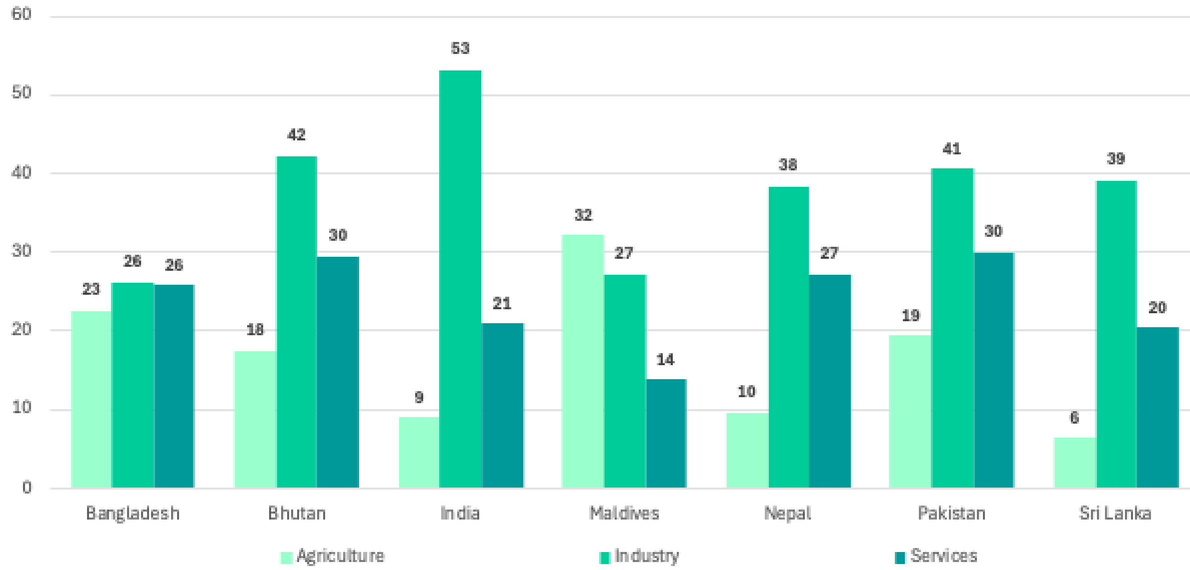
Figure 2. Share of green jobs by education level, circa 2022 (O*NET definition)



Source: Own elaboration based on microdata listed in Table 2.
Notes: (1) The shares are computed using the O*NET definition of green jobs, converted to ISCO-08 using Winkler *et al*. (2024)'s methodology. (2) In India and almost a quarter of employment in Sri Lanka, estimates are at the 3-digit level and are performed assuming an equal distribution of workers in 4-digit occupations within each 3-digit occupation.

Figure 3 shows whether there are more green jobs in agriculture, industry, or services. On average, there are 38 percent of green jobs in industry, 24 percent in services, and 17 percent in agriculture when applying the O*NET definition. However, we find heterogeneity once again, since these percentages vary substantially across countries. Agriculture is the sector with the most green jobs in the Maldives; industry in Bhutan, India, Nepal, Pakistan, and Sri Lanka; and the service sector is tied with industry in Bangladesh for the largest percentage of green jobs.

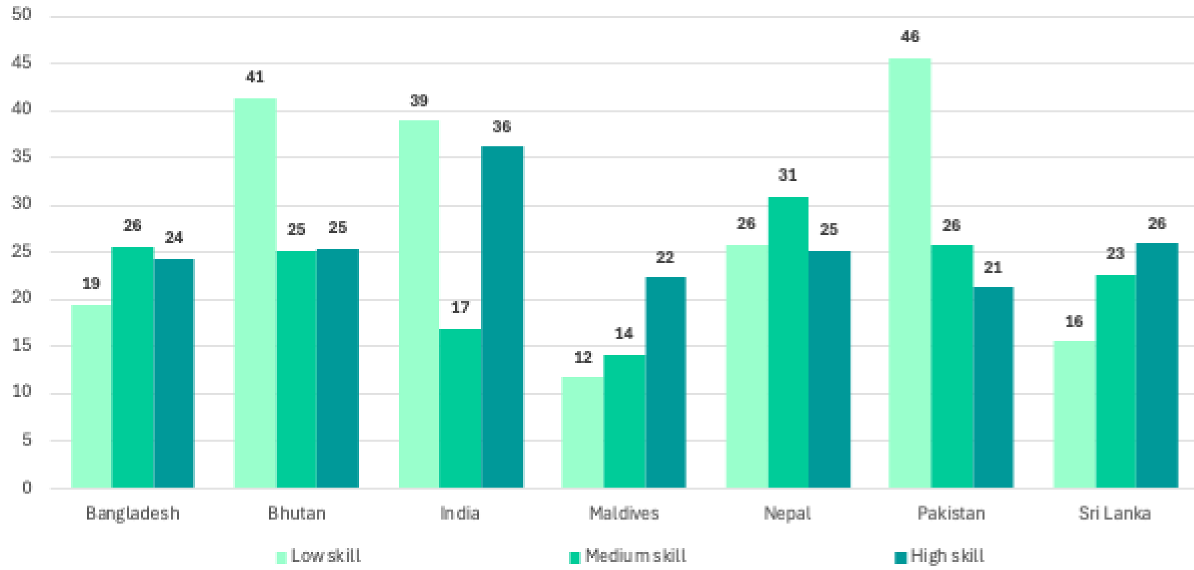
Figure 3. Percentage of green jobs by sector of activity, circa 2022 (O*NET definition).



Source: Authors' elaboration based on microdata listed in Table 2.
Notes: (1) The shares are computed using the O*NET definition of green jobs, converted to ISCO-08 using Winkler *et al*. (2024)'s methodology. (2) In India and almost a quarter of employment in Sri Lanka, estimates are at the 3-digit level and are performed assuming an equal distribution of workers in 4-digit occupations within each 3-digit occupation.

We now investigate the attributes of green jobs. Figure 4 shows the percentage of green workers by skill level, defined in three categories: low, medium, and high. Low skill corresponds to ISCO occupations in major group 9 (elementary occupations); medium skill to occupations in ISCO major groups 4-8 (clerks, service and market sales workers, skilled agricultural, craft workers, and machine operators); while high skill corresponds to occupations in ISCO major groups 1-3 (managers, professionals, and technicians). 28 percent of green workers are low-skilled, 23 percent are medium-skilled, and 26 percent are high-skilled on average. We find heterogeneity in these percentages across countries. While green jobs are concentrated in high-skill occupations in the Maldives and Sri Lanka, they are in medium-skill occupations in Bangladesh, Bhutan, and Nepal, and in low-skill occupations in India and Pakistan.

Figure 4. Percentage of green jobs by occupational skill level circa 2022 (O*NET definition)



Source: Authors' elaboration based on microdata listed in Table 2.
Notes: (1) The shares are computed using the O*NET definition of green jobs, converted to ISCO-08 using Winkler *et al*. (2024)'s methodology. (2) In India and almost a quarter of employment in Sri Lanka, estimates are at the 3-digit level and are performed assuming an equal distribution of workers in 4-digit occupations within each 3-digit occupation. (3) Low skill: ISCO major group 9 (Elementary occupations); Medium skill: ISCO major groups 4-8 (Clerks, Service and market sales workers, Skilled agricultural, Craft workers and Machine operators); High skill: ISCO major groups 1-3 (Managers, Professionals and Technicians).

Twenty-eight percent of green workers have vocational training in South Asia, and 25 percent do not have vocational training. These differences vary across countries. For instance, 48 percent of green workers have vocational training in Bhutan, and 26 percent do not. These trends are reversed in Pakistan, where 31 percent of green workers do not have vocational training, while 22 percent have had training. For the remaining countries with available data, the differences between green jobs where workers underwent vocational training and those that did not are smaller, ranging between 1 and 2 percentage points. Information on vocational training is unavailable for the Maldives and Pakistan.[17]

[17] The specific question on vocational training differs by country. The underlying questions are: "Did you attend any vocational training in the last 12 months?" in Bangladesh; "Are you currently attending, or have you attended in the past to training institutes?" (as opposed to ECCD/School/College/Universities, Monastic education, and non-formal education) in Bhutan; "Have you ever received vocational training?" in India; "Do you have formal vocational/professional training?" in Nepal; "Is vocational/technical institution your current education status?" (as

Table 5 presents statistics by country on employment status. We find that most green jobs in South Asia are employers (51 percent), followed by self-employed workers (29 percent), paid employees (23 percent), and finally, contributing family workers (20 percent). Cross-country estimates show that not all nations follow this regional pattern. In Bangladesh, employers and contributing family workers have the largest percentage of green workers. After employers, many countries have different percentages of green jobs in self-employment (between 19-48 percent), paid employees (between 18-31 percent), and contributing family workers (ranging from 7 to 33 percent). This suggests that the types of work being performed vary depending on the country we are observing.

Table 5. Percentage of green jobs, circa 2022 (O*NET definition)
By employment status group, social security contributions, and written labor contract

Country	Employment status				Social security contributions		Written labor contract	
	Paid employee	Contributing family worker	Employer	Self-employed	Without social security	With social security	Without contract	With contract
Bangladesh	18	33	33	30	n.a.	n.a.	16	19
Bhutan	25	20	60	30	n.a.	n.a.	n.a.	n.a.
India	31	13	41	19	34	23	34	21
Maldives	15	15	61	21	15	14	16	14
Nepal	22	24	49	48	23	16	30	15
Pakistan	26	26	60	32	n.a.	n.a.	30	14
Sri Lanka	21	7	55	23	23	17	23	17
Regional average	23	20	51	29	24	18	25	17

Source: Own elaboration based on microdata listed in Table 2.
Notes: (1) The shares are computed using the O*NET definition of green jobs, converted to ISCO-08 using Winkler-Seales *et al*. (2024)'s methodology. (2) When necessary, conversion to ISCO-88 is done using the ILO's ISCO-08 to ISCO-88 crosswalk and estimates at the 3-digit level are performed assuming an equal distribution of workers in 4-digit occupations within each 3-digit occupation. n.a.-Not available

opposed to School, University, Other Educational Institution, and does not attend/never attended, asked to both those who currently attend and those who do not) in Sri Lanka.

For paid employees, we can check whether they contribute to social security and have a written contract, but not for the other types of employment. We see in the fifth and sixth columns of Table 4 that green employees do not necessarily have formal jobs compared to non-green workers, where we define informality as contributing to social security.[18] On average, 24 percent of green workers have no social security, and 18 percent have social security. This finding is confirmed when looking at the contractual situation, where fewer green employees report having a written labor contract (25 percent versus 17 percent). We observe that percentages vary across countries, with social security contributions and written contracts for paid employees higher in some nations than others.

What are the most common green occupations in each country? Figure 5 presents the top ten occupations with the greatest percentage contribution to green employment in each country, from the lowest to the highest, showing the percentage of total green employment that they represent.

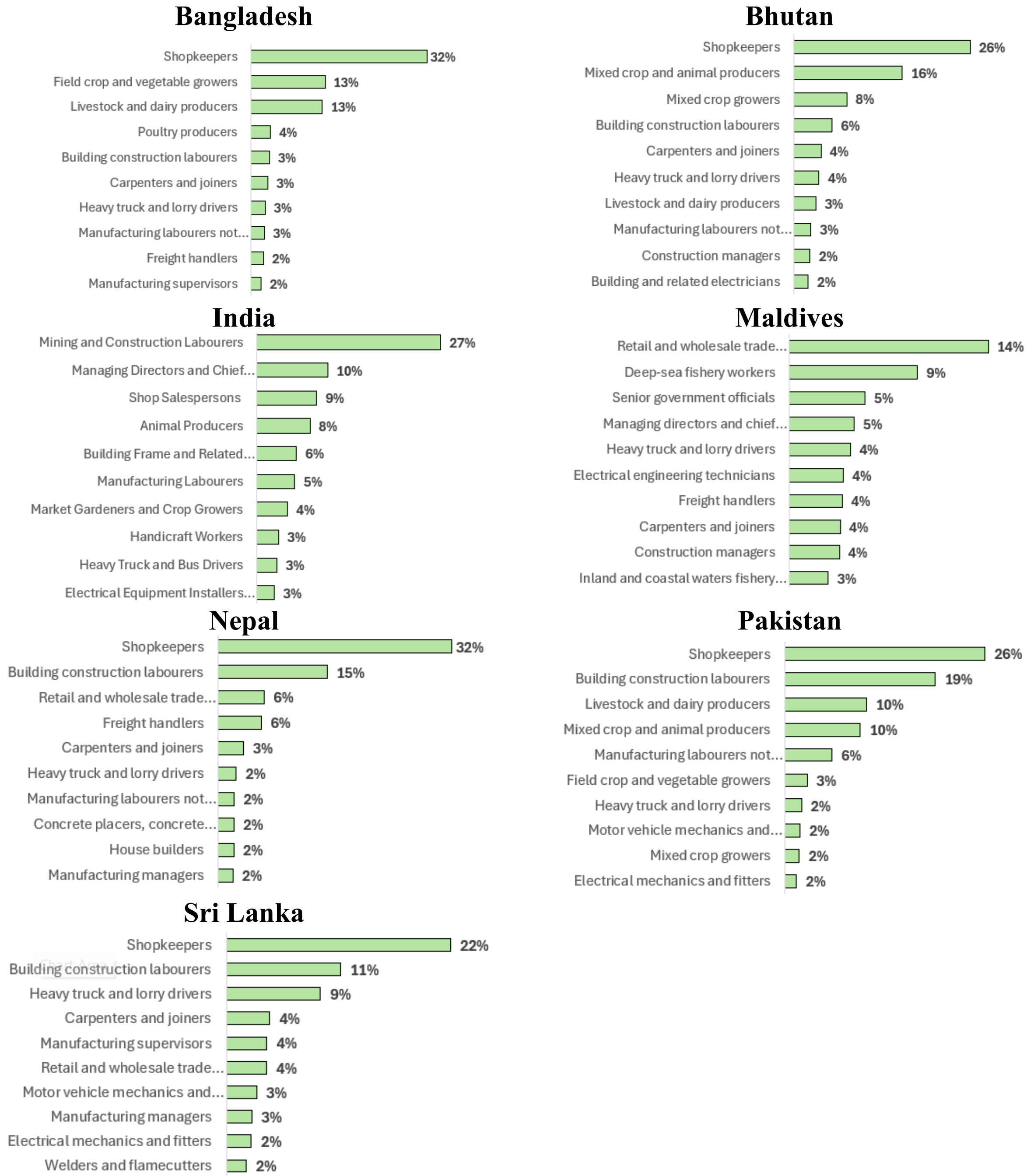
Shopkeepers are the most common green occupation in Bangladesh, Bhutan, Nepal, Pakistan, and Sri Lanka. In the remaining countries, these are Mining and Construction Laborers[19] in India, and Retail and wholesale trade managers in the Maldives. The remainder of the top ten occupations varies across countries, with some having greater participation of agricultural,

[18] This differs from work in World Bank (2023) where the authors find that green jobs tend to be more formal in South Asia. However, they define informal workers as self-employed workers and formal workers as the complement. This aligns with our estimates, but both measurements capture different definitions of labor informality status (Gasparini and Tornarolli, 2009).

[19] For India, the analysis is conducted at the 3-digit ISCO level because the labor force data do not allow identifying occupations at the 4-digit level. As a result, the category "Mining and Construction Labourers" (ISCO 931) aggregates three distinct 4-digit occupations: *mining and quarrying labourers (9311)*, *civil engineering labourers (9312)*, and *building construction labourers (9313)*. Only the latter two—especially *building construction labourers*, 81% of which are classified as "green enhanced skills" in the O*NET-based mapping—display non-zero probabilities of being classified as green occupations, whereas *mining and quarrying labourers* have a probability of zero. When these are combined into a single 3-digit occupation, the relatively large size of the group and the combined green probabilities of 9312 and 9313 lead to "Mining and Construction Labourers" appearing as the largest contributor to green employment. This is therefore a result of working at 3 digits, rather than an indication that mining activities themselves are green.

manufacturing, or service occupations, reflecting the differences in labor markets. We note that while some of these occupations may seem counterintuitive as having the largest percentage of green jobs, they result from applying the O*NET definition to countries for which it was not originally designed. For instance, in the case of the shopkeepers, it is because SOC 11-1021.00, General and Operations Managers, is listed by O*NET as a Green Enhanced Skills occupation. Since the ISCO-08 'Shopkeepers' is included as one of the multiple ISCO-08 categories that are part of SOC 11-1021.00 in the official BLS crosswalk, Shopkeepers are considered 100 percent green. This points to an important conceptual nuance (see also section 4): a large share of "green employment" should be viewed as indirectly green because it includes (i) existing jobs that are expected to see higher demand due to the green transition (green increased demand) but do not require significant changes in skills and knowledge; and (ii) jobs expected to require changes in skills (green enhanced skills), even if those changes have not yet materialized.

Figure 5. Ten occupations with the greatest contribution to green employment, circa 2022.



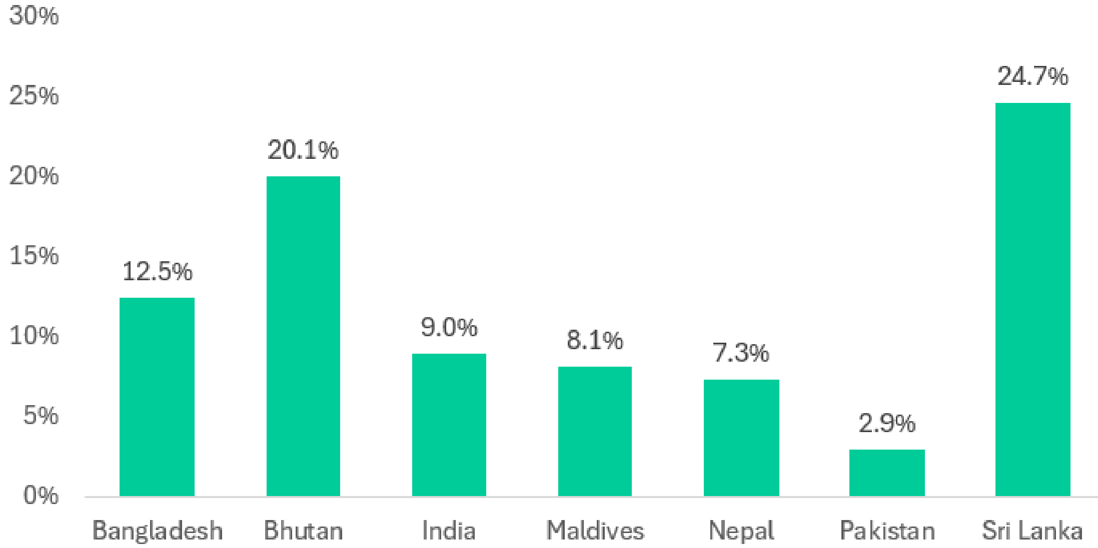
Source: Authors' elaboration based on microdata listed in Table 2.

Notes: (1) The percentages shown in the figure represent each occupation's contribution to total green employment in the country. This contribution is calculated in two steps. First, for each occupation, we compute the share of total employment that is green by multiplying its overall employment share by the proportion of green jobs in that occupation. Second, the contribution of each occupation to national green employment is obtained by dividing this value by the total share of green employment in the country—i.e., by the sum of green employment shares across all occupations. Thus, the percentages in the figure indicate how much each occupation accounts for in the country's total green employment. (2) The shares are computed using the O*NET definition of green jobs, converted to ISCO-08 using Winkler-Seales *et al*. (2024)'s methodology. (3) When necessary, conversion to ISCO-88 is done using the ILO's ISCO-08 to ISCO-88 crosswalk and estimates at the 3-digit level are performed assuming an equal distribution of workers in 4-digit occupations within each 3-digit occupation.

Do green jobs pay more than non-green jobs? We estimate Mincer regressions for each country, controlling for sex, age, and its square, and educational level. The full results are shown in Table A.10 in the Appendix, and Figure 6 summarizes estimated premiums. Overall, we find a significant and positive effect of working in a green job on hourly wages for all countries. On average, we find that green workers earn an average of 12.5 percent more in South Asia when compared to non-green workers, slightly larger compared to other estimates for the region (World Bank, 2023).[20] There is heterogeneity in the size of the green job premium across counties. The lowest premiums are in Pakistan (2.9 percent) and Nepal (7.4 percent), followed by the Maldives (8.1 percent) and India (9 percent), then by Bangladesh with a green premium of 12.5 percent. The two countries with the largest green job wage premiums are Bhutan with 20.1 percent and Sri Lanka with 24.6 percent.

[20] Estimates of the green wage premium reported in the World Bank's South Asia Development Update (World Bank, 2023) are around 7 percent, whereas in this study, we estimate a premium of 12.1 percent, reflecting several methodological and definitional differences. First, the two studies rely on different taxonomies to identify green jobs: the Development Update applies the classification by Granata and Posadas (2024), whereas this paper uses O*NET, leading to wage comparisons across distinct groups of workers and occupations. Second, the samples used for the estimations differ. The Development Update includes only men aged 15–64, while our analysis covers both men and women aged 25–55, and the underlying household surveys vary in coverage across studies. Third, regional averages are constructed differently. The Development Update reports a 7 percent premium based on a labor force–weighted average, which gives substantial weight to India—the region's largest economy—where the green wage premium is estimated at 9 percent. In contrast, our estimate of 12.1 percent is a simple average of country-level results, giving relatively greater weight to countries with higher premiums, such as Sri Lanka (identified by both studies as having the highest premiums) and Bhutan (included in our analysis but not in the Development Update). Fourth, the Development Update includes industry fixed effects in its regression specification, while we do not, since part of the green wage premium may arise from access to higher-paying sectors—one of the channels through which green skills influence wages. Finally, the earnings measures differ: the Development Update uses monthly earnings, capturing both pay level and hours worked, whereas we use hourly wages to isolate differences in pay rates alone.

Figure 6. Green Wage Premium in South Asia, circa 2022.

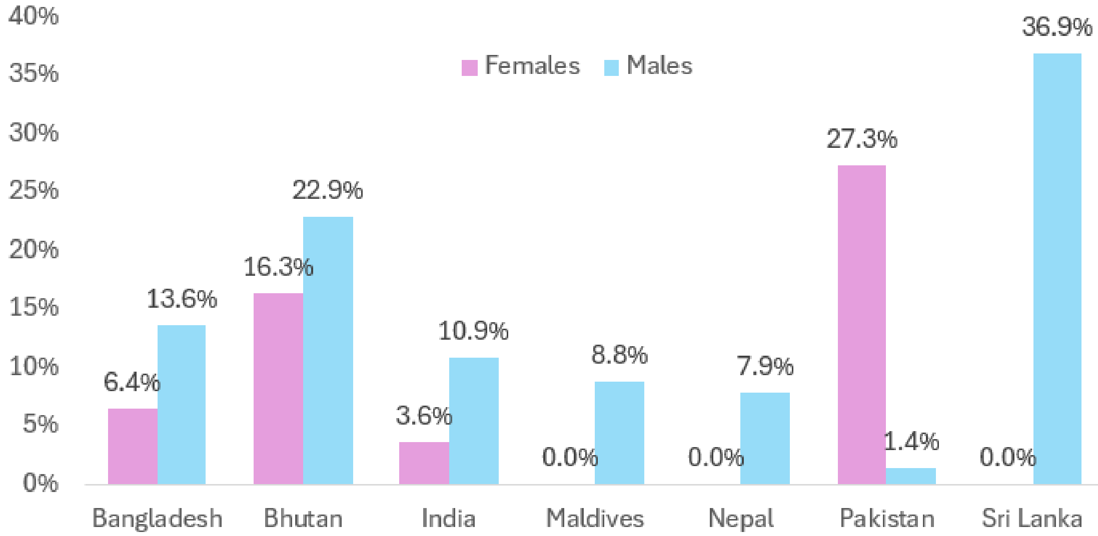


Source: Authors' elaboration based on microdata listed in Table 2.
Notes: The Green Wage Premium represents the percentage increase in hourly wages for workers in green jobs compared to those in non-green jobs and is estimated as (exp(β)−1). The coefficient β is derived from a Mincer equation estimated by OLS of the logarithm of hourly wages in the primary occupation for workers aged 25–55 on the green job indicator (O*NET definition with Winkler-Seales *et al*. (2024)'s methodology), controlling for sex, age, age squared and educational dummies. In this context, a coefficient β of 0.066 indicates that workers in green jobs earn approximately 6.8% more per hour than those in non-green jobs with the same sex, age and education.

Given that we found that green jobs in South Asia are mostly male-dominated from Table 3, we also estimated regressions that interact the green jobs indicator with sex to determine if premiums are different for women and men, as well as separate regressions.[21] These estimates are not meant to be causal since we face selection problems in the labor force, with women having historically low participation in South Asia. We then estimate green wage premiums by sex for employed men and women and plot them by country in Figure 7. On average, men have a 14.6 percent green job premium, and women have a 7.7 percent premium. These premiums differ across countries. The green wage premium is highest for men in Sri Lanka and larger for women in Pakistan, due to the selection issues into the labor force but which merits further study. In all other countries, the green job wage premium is higher for men, with gaps ranging between 7-8 percent.

[21] The full regression results are shown in Tables A.11 and A.12 in the Appendix.

Figure 7. Green Wage Premium in South Asia by sex, circa 2022



Source: Authors' elaboration based on microdata listed in Table 2.
Notes: The Green Wage Premium represents the percentage increase in hourly wages for workers in green jobs compared to those in non-green jobs and is estimated as (exp(β)−1). The coefficients β are derived from Mincer equations estimated by OLS with separate samples of male and female workers aged 25–55, where the dependent variable is the logarithm of hourly wages in the primary occupation and the independent variable is the green job indicator (O*NET definition with Winkler-Seales *et al*. (2024)'s methodology). Controls for age, age squared, and educational dummies are included. In this context, a coefficient β of 0.066 indicates that workers in green jobs earn approximately 6.8% more per hour than those in non-green jobs with the same sex, age, and education. Coefficients that are not statistically significant at 10 percent at least are represented as zero (females in the Maldives).

The evidence in this section aims to determine whether green workers are more likely to have certain attributes, but perhaps a more convincing exercise would be to compare green workers with non-green workers as a sort of "counterfactual". We do this in Table A.13 in the Appendix, by comparing mean attributes between green and non-green workers with t-tests. Many of our general findings here are replicated when comparing green and non-green workers. Green workers tend to be male, younger, better educated, in some cases higher-skilled, and located mainly in manufacturing and service sectors rather than agriculture. However, these findings vary by country, which once again highlights that green employees are likely to differ depending on the specific labor market and economy. We also estimate regressions on some selected determinants of being in a green job in Table A.14 in the Appendix finding similar results for age and education profiles.

4. Skill investment needs to support green transitions in South Asian countries

A central policy challenge for South Asian countries is determining how much and what type of skill investment is required to support the green transition. Governments must decide whether to focus on reconverting non-green workers with entirely new skills, providing moderate reskilling, or upskilling existing workers to enable smoother transitions. Our estimates extend beyond simply quantifying the share of green versus non-green jobs—they shed light on the degree of skill transferability across occupations. This distinction is crucial both for estimating the scale of investment required to meet national sustainability targets and for clarifying the role of education systems and firms (through on-the-job training) in equipping workers with the skills required to support the green transition.

This section builds on the O*NET framework, which classifies green occupations into three categories based on skill requirements: (i) green increased demand, jobs that already exist and require no new skills; (ii) green enhanced skills, jobs that already exist but demand some new skills; and (iii) green new and emerging, jobs that arise directly from the green transition. To go one step further, we extend this classification to non-green occupations by drawing on Bowen et al.'s (2018) notion of "green-rival" jobs and refining it using O*NET's Related Occupations Matrix. In doing so, we distinguish between: (iv) *need reskilling* jobs—non-green occupations that have at least one related green occupation classified by O*NET as a Career Changer, and thus require limited retraining; (v) *need upskilling* jobs—non-green occupations that do not have a Career Changer link to a green job but have at least one Career Starter link, implying more substantial retraining; and (vi) *need reconversion* jobs—non-green occupations with no related green job, where workers would require a more radical change in skills to transition.

The O*NET Related Occupations Matrix provides the empirical basis for this refinement by measuring the ease of transition between similar occupations. The matrix links each occupation code to a list of related occupations to which a worker could switch relatively easily. Two types of related occupations are distinguished: *Career Changers*, which share job-specific aspects (such as skills, experience, and work context) and therefore are better suited for short-run transitions; and *Career Starters*, which share worker-specific aspects (such as abilities and occupational interests) and therefore require more retraining, being more suited for medium- to long-run transitions. By leveraging this information, we can go beyond Bowen *et al*.'s broad "green-rival" and "other" categories and provide a more granular taxonomy of non-green occupations that highlights the different levels of skill investment required for the green transition.

Before presenting our estimates, it is helpful to outline some key features of the seven South Asian labor markets included in this study. The average employment rate is 51 percent, with a mean unemployment rate of 3 percent, although both indicators vary widely across countries—from a 32 percent employment rate in Nepal to 59 percent in Bhutan, and from a 2 percent unemployment rate in Bangladesh to 5 percent in Nepal. Agriculture remains the main source of employment, except in the Maldives, Nepal, Pakistan, and Sri Lanka, where services make up most jobs. Men are nearly twice as likely as women to be employed, rural employment surpasses urban, and most workers have no more than a secondary education. Informality is the norm—most workers are either self-employed or wage earners without social security contributions or written contracts, except in the Maldives and Sri Lanka, where formal work is relatively more common.

Table 6 presents our estimates of the six categories of green and non-green jobs using the O*NET definition and the taxonomy proposed by Bowen *et al*. (2018). Green jobs account for 24 percent of employment in South Asia, with most falling into the "green enhanced skills" category

(54 percent), followed by "green increased demand" (41 percent). Truly novel occupations—"green new and emerging"—represent only 5 percent of all green occupations, reflecting both the early stage of the region's green transition and the dated nature of the O*NET version 22.0 classification that we use in this paper, which was developed on May 18, 2017.

Table 6. Characterization of green employment and need of reskilling, upskilling, and reconversion, circa 2022

(a) Green jobs

Country	Percentage of green workers in category:		
	Green new and emerging	Green enhanced skills	Green increased demand
Bangladesh	3	46	51
Bhutan	6	47	47
India	3	55	42
Maldives	8	55	37
Nepal	5	67	28
Pakistan	3	53	44
Sri Lanka	8	51	41
Regional average	**5**	**54**	**41**

(b) Non-green jobs

Country	Percentage of non- green workers in category:		
	Need reskilling	Need upskilling	Need reconversion
Bangladesh	61	12	27
Bhutan	64	13	23
India	68	13	19
Maldives	38	17	45
Nepal	48	24	28
Pakistan	61	14	25
Sri Lanka	55	18	27
Regional average	**57**	**16**	**27**

Source: Own elaboration based on microdata listed in Table 2.

Notes: (1) Green jobs definitions are presented in Table 1. (2) Need reskilling (upskilling) are green rival occupations (Bowen et al. 2017) who have a Career Changer (Starter) related occupation that is green, while "Need reconversion" are non-green occupations who are not green rival either. The O*NET Related Occupations Matrix is used to measure the ease of transition between similar occupations. This matrix links each occupation code to a list of related occupations to which a person could switch relatively easily. There are two types of related occupations: Career Changers occupations, which have similar job-specific aspects (such as skills, experience, and work context) and are therefore more suited for job transitions in the short run, and Career Starters occupations, which share similar worker-specific aspects (such as abilities and occupational interests) and thus require more retraining, being better suited for job transitions in the medium and longer run. (3) When necessary, estimates at the 3-digit level are performed assuming an equal distribution of workers in 4-digit occupations within each 3-digit occupation.

Throughout this paper, we have highlighted differences across countries, which also apply to the estimates in Table 5. While the results that most green jobs already exist and are not new occupations hold in most cases, some countries have a larger fraction of the green workforce in occupations that do not require new skills (green increased demand), such as Bangladesh. All remaining countries have a larger percentage of the green workforce in occupations that are green but require new skills for workers to have (green enhanced skills). However, the difference in the percentage of these categories of green workers differs. While we observe the same amount of these two types of green jobs in Bhutan, differences between them range from 9 to 20 percent in India, Maldives, Pakistan, and Sri Lanka, and there are more than twice as many green enhanced skills workers (67 percent) in Nepal as green increased demand (28 percent) employees.

In South Asia, the majority of employment, approximately 76 percent, remains concentrated in non-green occupations. Of that total, our estimates indicate that 57 percent of jobs could transition to green activities with only minor reskilling, 16 percent would require more substantial upskilling, and 27 percent would necessitate a complete reconversion involving significant investments in retraining. These estimates imply that nearly three-quarters of non-green jobs possess a feasible pathway toward greening, provided that education and formal and informal training systems can mobilize relatively modest levels of investment in skill development.

Cross-country heterogeneity in these requirements is considerable. In the Maldives, for instance, minor reskilling is needed for 38 percent of non-green jobs, while in India this share rises to 68 percent. The need for moderate upskilling is lowest in Bangladesh at 12 percent and peaks in Nepal at 24 percent. By contrast, the share of jobs requiring full reconversion and significant investments in skills is most pronounced in the Maldives (45 percent) but substantially lower in India (19 percent). These differences highlight the importance of tailoring skills policies to country-specific labor market structures and the varying degrees of challenge involved in supporting the green transition across the region.

Our findings underscore that while the scale of transformation is substantial, the majority of non-green jobs can adapt through incremental training. This places education and formal and informal training systems at the center of the policy response, with implications not only for the design of reskilling and upskilling programs but also for how governments prioritize fiscal resources and engage employers and firms in co-financing the green skills development transition needs.

Because the majority of retraining needs for non-green jobs involve only small or moderate investments—57 percent of non-green jobs could transition with limited reskilling and 16 percent with moderate upskilling—informal and on-the-job training are likely to play a central role in contributing to the green transition, alongside the formal education system. Bowen *et al*. (2018) find that many green and non-green jobs differ only in a limited set of skill-specific aspects, implying that much of the required retraining can occur through on-the-job learning rather than formal education.

For "green increased demand" jobs—non-green occupations with close green counterparts—the transition may often require only brief periods of on-the-job training, as the core tasks and skill sets are largely similar (Bowen *et al*., 2018). For example, construction workers shifting to roles in energy-efficient building projects may only need short modules on the use of new materials or equipment, while retaining their core occupational skills. By contrast, moving directly into green roles, such as "green enhanced skills" or "green new and emerging" occupations, typically involves acquiring a broader set of competences from multiple sources. A technician transitioning into solar panel installation, for instance, may require not only practical on-the-job training but also specialized coursework in electrical systems and safety protocols, along with certification to meet industry standards. Similarly, roles in environmental auditing or renewable energy engineering often demand higher levels of formal education, relevant prior experience, and professional qualifications in addition to on-the-job training. These distinctions imply that training systems need to be designed in a layered manner—combining short, modular on-the-job learning opportunities for jobs with close green analogues, while also providing structured certification programs and formal education pathways for workers aiming to enter high-skill, directly green occupations.

The fact that we documented the existence of a wage premium for green jobs suggests that both workers and firms may have incentives to invest in retraining without necessarily relying heavily on public subsidies. Workers benefit from higher earnings associated with greener roles, which makes them more willing to engage in on-the-job training or pursue additional qualifications. For firms, the productivity gains from adopting greener practices can help offset the upfront costs of retraining employees. In cases where green and non-green jobs differ only marginally in required skills, employers may find it cost-effective to provide training internally, recouping the expense through enhanced worker productivity and retention.

At the same time, the wage premium for green jobs also underscores the importance of ensuring equitable access to reskilling and upskilling opportunities, since workers who cannot afford to privately invest in further training or education may be excluded from the benefits of greener jobs. In this sense, while private incentives can play a large role in funding the transition, public investments in green skills development remain critical to close gaps—particularly for disadvantaged groups and for transitions into high-skill green jobs that require higher investments in formal education and certification.[22]

From a policy perspective, these findings highlight the need to strengthen firm-based training systems and promote public–private partnerships. Such collaboration can mobilize resources, align training with labor market demands, and ensure that both short-cycle programs and formal education pathways are prepared to meet the diverse skill requirements of the green transition. Education systems also have the potential to play a transformative role—not only by preparing workers for greener jobs but also by shaping the direction of technological change itself. Acemoglu and Autor's (2011) framework of directed technological change shows that an increased supply of skilled workers can drive skill-biased technological progress. By analogy, expanding the pool of workers trained in green skills could accelerate "green-biased" technological change, fostering a more sustainable economy over time. This suggests that, beyond supporting individual transitions into greener occupations, education policies that invest in equipping future workers with green skills can influence the trajectory of innovation itself, amplifying the long-term benefits of the green transition.

Lastly, it is also important to consider the time frame of the green transition. Our paper focuses on the current workforce as the primary pool of labor force that needs to adapt to a greener economy. In reality, however, the transition will unfold gradually, meaning that over time, the green workforce will include not only re-skilled and up-skilled workers but also new entrants who would have been formally educated and trained to respond to new and emerging green job

[22] An important area for future research is to examine the distributional consequences of green transitions to ensure they are inclusive and equitable. A key question is whether reskilling and upskilling the workers identified in this paper would reduce or exacerbate earnings disparities, and by extension, overall income inequality. Understanding these dynamics is essential for designing training and education policies that not only support the green transition but also promote shared prosperity.

demands. Investing in green skills for young people through the formal education system is often less costly and more efficient than reskilling and upskilling experienced workers later in their careers, particularly for high-skilled occupations. This underscores the importance of building education reforms that target future cohorts at lower marginal costs, whereas current training investments enable existing workers to adapt in real time. Therefore, education policy should differentiate policies—near-term reskilling and upskilling for today's workers, alongside curriculum and credential reforms that equip tomorrow's workforce for new and emerging green jobs demands.

5. Conclusion

This paper examines the skill investment needs required to support green transitions in seven countries in South Asia: Bangladesh, Bhutan, India, the Maldives, Nepal, Pakistan, and Sri Lanka. We present estimates of the share of green workers across different categories of sustainable employment and quantify how many non-green workers could transition toward green jobs with different levels of investment in skills development. We also discuss measurement challenges that arise when estimating the share and types of green jobs, which are important for monitoring and evaluation efforts. The evidence presented aims to inform strategies for measuring workforce greening and for assessing the scale of skills development needed to support the green transition.

Our results show that about 3 out of 4 non-green jobs in South Asia could transition into greener occupations with only small or moderate levels of training investment, while 1 in 4 would require full reconversion, as their current skills do not align with green occupation. Country-level patterns vary—between 38 and 68 percent of non-green jobs could transition with limited reskilling, 12 to 24 percent with moderate upskilling, and 19 to 45 percent would require reconversion. We interpret these estimates as suggestive that the occupational mobility into green jobs is feasible and scalable in the region, but countries will need to tailor skills development strategies to their specific labor market conditions and stages of progress toward sustainability.

Measuring green jobs is essential to monitor the transition, even if data limitations require making compromises. While different definitions can yield distinct results, the priority is to develop measures that enable informed policy decisions. The O*NET framework is useful for assessing skill needs in a consistent manner across countries, but country-specific definitions such as India's would be better suited for tracking progress against national targets. Improvements in survey design, such as collecting occupational codes at the six-digit rather than four-digits, would for instance reduce reliance on crosswalks and allow more precise identification of green jobs.

Our findings suggest that on-the-job training will play a critical role in supporting the green transition. Because a majority of training needs for non-green jobs to transition into greener jobs seem to require only small to moderate investments—57 percent of non-green jobs could transition with limited reskilling and 16 percent with moderate upskilling—workplace learning is likely to be central, complementing the formal education system. By contrast, transitions from non-green jobs into "green enhanced skills" or "green new and emerging" occupations demand broader competences and more structured investments in certification and higher education. A layered skills development approach is therefore needed, combining short, modular on-the-job training for non-green jobs with close green counterparts with longer-cycle programs for higher-skilled green occupations.

At the same time, we find evidence of a wage premium for green jobs, suggesting that private incentives can play an important role in financing the skills training required for the green transition. Workers benefit from higher earnings associated with green jobs, making them more willing to invest in training, while firms gain from productivity increases that can help offset on-the-job retraining costs. Where green and non-green jobs differ only marginally in required skills, employers may find it cost-effective to provide training internally. These dynamics underscore the need to strengthen firm-based training systems and foster public–private partnerships that can help mobilize resources, align training with labor market demands, and ensure that both short-cycle on-the-job training programs and longer-cycle formal education ones are prepared to meet the diverse skill requirements of the green transition.

Overall, the green transition in South Asia will require a dual policy focus—supporting adaptation efforts from today's workforce through reskilling and upskilling, while simultaneously preparing tomorrow's workforce through education sector reforms. Most non-green jobs can shift with small or modest training, making on-the-job training a central component of the transition, but high-skill green roles will continue to demand deeper investments in formal education and certification. As the transition unfolds gradually, combining near-term training for current workers with forward-looking curriculum and credential reforms for future cohorts offers a cost-effective and sustainable approach to building a workforce ready to meet new and emerging green demands.

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Appendix: Supplementary Tables

Table A.1. Comparing approaches to measuring green jobs in this paper

Approach	Definition	Categories	Metric	Description
Skills-based	European Classification of Occupations, Skills ad Competences (ESCO)	• Occupations with green skills • Occupations with essential green skills	Share of green skills intensity using the lowest threshold	The ESCO "skills-based" definition counts workers in occupations that require at least one green skill, as defined by the ESCO taxonomy. This means it includes workers who possess a green skill, even if they do not actively perform a green task.
Task-based	O*NET	• Green increased demand • Green enhanced skills • Green new and emerging	Share of green tasks intensity	The task-based approach identifies workers engaged in green tasks using (i) O*NET classifications; or (ii) text analysis of ISCO-08 task descriptions as developed by Granata & Posadas (2024) (i.e. this is a dictionary of green terms applicable to emerging economies). This implies that this definition may include workers performing green tasks even if they lack specific green skills. O*NET, designed for the U.S. economy, classifies green occupations within 12 major sectors. In contrast, Granata & Posadas (2024) use a broader classification, covering more economic sectors based on the labor force survey's sampling design. Granata & Posadas developed a dictionary of green-related terms to identify green tasks, so it is more globally applicable. However, it relies on ISCO-08 occupational descriptions, which may be incomplete or outdated, posing a potential limitation. Another key difference is that Granata & Posadas count all workers performing green tasks, whereas O*NET's "green increased demand" category includes occupations expected to grow—even if workers do not perform green tasks. O*NET supports cross-country comparisons with other regions where similar studies exist, such as LAC, ECA, the OECD, and the EU. However, applying it to South Asian countries involved making the underlying assumption that these countries share the same production structure—technology, capital, labor, tasks, and
	Granata & Posadas (2024)	• Non-zero Green Task Intensity (Broad definition) • Non-zero Green Task Intensity (Narrow definition)	Share of green tasks intensity (narrow and broad definitions)	

			skills—as the U.S. This assumption may introduce measurement errors due to limitations in crosswalks between classification systems.
N/A	India Skill Council of Green Jobs	N/A	The India taxonomy, while attractive as it comes from the most advanced country in the region in terms of the green transition, does not allow for assessing the underlying assumptions as the methodologies behind its development are not publicly available.

Source: Authors' elaboration based on Granata and Posadas (2024).

Table A.2. List of Green Increased Demand occupations at ISCO-08 (O*NET adaptation from Winkler-Seales et al. 2024)

ISCO-08	ISCO-08 description	Probability (green increased demand)
2113	Chemists	100%
2145	Chemical engineers	100%
3122	Manufacturing supervisors	100%
3133	Chemical processing plant controllers	100%
3143	Forestry technicians	100%
3359	Regulatory government associate professionals not elsewhere classified	100%
4322	Production clerks	100%
4323	Transport clerks	100%
7413	Electrical line installers and repairers	100%
8182	Steam engine and boiler operators	100%
9624	Water and firewood collectors	100%
9333	Freight handlers	99%
7411	Building and related electricians	99%
7312	Musical instrument makers and tuners	98%
7234	Bicycle and related repairers	97%
3131	Power production plant operators	94%
7114	Concrete placers, concrete finishers and related workers	91%
7214	Structural-metal preparers and erectors	89%
7311	Precision-instrument makers and repairers	88%
9329	Manufacturing labourers not elsewhere classified	82%
3132	Incinerator and water treatment plant operators	81%
8342	Earthmoving and related plant operators	80%
7232	Aircraft engine mechanics and repairers	78%
7421	Electronics mechanics and servicers	76%
7233	Agricultural and industrial machinery mechanics and repairers	75%
7127	Air conditioning and refrigeration mechanics	73%
9215	Forestry labourers	67%
7115	Carpenters and joiners	67%
7412	Electrical mechanics and fitters	64%
7212	Welders and flamecutters	61%
2263	Environmental and occupational health and hygiene professionals	60%
8344	Lifting truck operators	60%
7124	Insulation workers	56%
8114	Cement, stone and other mineral products machine operators	55%
2163	Product and garment designers	54%
8211	Mechanical machinery assemblers	53%
2141	Industrial and production engineers	50%
8219	Assemblers not elsewhere classified	50%
7422	Information and communications technology installers and servicers	48%
8131	Chemical products plant and machine operators	47%
8212	Electrical and electronic equipment assemblers	46%

3111	Chemical and physical science technicians	45%
8181	Glass and ceramics plant operators	41%
6222	Inland and coastal waters fishery workers	40%
6223	Deep-sea fishery workers	40%
6224	Hunters and trappers	40%
4222	Contact centre information clerks	37%
6121	Livestock and dairy producers	36%
6122	Poultry producers	36%
6123	Apiarists and sericulturists	36%
6129	Animal producers not elsewhere classified	36%
6221	Aquaculture workers	36%
3323	Buyers	33%
3114	Electronics engineering technicians	33%
3155	Air traffic safety electronics technicians	33%
3522	Telecommunications engineering technicians	33%
2512	Software developers	31%
7223	Metal working machine tool setters and operators	31%
3113	Electrical engineering technicians	30%
8142	Plastic products machine operators	28%
7231	Motor vehicle mechanics and repairers	27%
7515	Food and beverage tasters and graders	26%
2132	Farming, forestry and fisheries advisers	26%
6210	Forestry and related workers	24%
2133	Environmental protection professionals	20%
6111	Field crop and vegetable growers	18%
6112	Tree and shrub crop growers	18%
6114	Mixed crop growers	18%
2114	Geologists and geophysicists	18%
6130	Mixed crop and animal producers	17%
3118	Draughtspersons	16%
8331	Bus and tram drivers	16%
1321	Manufacturing managers	14%
2146	Mining engineers, metallurgists and related professionals	11%
7213	Sheet-metal workers	9%
8312	Railway brake, signal and switch operators	9%
1223	Research and development managers	8%
9312	Civil engineering labourers	8%
8311	Locomotive engine drivers	8%
2131	Biologists, botanists, zoologists and related professionals	7%
9622	Odd job persons	6%
2149	Engineering professionals not elsewhere classified	3%
3257	Environmental and occupational health inspectors and associates	3%
9313	Building construction labourers	3%
5419	Protective services workers not elsewhere classified	1%

Source: Winkler-Seales *et al*. (2024).

Table A.3. List of Green Enhanced Skills occupations at ISCO-08 (O*NET adaptation from Winkler-Seales et al. 2024)

ISCO-08	ISCO-08 description	Probability (green enhanced skills)
1323	Construction managers	100%
1420	Retail and wholesale trade managers	100%
2112	Meteorologists	100%
2151	Electrical engineers	100%
2161	Building architects	100%
2162	Landscape architects	100%
2164	Town and traffic planners	100%
2356	Information technology trainers	100%
2412	Financial and investment advisers	100%
2424	Training and staff development professionals	100%
2432	Public relations professionals	100%
2619	Legal professionals not elsewhere classified	100%
5221	Shopkeepers	100%
7111	House builders	100%
7121	Roofers	100%
7543	Product graders and testers (excluding foods and beverages)	100%
9612	Refuse sorters	100%
1120	Managing directors and chief executives	92%
1112	Senior government officials	92%
3331	Clearing and forwarding agents	88%
1343	Aged care services managers	86%
7213	Sheet-metal workers	86%
9622	Odd job persons	83%
2114	Geologists and geophysicists	82%
8332	Heavy truck and lorry drivers	81%
9313	Building construction labourers	81%
1114	Senior officials of special-interest organizations	81%
1346	Financial and insurance services branch managers	79%
2413	Financial analysts	70%
7126	Plumbers and pipe fitters	61%
1324	Supply, distribution and related managers	50%
2142	Civil engineers	50%
2143	Environmental engineers	50%
2153	Telecommunications engineers	50%
2132	Farming, forestry and fisheries advisers	48%
8211	Mechanical machinery assemblers	47%
7119	Building frame and related trades workers not elsewhere classified	46%
2144	Mechanical engineers	43%
1221	Sales and marketing managers	39%
1223	Research and development managers	38%
3113	Electrical engineering technicians	35%

2152	Electronics engineers	34%
3112	Civil engineering technicians	34%
7223	Metal working machine tool setters and operators	34%
3142	Agricultural technicians	33%
3323	Buyers	33%
3114	Electronics engineering technicians	33%
3155	Air traffic safety electronics technicians	33%
3522	Telecommunications engineering technicians	33%
8113	Well drillers and borers and related workers	30%
3141	Life science technicians (excluding medical)	30%
8131	Chemical products plant and machine operators	28%
2642	Journalists	28%
2433	Technical and medical sales professionals (excluding ICT)	28%
7231	Motor vehicle mechanics and repairers	28%
3119	Physical and engineering science technicians not elsewhere classified	25%
1311	Agricultural and forestry production managers	25%
1312	Aquaculture and fisheries production managers	25%
2434	Information and communications technology sales professionals	25%
7513	Dairy-products makers	24%
4321	Stock clerks	24%
9611	Garbage and recycling collectors	22%
8111	Miners and quarriers	15%
7127	Air conditioning and refrigeration mechanics	14%
3117	Mining and metallurgical technicians	10%
2149	Engineering professionals not elsewhere classified	7%
3111	Chemical and physical science technicians	7%
3131	Power production plant operators	6%
2131	Biologists, botanists, zoologists and related professionals	5%
2133	Environmental protection professionals	5%
3257	Environmental and occupational health inspectors and associates	5%
3322	Commercial sales representatives	5%
3115	Mechanical engineering technicians	5%

Source: Winkler-Seales *et al*. (2024).

Table A.4. List of Green New and Emerging occupations at ISCO-08 (O*NET adaptation from Winkler-Seales et al. 2024)

ISCO-08	ISCO-08 description	Probability (green new and emerging)
3116	Chemical engineering technicians	85%
3117	Mining and metallurgical technicians	72%
1321	Manufacturing managers	71%
3115	Mechanical engineering technicians	66%
1213	Policy and planning managers	60%
1322	Mining managers	60%
1349	Professional services managers not elsewhere classified	60%
1439	Services managers not elsewhere classified	60%
1431	Sports, recreation and cultural centre managers	59%
2133	Environmental protection professionals	59%
2149	Engineering professionals not elsewhere classified	57%
2144	Mechanical engineers	53%
2142	Civil engineers	50%
2143	Environmental engineers	50%
2631	Economists	50%
3121	Mining supervisors	50%
3123	Construction supervisors	50%
1223	Research and development managers	46%
2633	Philosophers, historians and political scientists	40%
1113	Traditional chiefs and heads of villages	40%
1219	Business services and administration managers not elsewhere classified	30%
3119	Physical and engineering science technicians not elsewhere classified	30%
2422	Policy administration professionals	29%
2433	Technical and medical sales professionals (excluding ICT)	28%
1324	Supply, distribution and related managers	25%
2434	Information and communications technology sales professionals	25%
3322	Commercial sales representatives	23%
3111	Chemical and physical science technicians	22%
7119	Building frame and related trades workers not elsewhere classified	21%
3324	Trade brokers	20%
3339	Business services agents not elsewhere classified	19%
2643	Translators, interpreters and other linguists	19%
3311	Securities and finance dealers and brokers	16%
2519	Software and applications developers and analysts not elsewhere classified	15%
2421	Management and organization analysts	13%
1222	Advertising and public relations managers	13%
2529	Database and network professionals not elsewhere classified	12%
1114	Senior officials of special-interest organizations	10%
3353	Government social benefits officials	10%
3354	Government licensing officials	10%

3331	Clearing and forwarding agents	6%
3113	Electrical engineering technicians	5%
9622	Odd job persons	5%
8114	Cement, stone and other mineral products machine operators	4%
3351	Customs and border inspectors	4%
1120	Managing directors and chief executives	4%
1112	Senior government officials	4%
9329	Manufacturing labourers not elsewhere classified	3%
7411	Building and related electricians	1%
3132	Incinerator and water treatment plant operators	1%
7233	Agricultural and industrial machinery mechanics and repairers	0%

Source: Winkler-Seales *et al*. (2024).

Table A.5. List of Non-zero Green Task Intensity occupations at ISCO-08 (Broad definition in Granata and Posadas 2022)

ISCO-08	ISCO-08 description	Green Task Intensity (Broad definition)
1311	Agricultural and forestry production managers	100%
2132	Farming, forestry and fisheries advisers	100%
3143	Forestry technicians	100%
9612	Refuse sorters	100%
2112	Meteorologists	89%
2143	Environmental engineers	89%
9215	Forestry labourers	88%
2133	Environmental protection professionals	86%
6111	Field crop and vegetable growers	82%
6112	Tree and shrub crop growers	82%
6210	Forestry and related workers	80%
9611	Garbage and recycling collectors	75%
6123	Apiarists and sericulturists	67%
6114	Mixed crop growers	64%
8341	Mobile farm and forestry plant operators	63%
7115	Carpenters and joiners	60%
2142	Civil engineers	57%
7233	Agricultural and industrial machinery mechanics and repairers	57%
7412	Electrical mechanics and fitters	57%
7422	Information and communications technology installers and servicers	57%
6113	Gardeners, horticultural and nursery growers	55%
2131	Biologists, botanists, zoologists and related professionals	50%
3132	Incinerator and water treatment plant operators	50%
3257	Environmental and occupational health inspectors and associates	50%
6130	Mixed crop and animal producers	50%
7215	Riggers and cable splicers	50%
7234	Bicycle and related repairers	50%
9624	Water and firewood collectors	50%
6221	Aquaculture workers	44%
7213	Sheet-metal workers	43%
2263	Environmental and occupational health and hygiene professionals	40%
3119	Physical and engineering science technicians not elsewhere classified	40%
3151	Ships' engineers	40%
7232	Aircraft engine mechanics and repairers	40%
1312	Aquaculture and fisheries production managers	38%
7536	Shoemakers and related workers	38%
3118	Draughtspersons	38%
3142	Agricultural technicians	38%
9211	Crop farm labourers	38%
7222	Toolmakers and related workers	36%

3112	Civil engineering technicians	33%
3113	Electrical engineering technicians	33%
5411	Fire-fighters	33%
7112	Bricklayers and related workers	33%
7124	Insulation workers	33%
7413	Electrical line installers and repairers	33%
7421	Electronics mechanics and servicers	33%
8332	Heavy truck and lorry drivers	33%
6310	Subsistence crop farmers	29%
8142	Plastic products machine operators	29%
8331	Bus and tram drivers	29%
9622	Odd job persons	29%
9213	Mixed crop and livestock farm labourers	27%
2113	Chemists	25%
2114	Geologists and geophysicists	25%
2164	Town and traffic planners	25%
3155	Air traffic safety electronics technicians	25%
5153	Building caretakers	25%
7122	Floor layers and tile setters	25%
7127	Air conditioning and refrigeration mechanics	25%
7231	Motor vehicle mechanics and repairers	25%
7311	Precision-instrument makers and repairers	25%
7411	Building and related electricians	25%
7541	Underwater divers	25%
6330	Subsistence mixed crop and livestock farmers	22%
9214	Garden and horticultural labourers	22%
3116	Chemical engineering technicians	20%
3522	Telecommunications engineering technicians	20%
4223	Telephone switchboard operators	20%
5419	Protective services workers not elsewhere classified	20%
6222	Inland and coastal waters fishery workers	20%
6224	Hunters and trappers	20%
7114	Concrete placers, concrete finishers and related workers	20%
7126	Plumbers and pipe fitters	20%
7514	Fruit, vegetable and related preservers	20%
7515	Food and beverage tasters and graders	20%
8311	Locomotive engine drivers	20%
7531	Tailors, dressmakers, furriers and hatters	18%
3111	Chemical and physical science technicians	17%
3131	Power production plant operators	17%
3230	Traditional and complementary medicine associate professionals	17%
6122	Poultry producers	17%
7214	Structural-metal preparers and erectors	17%
7522	Cabinet-makers and related workers	17%
7523	Woodworking-machine tool setters and operators	17%

7534	Upholsterers and related workers	17%
8141	Rubber products machine operators	17%
8182	Steam engine and boiler operators	17%
6121	Livestock and dairy producers	15%
2144	Mechanical engineers	14%
2153	Telecommunications engineers	14%
3114	Electronics engineering technicians	14%
7111	House builders	14%
7113	Stonemasons, stone cutters, splitters and carvers	14%
7211	Metal moulders and coremakers	14%
7221	Blacksmiths, hammersmiths and forging press workers	14%
7224	Metal polishers, wheel grinders and tool sharpeners	14%
7323	Print finishing and binding workers	14%
9623	Meter readers and vending-machine collectors	14%
2152	Electronics engineers	13%
2162	Landscape architects	13%
3115	Mechanical engineering technicians	13%
3117	Mining and metallurgical technicians	13%
3152	Ships' deck officers and pilots	13%
6223	Deep-sea fishery workers	13%
6340	Subsistence fishers, hunters, trappers and gatherers	13%
7212	Welders and flamecutters	13%
8322	Car, taxi and van drivers	13%
2149	Engineering professionals not elsewhere classified	11%
2163	Product and garment designers	11%
7322	Printers	11%
8111	Miners and quarriers	11%
8157	Laundry machine operators	11%
9332	Drivers of animal-drawn vehicles and machinery	11%
2141	Industrial and production engineers	10%
3214	Medical and dental prosthetic technicians	10%
5112	Transport conductors	10%
8112	Mineral and stone processing plant operators	10%
8113	Well drillers and borers and related workers	10%
8114	Cement, stone and other mineral products machine operators	10%
7312	Musical instrument makers and tuners	9%
7313	Jewellery and precious-metal workers	9%
7542	Shotfirers and blasters	9%
8155	Fur and leather preparing machine operators	9%
2261	Dentists	8%
7533	Sewing, embroidery and related workers	8%
8152	Weaving and knitting machine operators	8%

Source: Granata and Posadas (2022).

Table A.6. List of Non-zero Green Task Intensity occupations at ISCO-08 (Narrow definition in Granata and Posadas 2022)

ISCO-08	ISCO-08 description	Green Task Intensity (Narrow definition)
2143	Environmental engineers	89%
2133	Environmental protection professionals	86%
9612	Refuse sorters	83%
2112	Meteorologists	78%
9611	Garbage and recycling collectors	75%
3132	Incinerator and water treatment plant operators	50%
3119	Physical and engineering science technicians not elsewhere classified	40%
3257	Environmental and occupational health inspectors and associates	40%
2131	Biologists, botanists, zoologists and related professionals	38%
5411	Fire-fighters	33%
7124	Insulation workers	33%
7234	Bicycle and related repairers	33%
2263	Environmental and occupational health and hygiene professionals	30%
2142	Civil engineers	29%
2113	Chemists	25%
2114	Geologists and geophysicists	25%
2132	Farming, forestry and fisheries advisers	25%
7122	Floor layers and tile setters	25%
3112	Civil engineering technicians	22%
3143	Forestry technicians	20%
5419	Protective services workers not elsewhere classified	20%
6210	Forestry and related workers	20%
3111	Chemical and physical science technicians	17%
3131	Power production plant operators	17%
8182	Steam engine and boiler operators	17%
8142	Plastic products machine operators	14%
9623	Meter readers and vending-machine collectors	14%
2162	Landscape architects	13%
2164	Town and traffic planners	13%
7231	Motor vehicle mechanics and repairers	13%
2149	Engineering professionals not elsewhere classified	11%
2163	Product and garment designers	11%
6221	Aquaculture workers	11%
2141	Industrial and production engineers	10%
1311	Agricultural and forestry production managers	8%
7541	Underwater divers	8%

Source: Granata and Posadas (2022).

Table A.7. List of green job qualifications and associated occupation based on ISCO-08 (India Skill Council of Green Jobs)

Number	Area	Qualification Title	Associated ISCO-08
1	Solar Energy	Solar PV Installer (Suryamitra)	7421
2	Solar Energy	Solar PV Installer – Electrical	7421
3	Solar Energy	Rooftop Solar Grid Junior Engineer	2151
4	Solar Energy	Solar PV Installation Helper	9313
5	Solar Energy	Solar Water Pumping Junior Engineer	7421
6	Solar Energy	Solar PV Module Manufacturing Technician	7422
7	Solar Energy	Solar Lighting Assembler	7411
8	Solar Energy	Solar Photovoltaic Entrepreneur	2431
9	Solar Energy	Solar PV Cell Manufacturing Technician	7422
10	Solar Energy	Solar Domestic Product Assembler	8212
11	Solar Energy	Agrivoltaics Installer Electrical	7421
12	Solar Energy	Solar Manufacturing Junior Technician	8212
13	Solar Energy	Solar Photovoltaic Technician	7421
14	Solar Energy	Junior Technician - Solar Cold Storage	7127
15	Solar Energy	Solar Enterprise Assistant Manager	2143 / 7421
16	Solar Energy	Solar Photovoltaic Site Survey Assistant	7422
17	Solar Energy	Solar Cold Storage Entrepreneur	6111
18	Solar Energy	Junior Technician-Solar EV Charging Station	3113
19	Solar Energy	Solar EV Charging Entrepreneur	3113
20	Solar Energy	Solar PV Structural Assistant Design Engineer	2144
21	Solar Energy	Solar PV Designer	2143
22	Solar Energy	Solar PV Business Development Executive	2433
23	Solar Energy	Solar PV Installer - Civil	3112
24	Solar Energy	Solar Proposal Evaluation Specialist	2412
25	Solar Energy	Solar PV Project Manager(E&C)	1323
26	Solar Energy	Solar PV Maintenance Technician - Electrical (Ground Mount)	7311
27	Green Hydrogen	Green Hydrogen Plant Technician	8131
28	Green Hydrogen	Green Hydrogen Plant Entrepreneur	2431
29	Green Hydrogen	Green Hydrogen Plant Junior Technician- Electrolyzer	8131
30	Green Hydrogen	Green Hydrogen Plant Junior Technician- Power Sources	8131
31	Green Hydrogen	Green Hydrogen Plant Junior Technician- Storage	8131
32	Green Hydrogen	Green Hydrogen Plant Junior Technician-Desalination	8131
33	Green Hydrogen	Electrolyzer Manufacturing Plant Technician	8131

34	Green Hydrogen	Electrolyzer Manufacturing Plant Supervisor	3122
35	Green Hydrogen	Fundamentals of Financing for Green Hydrogen Project	2412
36	Green Hydrogen	Overview of Instrumentation and Control for Green Hydrogen Plant	2141
37	Wind Energy	Project Assistant Planner – Wind Power Plant	3122
38	Wind Energy	Wind Resource Assessor and Site Surveyor-Wind Power Plant	2165
39	Wind Energy	Construction Technician- Wind Power Plant	3115
40	Wind Energy	CMS Engineer- Wind Power Plant	3115
41	Wind Energy	O&M Mechanical Technician – Wind Power Plant	3115
42	Wind Energy	O&M Electrical & Instrumentation Technician – Wind Power Plant	3113
43	Small Hydro	Small Hydro Power Plant Technician-(Jal Urja Mitra)	3115
44	Biomass Energy	Biomass Depot Operator	9333
45	Biomass Energy	Animal Waste Manure Aggregator	6121
46	Biomass Energy	Agri-residue Aggregator	8341
47	Biomass Energy	Feedstock Manager - Procurement and Composition	1324
48	Biomass Energy	Technician – Operations and Maintenance (Compressed Biogas/Waste to Energy)	3113
49	Biomass Energy	Supervisor – Operations & Maintenance (Compressed Biogas/Waste to Energy)	3122
50	Biomass Energy	Plant Head- Operations (Compressed Biogas/Waste to Energy)	1321
51	Biomass Energy	Bio-Energy Micro Entrepreneur	2433
52	Biomass Energy	Biomass Pellet Manufacturing Junior Technician	8142
53	Biomass Energy	Manager- Waste Management	1213
54	Clean Cooking	Improved Cookstove Installer	7112
55	Clean Cooking	Portable Improved Cookstove Assembler	8219
56	Clean Cooking	Clean Cookstove Sales and Maintenance Executive	5243
57	Clean Cooking	Clean Cookstove Distributor	5249
58	Sustainability	GHG Accounting and Sustainability Reporting	1213
59	Sustainability	Green Logistics Practices	3323
60	Sustainability	Optimize resource utilization at workplace	-
61	Sustainability	Adopt sustainable practices at the workplace	-
62	Waste Management	Plastic Recycling Operator	8143
63	Waste Management	Safai Mitra	5151
64	Waste Management	Biomedical Waste Management Nursing and Paramedical Staff	2221
65	Waste Management	Waste Optimisation Professional	2143 / 2263
66	Waste Management	Material Recovery Facility (MRF) Micro – Entrepreneur	1324
67	Waste Management	Plastic Recycling Micro Entrepreneur	3122
68	Water Management	Junior Technician - Rooftop Rainwater Harvesting	3113

69	Water Management	Rooftop Rain Water Harvesting Entrepreneur	2431
70	Water Management	Sewer Entry Professional	9613
71	Water Management	Desludging Operator	9613
72	Water Management	Junior Technician- Mechanized Sewer Cleaning	9613
73	Water Management	Wastewater Treatment Plant Helper	7412
74	Water Management	Wastewater treatment Plant Technician	3132
75	Ecotourism	Nature Conservator Cum Ecotourism Guide	5113
76	Forestry	Apiculturist (Wild bee) – NTFP (Non-Timber Forest Produce)	6210/6113/6115/6111
77	Forestry	Micro-Entrepreneur – NTFP (Non-Timber Forest Produce) – Plant Origin	7317

Source: List of green jobs qualifications from Skill Council for Green Jobs (2024). "Green Jobs Handbook". Skill Council for Green Jobs (SCGJ) qualification packs from SCGJ webpage (https://sscgj.in/) and National Qualification Register (NQR) qualification files and model curriculums from the National Qualifications Register webpage (https://www.nqr.gov.in/).

Table A.8. List of occupations at ISCO-08 with green skills (European Classification of Occupations, Skills ad Competences (ESCO)

ISCO-08	ISCO-08 description	Share of Green Skills
9611	Garbage and recycling collectors	60%
6210	Forestry and related workers	59%
9612	Refuse sorters	57%
9213	Mixed crop and livestock farm labourers	43%
2143	Environmental engineers	42%
6114	Mixed crop growers	40%
1311	Agricultural and forestry production managers	40%
6111	Field crop and vegetable growers	39%
9215	Forestry labourers	39%
6224	Hunters and trappers	38%
2133	Environmental protection professionals	38%
6130	Mixed crop and animal producers	36%
7544	Fumigators and other pest and weed controllers	33%
3132	Incinerator and water treatment plant operators	31%
7133	Building structure cleaners	29%
3143	Forestry technicians	29%
9214	Garden and horticultural labourers	28%
2132	Farming, forestry and fisheries advisers	26%
2162	Landscape architects	26%
5113	Travel guides	25%
6113	Gardeners, horticultural and nursery growers	25%
6112	Tree and shrub crop growers	23%
2142	Civil engineers	22%
2161	Building architects	22%
7124	Insulation workers	20%
2114	Geologists and geophysicists	19%
3116	Chemical engineering technicians	19%
3131	Power production plant operators	18%
1213	Policy and planning managers	17%
3257	Environmental and occupational health inspectors and associates	17%
3141	Life science technicians (excluding medical)	17%
8341	Mobile farm and forestry plant operators	17%
2433	Technical and medical sales professionals (excluding ICT)	16%
7126	Plumbers and pipe fitters	16%
3142	Agricultural technicians	16%
9211	Crop farm labourers	16%
3112	Civil engineering technicians	16%
1412	Restaurant managers	15%
2144	Mechanical engineers	15%
2149	Engineering professionals not elsewhere classified	14%
3322	Commercial sales representatives	13%

1411	Hotel managers	13%
7411	Building and related electricians	13%
7121	Roofers	13%
1323	Construction managers	13%
6123	Apiarists and sericulturists	13%
1321	Manufacturing managers	12%
6129	Animal producers not elsewhere classified	12%
5411	Fire-fighters	12%
3359	Regulatory government associate professionals not elsewhere classified	12%
9311	Mining and quarrying labourers	12%
9613	Sweepers and related labourers	12%
2131	Biologists, botanists, zoologists and related professionals	11%
3133	Chemical processing plant controllers	11%
2263	Environmental and occupational health and hygiene professionals	11%
2151	Electrical engineers	11%
5152	Domestic housekeepers	10%
3111	Chemical and physical science technicians	10%
3113	Electrical engineering technicians	10%
2164	Town and traffic planners	10%
2145	Chemical engineers	10%
9623	Meter readers and vending-machine collectors	10%
2421	Management and organization analysts	10%
2250	Veterinarians	10%
1219	Business services and administration managers not elsewhere classified	10%
7127	Air conditioning and refrigeration mechanics	10%
8171	Pulp and papermaking plant operators	9%
7412	Electrical mechanics and fitters	9%
9412	Kitchen helpers	9%
7119	Building frame and related trades workers not elsewhere classified	9%
2112	Meteorologists	9%
9123	Window cleaners	9%
6122	Poultry producers	8%
2422	Policy administration professionals	8%
1312	Aquaculture and fisheries production managers	8%
5419	Protective services workers not elsewhere classified	8%
8111	Miners and quarriers	8%
9122	Vehicle cleaners	8%
3434	Chefs	8%
6221	Aquaculture workers	8%
3118	Draughtspersons	8%
1349	Professional services managers not elsewhere classified	8%
3324	Trade brokers	8%
8332	Heavy truck and lorry drivers	7%
3119	Physical and engineering science technicians not elsewhere classified	7%
7413	Electrical line installers and repairers	7%

3115	Mechanical engineering technicians	7%
3117	Mining and metallurgical technicians	7%
3151	Ships' engineers	7%
6121	Livestock and dairy producers	7%
9112	Cleaners and helpers in offices, hotels and other establishments	7%
7115	Carpenters and joiners	7%
3122	Manufacturing supervisors	6%
7111	House builders	6%
8182	Steam engine and boiler operators	6%
2141	Industrial and production engineers	6%
9312	Civil engineering labourers	6%
2146	Mining engineers, metallurgists and related professionals	6%
8131	Chemical products plant and machine operators	6%
4221	Travel consultants and clerks	6%
3123	Construction supervisors	6%
1120	Managing directors and chief executives	5%
7131	Painters and related workers	5%
3139	Process control technicians not elsewhere classified	5%
5164	Pet groomers and animal care workers	5%
1322	Mining managers	5%
8211	Mechanical machinery assemblers	5%
3121	Mining supervisors	5%
6223	Deep-sea fishery workers	5%
7513	Dairy-products makers	5%
7521	Wood treaters	5%
7542	Shotfirers and blasters	5%
7214	Structural-metal preparers and erectors	5%
8344	Lifting truck operators	5%
9333	Freight handlers	5%
3423	Fitness and recreation instructors and program leaders	5%
3332	Conference and event planners	5%
4321	Stock clerks	5%
2165	Cartographers and surveyors	5%
9129	Other cleaning workers	5%
9212	Livestock farm labourers	5%
9329	Manufacturing labourers not elsewhere classified	5%
1324	Supply, distribution and related managers	5%
5153	Building caretakers	5%
5120	Cooks	5%
1439	Services managers not elsewhere classified	5%
7125	Glaziers	4%
5163	Undertakers and embalmers	4%
3153	Aircraft pilots and related associate professionals	4%
6222	Inland and coastal waters fishery workers	4%
7541	Underwater divers	4%

7515	Food and beverage tasters and graders	4%
7532	Garment and related pattern-makers and cutters	4%
7514	Fruit, vegetable and related preservers	4%
9622	Odd job persons	4%
1212	Human resource managers	4%
2320	Vocational education teachers	4%
8183	Packing, bottling and labelling machine operators	4%
2611	Lawyers	4%
2152	Electronics engineers	4%
2113	Chemists	4%
3230	Traditional and complementary medicine associate professionals	4%
7233	Agricultural and industrial machinery mechanics and repairers	4%
9216	Fishery and aquaculture labourers	4%
4323	Transport clerks	4%
3152	Ships' deck officers and pilots	4%
3155	Air traffic safety electronics technicians	4%
7535	Pelt dressers, tanners and fellmongers	4%
8156	Shoemaking and related machine operators	4%
8143	Paper products machine operators	4%
3323	Buyers	3%
8350	Ships' deck crews and related workers	3%
8153	Sewing machine operators	3%
7318	Handicraft workers in textile, leather and related materials	3%
8160	Food and related products machine operators	3%
3240	Veterinary technicians and assistants	3%
1330	Information and communications technology service managers	3%
7421	Electronics mechanics and servicers	3%
1223	Research and development managers	3%
8155	Fur and leather preparing machine operators	3%
7543	Product graders and testers (excluding foods and beverages)	3%
7512	Bakers, pastry-cooks and confectionery makers	3%
4322	Production clerks	3%
7234	Bicycle and related repairers	3%
7315	Glass makers, cutters, grinders and finishers	3%
8154	Bleaching, dyeing and fabric cleaning machine operators	3%
7522	Cabinet-makers and related workers	3%
2413	Financial analysts	3%
4412	Mail carriers and sorting clerks	3%
7317	Handicraft workers in wood, basketry and related materials	3%
7319	Handicraft workers not elsewhere classified	3%
2659	Creative and performing artists not elsewhere classified	3%
7523	Woodworking-machine tool setters and operators	3%
1420	Retail and wholesale trade managers	3%
7536	Shoemakers and related workers	3%
8141	Rubber products machine operators	3%

8112	Mineral and stone processing plant operators	3%
5246	Food service counter attendants	3%
2330	Secondary education teachers	3%
5245	Service station attendants	3%
7132	Spray painters and varnishers	2%
7122	Floor layers and tile setters	2%
8342	Earthmoving and related plant operators	2%
8189	Stationary plant and machine operators not elsewhere classified	2%
7511	Butchers, fishmongers and related food preparers	2%
1344	Social welfare managers	2%
1221	Sales and marketing managers	2%
3134	Petroleum and natural gas refining plant operators	2%
9321	Hand packers	2%
8172	Wood processing plant operators	2%
7231	Motor vehicle mechanics and repairers	2%
5329	Personal care workers in health services not elsewhere classified	2%
3154	Air traffic controllers	2%
3431	Photographers	2%
8212	Electrical and electronic equipment assemblers	2%
2511	Systems analysts	2%
4226	Receptionists (general)	2%
5151	Cleaning and housekeeping supervisors in offices, hotels and other establishments	2%
8181	Glass and ceramics plant operators	2%
7112	Bricklayers and related workers	2%
8331	Bus and tram drivers	2%
9313	Building construction labourers	2%
2632	Sociologists, anthropologists and related professionals	2%
3114	Electronics engineering technicians	2%
3432	Interior designers and decorators	2%
3355	Police inspectors and detectives	2%
7123	Plasterers	2%
7222	Toolmakers and related workers	2%
3311	Securities and finance dealers and brokers	2%
7312	Musical instrument makers and tuners	2%
2412	Financial and investment advisers	2%
2111	Physicists and astronomers	2%
4211	Bank tellers and related clerks	2%
7516	Tobacco preparers and tobacco products makers	2%
3331	Clearing and forwarding agents	2%
2431	Advertising and marketing professionals	2%
3353	Government social benefits officials	2%
8122	Metal finishing, plating and coating machine operators	2%
3413	Religious associate professionals	2%
5165	Driving instructors	2%

2310	University and higher education teachers	2%
1222	Advertising and public relations managers	2%
3334	Real estate agents and property managers	2%
5223	Shop sales assistants	2%
3213	Pharmaceutical technicians and assistants	2%
7114	Concrete placers, concrete finishers and related workers	2%
8113	Well drillers and borers and related workers	2%
8142	Plastic products machine operators	2%
5131	Waiters	2%
2265	Dieticians and nutritionists	2%
8121	Metal processing plant operators	1%
8219	Assemblers not elsewhere classified	1%
2163	Product and garment designers	1%
3212	Medical and pathology laboratory technicians	1%
8114	Cement, stone and other mineral products machine operators	1%
2622	Librarians and related information professionals	1%
7213	Sheet-metal workers	1%
7533	Sewing, embroidery and related workers	1%
5111	Travel attendants and travel stewards	1%
7422	Information and communications technology installers and servicers	1%
2654	Film, stage and related directors and producers	1%
2230	Traditional and complementary medicine professionals	1%
7113	Stonemasons, stone cutters, splitters and carvers	1%
7323	Print finishing and binding workers	1%
3211	Medical imaging and therapeutic equipment technicians	1%
2262	Pharmacists	1%
2619	Legal professionals not elsewhere classified	1%
8343	Crane, hoist and related plant operators	1%
2269	Health professionals not elsewhere classified	1%
1431	Sports, recreation and cultural centre managers	1%
3259	Health associate professionals not elsewhere classified	1%
8151	Fibre preparing, spinning and winding machine operators	1%
110	Commissioned armed forces officers	1%
3412	Social work associate professionals	1%
2120	Mathematicians, actuaries and statisticians	1%
7531	Tailors, dressmakers, furriers and hatters	1%
1211	Finance managers	1%
3433	Gallery, museum and library technicians	1%
7223	Metal working machine tool setters and operators	1%
2432	Public relations professionals	1%
9629	Elementary workers not elsewhere classified	1%
1345	Education managers	1%
8159	Textile, fur and leather products machine operators not elsewhere classified	1%
3315	Valuers and loss assessors	1%

7316	Sign writers, decorative painters, engravers and etchers	1%
3312	Credit and loans officers	1%
1341	Child care services managers	1%
7215	Riggers and cable splicers	1%
2423	Personnel and careers professionals	1%
1112	Senior government officials	1%
1346	Financial and insurance services branch managers	1%
7311	Precision-instrument makers and repairers	1%
2621	Archivists and curators	1%
2166	Graphic and multimedia designers	1%
310	Armed forces occupations, other ranks	1%
7212	Welders and flamecutters	0%
3435	Other artistic and cultural associate professionals	0%
2411	Accountants	0%
3521	Broadcasting and audio-visual technicians	0%
5142	Beauticians and related workers	0%
2359	Teaching professionals not elsewhere classified	0%
2529	Database and network professionals not elsewhere classified	0%
2635	Social work and counselling professionals	0%

Source: Own elaboration based on ESCO database version 1.2.0 (downloaded on 05/27/2024 from https://esco.ec.europa.eu/en/use-esco/download)

Table A.9. List of occupations at ISCO-08 with essential green skills (European Classification of Occupations, Skills ad Competences (ESCO)

ISCO-08	ISCO-08 description	Share of Essential Skills that are Green
6210	Forestry and related workers	68%
1311	Agricultural and forestry production managers	65%
6224	Hunters and trappers	50%
9612	Refuse sorters	47%
2143	Environmental engineers	45%
9611	Garbage and recycling collectors	44%
2133	Environmental protection professionals	43%
6111	Field crop and vegetable growers	42%
6114	Mixed crop growers	40%
3143	Forestry technicians	35%
9215	Forestry labourers	35%
7544	Fumigators and other pest and weed controllers	31%
7124	Insulation workers	29%
3132	Incinerator and water treatment plant operators	27%
2132	Farming, forestry and fisheries advisers	27%
6130	Mixed crop and animal producers	26%
3131	Power production plant operators	26%
6113	Gardeners, horticultural and nursery growers	25%
7133	Building structure cleaners	24%
6112	Tree and shrub crop growers	22%
9214	Garden and horticultural labourers	20%
9311	Mining and quarrying labourers	20%
2149	Engineering professionals not elsewhere classified	20%
8341	Mobile farm and forestry plant operators	20%
2161	Building architects	19%
2433	Technical and medical sales professionals (excluding ICT)	19%
5113	Travel guides	19%
9213	Mixed crop and livestock farm labourers	19%
1213	Policy and planning managers	18%
2114	Geologists and geophysicists	17%
3116	Chemical engineering technicians	17%
3322	Commercial sales representatives	17%
2144	Mechanical engineers	16%
2151	Electrical engineers	15%
7411	Building and related electricians	15%
3257	Environmental and occupational health inspectors and associates	15%
3112	Civil engineering technicians	15%
2142	Civil engineers	14%
1412	Restaurant managers	14%
2421	Management and organization analysts	13%
3113	Electrical engineering technicians	13%

3142	Agricultural technicians	13%
3141	Life science technicians (excluding medical)	13%
9412	Kitchen helpers	13%
2162	Landscape architects	12%
9123	Window cleaners	12%
1312	Aquaculture and fisheries production managers	12%
7126	Plumbers and pipe fitters	11%
2164	Town and traffic planners	11%
9622	Odd job persons	11%
1321	Manufacturing managers	10%
5152	Domestic housekeepers	10%
1219	Business services and administration managers not elsewhere classified	10%
6223	Deep-sea fishery workers	10%
2250	Veterinarians	9%
3133	Chemical processing plant controllers	9%
2263	Environmental and occupational health and hygiene professionals	9%
3359	Regulatory government associate professionals not elsewhere classified	9%
2131	Biologists, botanists, zoologists and related professionals	9%
3119	Physical and engineering science technicians not elsewhere classified	9%
5411	Fire-fighters	9%
5419	Protective services workers not elsewhere classified	8%
3111	Chemical and physical science technicians	8%
3434	Chefs	8%
1349	Professional services managers not elsewhere classified	8%
6221	Aquaculture workers	8%
2145	Chemical engineers	8%
7234	Bicycle and related repairers	8%
9613	Sweepers and related labourers	8%
9212	Livestock farm labourers	8%
4221	Travel consultants and clerks	7%
6123	Apiarists and sericulturists	7%
7115	Carpenters and joiners	7%
5164	Pet groomers and animal care workers	7%
6129	Animal producers not elsewhere classified	7%
7119	Building frame and related trades workers not elsewhere classified	7%
2422	Policy administration professionals	7%
6222	Inland and coastal waters fishery workers	7%
8332	Heavy truck and lorry drivers	7%
6122	Poultry producers	7%
7412	Electrical mechanics and fitters	7%
9122	Vehicle cleaners	7%
9129	Other cleaning workers	7%
3122	Manufacturing supervisors	6%
3423	Fitness and recreation instructors and program leaders	6%
7131	Painters and related workers	6%

7413	Electrical line installers and repairers	6%
7542	Shotfirers and blasters	6%
8344	Lifting truck operators	6%
7214	Structural-metal preparers and erectors	6%
9321	Hand packers	6%
2141	Industrial and production engineers	6%
1323	Construction managers	6%
3117	Mining and metallurgical technicians	6%
8155	Fur and leather preparing machine operators	6%
9329	Manufacturing labourers not elsewhere classified	6%
1330	Information and communications technology service managers	5%
3123	Construction supervisors	5%
8156	Shoemaking and related machine operators	5%
3115	Mechanical engineering technicians	5%
3240	Veterinary technicians and assistants	5%
7112	Bricklayers and related workers	5%
8154	Bleaching, dyeing and fabric cleaning machine operators	5%
6121	Livestock and dairy producers	5%
1120	Managing directors and chief executives	5%
3118	Draughtspersons	5%
9313	Building construction labourers	5%
2146	Mining engineers, metallurgists and related professionals	5%
9312	Civil engineering labourers	5%
8189	Stationary plant and machine operators not elsewhere classified	5%
7122	Floor layers and tile setters	5%
7421	Electronics mechanics and servicers	4%
8131	Chemical products plant and machine operators	4%
1322	Mining managers	4%
7121	Roofers	4%
7317	Handicraft workers in wood, basketry and related materials	4%
3324	Trade brokers	4%
3155	Air traffic safety electronics technicians	4%
4412	Mail carriers and sorting clerks	4%
7111	House builders	4%
8182	Steam engine and boiler operators	4%
3151	Ships' engineers	4%
7233	Agricultural and industrial machinery mechanics and repairers	4%
7123	Plasterers	4%
3230	Traditional and complementary medicine associate professionals	4%
9216	Fishery and aquaculture labourers	4%
1222	Advertising and public relations managers	4%
5153	Building caretakers	4%
8350	Ships' deck crews and related workers	4%
2152	Electronics engineers	4%
1324	Supply, distribution and related managers	4%

1439	Services managers not elsewhere classified	4%
4321	Stock clerks	4%
2622	Librarians and related information professionals	4%
4226	Receptionists (general)	4%
7114	Concrete placers, concrete finishers and related workers	4%
8181	Glass and ceramics plant operators	4%
7231	Motor vehicle mechanics and repairers	4%
8171	Pulp and papermaking plant operators	4%
9112	Cleaners and helpers in offices, hotels and other establishments	4%
4323	Transport clerks	3%
7132	Spray painters and varnishers	3%
2112	Meteorologists	3%
1221	Sales and marketing managers	3%
7125	Glaziers	3%
7521	Wood treaters	3%
9333	Freight handlers	3%
5246	Food service counter attendants	3%
7127	Air conditioning and refrigeration mechanics	3%
7513	Dairy-products makers	3%
5245	Service station attendants	3%
7515	Food and beverage tasters and graders	3%
8211	Mechanical machinery assemblers	3%
7312	Musical instrument makers and tuners	3%
7543	Product graders and testers (excluding foods and beverages)	3%
7536	Shoemakers and related workers	3%
8111	Miners and quarriers	3%
1212	Human resource managers	3%
5165	Driving instructors	3%
7113	Stonemasons, stone cutters, splitters and carvers	3%
7319	Handicraft workers not elsewhere classified	3%
8342	Earthmoving and related plant operators	3%
1420	Retail and wholesale trade managers	3%
2511	Systems analysts	3%
2659	Creative and performing artists not elsewhere classified	3%
3154	Air traffic controllers	3%
7541	Underwater divers	3%
8183	Packing, bottling and labelling machine operators	3%
1223	Research and development managers	3%
3431	Photographers	3%
2330	Secondary education teachers	2%
8160	Food and related products machine operators	2%
3331	Clearing and forwarding agents	2%
1411	Hotel managers	2%
3152	Ships' deck officers and pilots	2%
8113	Well drillers and borers and related workers	2%

7523	Woodworking-machine tool setters and operators	2%
3153	Aircraft pilots and related associate professionals	2%
2163	Product and garment designers	2%
8343	Crane, hoist and related plant operators	2%
3213	Pharmaceutical technicians and assistants	2%
7532	Garment and related pattern-makers and cutters	2%
8172	Wood processing plant operators	2%
2654	Film, stage and related directors and producers	2%
7318	Handicraft workers in textile, leather and related materials	2%
7422	Information and communications technology installers and servicers	2%
3323	Buyers	2%
1211	Finance managers	2%
3311	Securities and finance dealers and brokers	2%
2165	Cartographers and surveyors	2%
3211	Medical imaging and therapeutic equipment technicians	2%
5223	Shop sales assistants	2%
7522	Cabinet-makers and related workers	1%
2113	Chemists	1%
2262	Pharmacists	1%
7213	Sheet-metal workers	1%
7222	Toolmakers and related workers	1%
2310	University and higher education teachers	1%
7215	Riggers and cable splicers	1%
7512	Bakers, pastry-cooks and confectionery makers	1%
2412	Financial and investment advisers	1%
2432	Public relations professionals	1%
3315	Valuers and loss assessors	1%
8114	Cement, stone and other mineral products machine operators	1%
2619	Legal professionals not elsewhere classified	1%
3332	Conference and event planners	1%
3334	Real estate agents and property managers	1%
7511	Butchers, fishmongers and related food preparers	1%
1431	Sports, recreation and cultural centre managers	1%
1344	Social welfare managers	1%
2320	Vocational education teachers	1%
2423	Personnel and careers professionals	1%
7311	Precision-instrument makers and repairers	1%
310	Armed forces occupations, other ranks	1%
3312	Credit and loans officers	1%
2269	Health professionals not elsewhere classified	1%
2265	Dieticians and nutritionists	1%
1346	Financial and insurance services branch managers	1%
7212	Welders and flamecutters	1%
8141	Rubber products machine operators	1%
3259	Health associate professionals not elsewhere classified	1%

8219	Assemblers not elsewhere classified	1%
3432	Interior designers and decorators	1%
2431	Advertising and marketing professionals	1%
3412	Social work associate professionals	1%
3114	Electronics engineering technicians	1%
3435	Other artistic and cultural associate professionals	1%
2529	Database and network professionals not elsewhere classified	1%
7223	Metal working machine tool setters and operators	1%
3521	Broadcasting and audio-visual technicians	1%
2632	Sociologists, anthropologists and related professionals	1%
2166	Graphic and multimedia designers	1%
2359	Teaching professionals not elsewhere classified	1%
2635	Social work and counselling professionals	0%

Source: Own elaboration based on ESCO database version 1.2.0 (downloaded on 05/27/2024 from https://esco.ec.europa.eu/en/use-esco/download)

Table A.10. Mincer regressions of hourly wages in South Asia, circa 2022

	log (Hourly wages)						
	Bangladesh	Bhutan	India	Maldives	Nepal	Pakistan	Sri Lanka
Green job	0.118***	0.183***	0.086***	0.078**	0.071**	0.029***	0.220***
	(0.008)	(0.024)	(0.005)	(0.035)	(0.035)	(0.006)	(0.024)
Male	0.261***	0.112***	0.432***	0.176***	0.396***	0.211***	0.340***
	(0.008)	(0.021)	(0.004)	(0.022)	(0.028)	(0.010)	(0.020)
Age	0.035***	0.051***	0.044***	0.065***	0.036**	0.015***	0.023**
	(0.003)	(0.012)	(0.002)	(0.012)	(0.014)	(0.003)	(0.010)
Age squared	-0.000***	-0.001***	-0.000***	-0.001***	-0.000**	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Secondary education	0.285***	0.377***	0.218***	0.396***	0.256***	0.327***	0.624***
	(0.006)	(0.028)	(0.004)	(0.026)	(0.027)	(0.005)	(0.041)
Tertiary education	0.996***	1.015***	0.842***	0.969***	0.920***	1.076***	1.611***
	(0.008)	(0.028)	(0.006)	(0.033)	(0.036)	(0.009)	(0.045)
Constant	2.808***	2.745***	2.389***	2.090***	3.135***	3.657***	3.603***
	(0.056)	(0.217)	(0.038)	(0.220)	(0.277)	(0.053)	(0.190)
Observations	54,739	6,265	107,987	6,573	4,171	46,290	13,817
R-squared	0.263	0.207	0.292	0.119	0.193	0.335	0.129

Source: Own elaboration based on microdata listed in Table 2.

Notes: 1) Robust standard errors in parentheses. 2) *** p<0.01, ** p<0.05, * p<0.1. 3) Mincer equations estimated by OLS, where the dependent variable is the logarithm of hourly wages in the primary occupation for workers aged 25–55.

Table A.11. Mincer regressions of hourly wages in South Asia with sex heterogeneity, circa 2022

	log (Hourly wages)						
	Bangladesh	Bhutan	India	Maldives	Nepal	Pakistan	Sri Lanka
Green job	0.029	0.146***	-0.016	-0.038	-0.003	0.206***	-0.029
	(0.037)	(0.044)	(0.015)	(0.118)	(0.101)	(0.047)	(0.046)
Green job x Male	0.095**	0.057	0.124***	0.130	0.092	-0.182***	0.341***
	(0.038)	(0.052)	(0.016)	(0.123)	(0.106)	(0.047)	(0.053)
Male	0.254***	0.095***	0.407***	0.169***	0.383***	0.219***	0.281***
	(0.008)	(0.024)	(0.006)	(0.023)	(0.029)	(0.010)	(0.022)
Age	0.035***	0.052***	0.044***	0.065***	0.036**	0.015***	0.023**
	(0.003)	(0.012)	(0.002)	(0.012)	(0.014)	(0.003)	(0.010)
Age squared	-0.000***	-0.001***	-0.000***	-0.001***	-0.000**	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Secondary education	0.285***	0.377***	0.217***	0.396***	0.255***	0.326***	0.622***
	(0.006)	(0.028)	(0.004)	(0.026)	(0.027)	(0.005)	(0.041)
Tertiary education	0.996***	1.014***	0.840***	0.970***	0.920***	1.076***	1.605***
	(0.008)	(0.028)	(0.006)	(0.033)	(0.036)	(0.009)	(0.045)
Constant	2.814***	2.750***	2.403***	2.098***	3.143***	3.651***	3.639***
	(0.056)	(0.217)	(0.038)	(0.221)	(0.277)	(0.054)	(0.190)
Observations	54,739	6,265	107,987	6,573	4,171	46,290	13,817
R-squared	0.263	0.207	0.292	0.119	0.193	0.336	0.132

Source: Own elaboration based on microdata listed in Table 2.

Notes: 1) Robust standard errors in parentheses. 2) *** p<0.01, ** p<0.05, * p<0.1. 3) Mincer equations estimated by OLS, where the dependent variable is the logarithm of hourly wages in the primary occupation for workers aged 25–55.

Table A.12. Mincer regressions of hourly wages in South Asia by sex, circa 2022

(a) Females

	log (Hourly wages)						
	Bangladesh	Bhutan	India	Maldives	Nepal	Pakistan	Sri Lanka
Green job	0.062*	0.151***	0.035**	-0.039	0.027	0.242***	-0.018
	(0.036)	(0.045)	(0.015)	(0.118)	(0.103)	(0.045)	(0.046)
Age	0.027***	0.017	0.031***	0.062***	0.043	0.015	-0.009
	(0.008)	(0.025)	(0.005)	(0.020)	(0.027)	(0.011)	(0.018)
Age squared	-0.000***	0.000	-0.000***	-0.001***	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Secondary education	0.500***	0.523***	0.180***	0.396***	0.374***	0.647***	0.723***
	(0.018)	(0.058)	(0.008)	(0.049)	(0.053)	(0.025)	(0.077)
Tertiary education	1.325***	1.224***	1.063***	0.992***	1.091***	1.294***	1.740***
	(0.019)	(0.059)	(0.014)	(0.054)	(0.061)	(0.021)	(0.078)
Constant	2.895***	3.135***	2.660***	2.230***	2.839***	3.560***	4.267***
	(0.152)	(0.443)	(0.091)	(0.368)	(0.515)	(0.194)	(0.355)
Observations	9,065	2,168	27,362	2,732	1,386	5,579	4,746
R-squared	0.369	0.203	0.249	0.121	0.180	0.426	0.151

Table A.12. Mincer regressions of hourly wages in South Asia by sex, circa 2022 (continued)
(b) Males

	log (Hourly wages)						
	Bangladesh	Bhutan	India	Maldives	Nepal	Pakistan	Sri Lanka
Green job	0.128***	0.206***	0.103***	0.084**	0.076**	0.014**	0.314***
	(0.008)	(0.027)	(0.006)	(0.037)	(0.035)	(0.006)	(0.027)
Age	0.036***	0.061***	0.052***	0.068***	0.032*	0.017***	0.042***
	(0.003)	(0.013)	(0.002)	(0.014)	(0.017)	(0.003)	(0.011)
Age squared	-0.000***	-0.001***	-0.000***	-0.001***	-0.000	-0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Secondary education	0.244***	0.322***	0.217***	0.387***	0.199***	0.295***	0.574***
	(0.006)	(0.032)	(0.004)	(0.030)	(0.031)	(0.006)	(0.049)
Tertiary education	0.914***	0.930***	0.766***	0.928***	0.839***	1.025***	1.489***
	(0.009)	(0.032)	(0.006)	(0.044)	(0.045)	(0.010)	(0.055)
Constant	3.047***	2.758***	2.680***	2.152***	3.687***	3.852***	3.541***
	(0.059)	(0.253)	(0.041)	(0.273)	(0.326)	(0.054)	(0.220)
Observations	45,674	4,097	80,625	3,841	2,785	40,711	9,071
R-squared	0.224	0.208	0.204	0.110	0.128	0.316	0.101

Source: Own elaboration based on microdata listed in Table 2.
Notes: 1) Robust standard errors in parentheses. 2) *** p<0.01, ** p<0.05, * p<0.1. 3) Mincer equations estimated by OLS, where the dependent variable is the logarithm of hourly wages in the primary occupation for workers aged 25–55.

Table A.13. Distribution of Subpopulations Across Green and Non-Green Occupations in South Asia

Subpopulation	Bangladesh		Bhutan	
	Green	Non-green	Green	Non-green
Males	25.9%	74.1%	28.3%	71.7%
Females	20.6%	79.4%	23.3%	76.7%
Difference	5.3%***	-5.3%***	5%***	-5%***
Young (15-34)	23.8%	76.2%	26.7%	73.3%
Not young (35+)	25.3%	74.7%	25.8%	74.2%
Difference	-1.6%***	1.6%***	0.9%	-0.9%
Urban	26.7%	73.3%	30.6%	69.4%
Rural	23.9%	76.1%	23.8%	76.2%
Difference	2.8%***	-2.8%***	6.8%***	-6.8%***
Highly educated (more than secondary)	23.5%	76.5%	31.4%	68.6%
Not Highly educated (secondary or less)	23.2%	76.8%	26.9%	73.1%
Difference	0.3%	-0.3%	4.5%**	-4.5%**
Highly skilled (Managers/Professionals/Technicians)	24.4%	75.6%	25.4%	74.6%
Not highly skilled (Non-green)	24.7%	75.3%	26.3%	73.7%
Difference	-0.3%	0.3%	-0.8%	0.8%
With Vocational training	23.2%	76.8%	47.9%	52.1%
Without Vocational training	24.7%	75.3%	26.0%	74.0%
Difference	-1.6%*	1.6%*	21.9%***	-21.9%***
Paid employees	17.9%	82.1%	25.4%	74.6%
Self-employed, employers and unpaid employees	30.5%	69.5%	26.5%	73.5%
Difference	-12.7%***	12.7%***	-1.1%*	1.1%*
With contract	18.7%	81.3%	-	-
Without contract	16.4%	83.6%	-	-
Difference	2.3%***	-2.3%***	-	-
With social security insurance	-	-	-	-
Without social security insurance	-	-	-	-
Difference	-	-	-	-
Agriculture sector	22.6%	77.4%	17.5%	82.5%
Non-agriculture sector	25.9%	74.1%	33.1%	66.9%
Difference	-3.3%***	3.3%***	-15.6%***	15.6%***
Industry sector	26.1%	73.9%	42.2%	57.8%
Non-industry sector	24.4%	75.6%	23.1%	76.9%
Difference	1.8%***	-1.8%***	19.1%***	-19.1%***
Services sector	25.8%	74.2%	29.5%	70.5%
Non-services sector	23.8%	76.2%	23.9%	76.1%
Difference	2%***	-2%***	5.7%***	-5.7%***

Source: Own elaboration based on microdata listed in Table 2.

Notes: (1) The shares are computed using the O*NET definition of green jobs, converted to ISCO-08 using the Winkler et al. (2024)'s methodology. (2) In India and almost a quarter of employment in Sri Lanka, estimates are at the 3-digit level and are performed assuming an equal distribution of workers in 4-digit occupations within each 3-digit occupation. (3) *** p<0.01, ** p<0.05, * p<0.1.

Table A.13. Distribution of Subpopulations Across Green and Non-Green Occupations in South Asia (continued)

Subpopulation	India		Maldives	
	Green	Non-green	Green	Non-green
Males	27.4%	72.6%	26.9%	73.1%
Females	16.1%	83.9%	4.3%	95.7%
Difference	11.3%***	-11.3%***	22.6%***	-22.6%***
Young (15-34)	26.6%	73.4%	13.8%	86.2%
Not young (35+)	22.6%	77.4%	20.8%	79.2%
Difference	4%***	-4%***	-7%***	7%***
Urban	29.0%	71.0%	-	-
Rural	22.3%	77.7%	-	-
Difference	6.7%***	-6.7%***	-	-
Highly educated (more than secondary)	22.7%	77.3%	19.1%	80.9%
Not Highly educated (secondary or less)	23.6%	76.4%	17.5%	82.5%
Difference	-0.9%*	0.9%*	1.6%	-1.6%
Highly skilled (Managers/Professionals/Technicians)	36.2%	63.8%	22.4%	77.6%
Not highly skilled (Non-green)	22.4%	77.6%	13.7%	86.3%
Difference	13.8%***	-13.8%***	8.7%***	-8.7%***
With Vocational training	25.3%	74.7%	-	-
Without Vocational training	24.2%	75.8%	-	-
Difference	1.1%***	-1.1%***	-	-
Paid employees	31.2%	68.8%	14.7%	85.3%
Self-employed, employers and unpaid employees	18.6%	81.4%	26.1%	73.9%
Difference	12.6%***	-12.6%***	-11.4%***	11.4%***
With contract	20.8%	79.2%	14.2%	85.8%
Without contract	34.1%	65.9%	16.2%	83.8%
Difference	-13.3%***	13.3%***	-2%	2%
With social security insurance	22.8%	77.2%	14.4%	85.6%
Without social security insurance	33.6%	66.4%	14.8%	85.2%
Difference	-10.8%***	10.8%***	-0.3%	0.3%
Agriculture sector	8.9%	91.1%	32.1%	67.9%
Non-agriculture sector	35.4%	64.6%	16.4%	83.6%
Difference	-26.5%***	26.5%***	15.7%***	-15.7%***
Industry sector	53.2%	46.8%	27.2%	72.8%
Non-industry sector	14.0%	86.0%	15.4%	84.6%
Difference	39.2%***	-39.2%***	11.8%***	-11.8%***
Services sector	20.9%	79.1%	13.8%	86.2%
Non-services sector	25.5%	74.5%	28.6%	71.4%
Difference	-4.6%***	4.6%***	-14.8%***	14.8%***

Source: Own elaboration based on microdata listed in Table 2.

Notes: (1) The shares are computed using the O*NET definition of green jobs, converted to ISCO-08 using the Winkler et al. (2024)'s methodology. (2) In India and almost a quarter of employment in Sri Lanka, estimates are at the 3-digit level and are performed assuming an equal distribution of workers in 4-digit occupations within each 3-digit occupation. (3) *** p<0.01, ** p<0.05, * p<0.1.

Table A.13. Distribution of Subpopulations Across Green and Non-Green Occupations in South Asia (continued)

Subpopulation	Nepal		Pakistan	
	Green	Non-green	Green	Non-green
Males	32.9%	67.1%	31.8%	68.2%
Females	20.2%	79.8%	18.2%	81.8%
Difference	12.7%***	-12.7%***	13.6%***	-13.6%***
Young (15-34)	25.6%	74.4%	29.4%	70.6%
Not young (35+)	30.8%	69.2%	28.5%	71.5%
Difference	-5.1%***	5.1%***	0.9%***	-0.9%***
Urban	28.2%	71.8%	31.3%	68.7%
Rural	29.0%	71.0%	27.5%	72.5%
Difference	-0.8%	0.8%	3.8%***	-3.8%***
Highly educated (more than secondary)	25.4%	74.6%	23.9%	76.1%
Not Highly educated (secondary or less)	28.6%	71.4%	28.1%	71.9%
Difference	-3.3%	3.3%	-4.1%***	4.1%***
Highly skilled (Managers/Professionals/Technicians)	25.2%	74.8%	21.3%	78.7%
Not highly skilled (Non-green)	29.2%	70.8%	29.7%	70.3%
Difference	-4.1%***	4.1%***	-8.4%***	8.4%***
With Vocational training	-	-	22.3%	77.7%
Without Vocational training	-	-	31.1%	68.9%
Difference	-	-	-8.8%***	8.8%***
Paid employees	21.8%	78.2%	26.3%	73.7%
Self-employed, employers and unpaid employees	41.6%	58.4%	30.5%	69.5%
Difference	-19.8%***	19.8%***	-4.1%***	4.1%***
With contract	15.3%	84.7%	14.2%	85.8%
Without contract	30.1%	69.9%	29.8%	70.2%
Difference	-14.8%***	14.8%***	-15.6%***	15.6%***
With social security insurance	16.0%	84.0%	-	-
Without social security insurance	22.6%	77.4%	-	-
Difference	-6.6%***	6.6%***	-	-
Agriculture sector	9.6%	90.4%	19.4%	80.6%
Non-agriculture sector	31.4%	68.6%	34.3%	65.7%
Difference	-21.8%***	21.8%***	-14.9%***	14.9%***
Industry sector	38.4%	61.6%	40.5%	59.5%
Non-industry sector	23.6%	76.4%	24.7%	75.3%
Difference	14.8%***	-14.8%***	15.8%***	-15.8%***
Services sector	27.2%	72.8%	30.0%	70.0%
Non-services sector	29.9%	70.1%	28.0%	72.0%
Difference	-2.7%**	2.7%**	2.1%***	-2.1%***

Source: Own elaboration based on microdata listed in Table 2.

Notes: (1) The shares are computed using the O*NET definition of green jobs, converted to ISCO-08 using the Winkler et al. (2024)'s methodology. (2) In India and almost a quarter of employment in Sri Lanka, estimates are at the 3-digit level and are performed assuming an equal distribution of workers in 4-digit occupations within each 3-digit occupation. (3) *** p<0.01, ** p<0.05, * p<0.1.

Table A.13. Distribution of Subpopulations Across Green and Non-Green Occupations in South Asia (continued)

Subpopulation	Sri Lanka	
	Green	Non-green
Males	26.7%	73.3%
Females	11.2%	88.8%
Difference	15.5%***	-15.5%***
Young (15-34)	22.0%	78.0%
Not young (35+)	21.3%	78.7%
Difference	0.7%	-0.7%
Urban	24.1%	75.9%
Rural	21.0%	79.0%
Difference	3.1%***	-3.1%***
Highly educated (more than secondary)	17.7%	82.3%
Not Highly educated (secondary or less)	19.5%	80.5%
Difference	-1.8%	1.8%
Highly skilled (Managers/Professionals/Technicians)	26.0%	74.0%
Not highly skilled (Non-green)	20.5%	79.5%
Difference	5.5%***	-5.5%***
With Vocational training	23.5%	76.5%
Without Vocational training	21.3%	78.7%
Difference	2.1%***	-2.1%***
Paid employees	20.6%	79.4%
Self-employed, employers and unpaid employees	22.7%	77.3%
Difference	-2.1%***	2.1%***
With contract	16.7%	83.3%
Without contract	22.8%	77.2%
Difference	-6.1%***	6.1%***
With social security insurance	16.9%	83.1%
Without social security insurance	23.1%	76.9%
Difference	-6.2%***	6.2%***
Agriculture sector	6.4%	93.6%
Non-agriculture sector	27.2%	72.8%
Difference	-20.8%***	20.8%***
Industry sector	39.2%	60.8%
Non-industry sector	15.3%	84.7%
Difference	24%***	-24%***
Services sector	20.5%	79.5%
Non-services sector	22.4%	77.6%
Difference	-1.9%***	1.9%***

Source: Own elaboration based on microdata listed in Table 2.
Notes: (1) The shares are computed using the O*NET definition of green jobs, converted to ISCO-08 using the Winkler et al. (2024)'s methodology. (2) In India and almost a quarter of employment in Sri Lanka, estimates are at the 3-digit level and are performed assuming an equal distribution of workers in 4-digit occupations within each 3-digit occupation. (3) *** p<0.01, ** p<0.05, * p<0.1.

Table A.14. Regressions of the probability of being in a green job in South Asia, circa 2022.

	Prob (Green job)						
	Bangladesh	Bhutan	India	Maldives	Nepal	Pakistan	Sri Lanka
Male	0.063***	0.036***	0.117***	0.222***	0.112***	0.123***	0.153***
	(0.002)	(0.008)	(0.001)	(0.005)	(0.009)	(0.002)	(0.004)
Aged [25-34]	0.023***	0.010	-0.002	0.018**	0.039***	-0.007***	0.013
	(0.003)	(0.012)	(0.003)	(0.009)	(0.013)	(0.002)	(0.008)
Aged [35-44]	0.037***	0.037***	-0.009***	0.038***	0.071***	-0.013***	0.030***
	(0.003)	(0.013)	(0.003)	(0.010)	(0.014)	(0.002)	(0.008)
Aged [45-54]	0.041***	0.068***	-0.025***	0.059***	0.070***	-0.027***	0.011
	(0.003)	(0.016)	(0.003)	(0.013)	(0.015)	(0.003)	(0.008)
Aged [55+]	0.038***	0.048**	-0.062***	0.046***	0.023	-0.039***	-0.022***
	(0.003)	(0.019)	(0.003)	(0.014)	(0.018)	(0.003)	(0.008)
Secondary education	0.064***	0.036***	-0.004**	-0.006	-0.003	-0.000	0.056***
	(0.002)	(0.009)	(0.002)	(0.009)	(0.010)	(0.002)	(0.006)
Tertiary education	0.002	0.025**	-0.045***	-0.022*	-0.118***	-0.078***	0.016*
	(0.003)	(0.012)	(0.002)	(0.012)	(0.014)	(0.003)	(0.009)
Constant	0.147***	0.220***	0.188***	0.008	0.178***	0.214***	0.059***
	(0.003)	(0.013)	(0.003)	(0.012)	(0.013)	(0.002)	(0.009)
Observations	164,005	8,923	163,785	9,238	8,199	165,447	28,865
R-squared	0.015	0.007	0.038	0.135	0.029	0.025	0.053

Source: Own elaboration based on microdata listed in Table 2.

Notes: 1) Robust standard errors in parentheses. 2) *** p<0.01, ** p<0.05, * p<0.1. 3) Regressions estimated by OLS, where the dependent variable is the green job indicator (O*NET definition with Winkler et al. (2024)'s methodology) for workers aged 15 and more.