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Understanding labor market transitions in the Green Economy: A synthetic panel approach for Colombia

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Abstract

The green transition is expected to be one of the most significant forces shaping labor markets in the coming years. As economies shift toward cleaner technologies, green jobs will expand, while employment in high-emission sectors will either decline or move into other sectors, depending on skill transferability and policy design. Labor transitions into and out of green jobs remain understudied, particularly in developing economies where data constraints limit empirical analysis. This paper addresses this gap, using household survey data and a synthetic panel approach, we estimate the probability of labor transitions employs a skills-based green index. The results show a high degree of labor market persistence, with low transition probabilities between green and non-green jobs. Additionally, workers with university education, formal employment or located in sectors and territories with greater institutional dynamism, show a greater capacity to adapt to this transformation. Conversely, workers with lower levels of education, informal workers and women face greater barriers to entering green employment. These findings have important policy implications for ensuring a just energy transition. Given the observed rigidities in green labor mobility, targeted upskilling and reskilling programs are important to enabling non-green workers to acquire the necessary skills for green jobs.

Keywords: Green jobs, labor mobility, wage inequality, just transition, informality.
JEL codes: J21, J24, Q52, J62.

1 Introduction

The transition away from fossil fuels is expected to be one of the most significant forces shaping labor markets in the coming years. As economies shift toward cleaner technologies and production processes, the demand for green jobs will increase, while employment in high-emission sectors could decline. However, the extent to which workers can transition into green jobs depends on their ability to transfer or adapt existing skills to new labor market demands, as well as the availability of alternative employment opportunities for those displaced by the green transition (Curtis et al., 2024).

Climate change is a major threat to economic growth and social well-being, and it is prompting policy makers, producers and consumers to shift their behaviors and adopt more sustainable practices. While the expansion of green jobs is widely anticipated, a critical challenge remains: ensuring that workers in traditional sectors can transition into green employment without exacerbating economic and social inequalities. The ability to transition successfully will not be uniform across the workforce. Workers with greater access to education and training opportunities will be better positioned to adapt, while those in low-skilled, informal, or rural employment may face greater barriers (IMF, 2022). In particular, age, gender, and skill level significantly influence labor mobility (Duman and Ananian, 2024). If access to reskilling opportunities is unequal, the green transition could exacerbate labor market polarization, with high-skilled workers benefiting from green job growth while low-skilled workers struggle to transition into new roles. This dynamic risks widening wage disparities and deepening economic inequality (Autor, 2014).

Understanding labor transitions is important to ensuring a just transition toward a sustainable economy. Individual transitions are fundamental for labor market and economic dynamism, as well as for social mobility, inclusiveness, and resilience (Vandeplas et al., 2022). The literature has extensively examined the cyclical, structural, and policy drivers of labor market transitions (Dang and Lanjouw, 2013; Cruces et al., 2015; Consoli et al., 2016; Curtis et al., 2024; Causa et al., 2024), yet the green dimension of these transitions remains underexplored (Curtis et al., 2024; Duman and Ananian, 2024). Despite the growing body of research on the green economy, there is still limited evidence on how workers move into green jobs, particularly in developing regions such as Latin America (Maurizio et al., 2023). This paper addresses this research gap by analyzing labor market transitions in Colombia, a country with significant natural resources for renewable energy production (BID, 2021).

This study contributes to the literature by providing empirical evidence on job transitions using cross-sectional household survey data. While there is a growing body of research on the characteristics of green jobs (Consoli et al., 2016; Ernst et al., 2019; Bergant et al., 2022; Bluedorn et al., 2022; Curtis et al., 2024), few studies have focused on the occupational mobility of workers. This paper estimates transition probabilities using a synthetic panel that models the outcome variable in each round as a function of time-invariant characteristics, and then uses these models to simulate transitions across states over time (Dang and Lanjouw, 2023). Besides, it applies a skills-based green job index, following Vona's (2018) approach (Vona et al., 2018), and tailors it to the International Standard Classification of Occupations (ISCO) to understand the Colombian context. In addition, it provides empirical evidence on job transitions towards green employment in a developing country setting, which remains underexplored in the existing literature.

It also considers the economic returns associated with such transitions, particularly in terms of wages. Wage incentives could define workers' willingness and ability to shift into environmentally sustainable occupations, especially in contexts where labor market segmentation and informality are prevalent. By examining both career transitions and wage differentials, this article explores how the green transition may interact with existing inequalities and assesses whether it offers real opportunities for upward mobility or, on the contrary, risks reinforcing structural disadvantages. In doing so, it contributes to the broader debate on how to ensure that no one is left behind in the shift to a more sustainable labor market.

The findings reveal labor market rigidity, with low transition probabilities between green and non-green jobs. In Colombia, between 2021 and 2023, only 11.3% of workers in non-green jobs transitioned into green occupations, while 89.6% of green workers remained in green jobs, and 88.7% of non-green workers stayed in non-green employment. However, certain groups, particularly those with university education (with an upward mobility rate of 18.1%), formal employment (11.9%), or located in sectors and territories with greater institutional dynamism, show a greater capacity to adapt to this transformation. Conversely, workers with lower levels of education, informal workers, and women, who exhibit lower transition rates and higher exit rates from green jobs, face greater barriers to entering and staying in green employment. These results align with existing literature which highlights skill mismatches, structural barriers, and gender disparities as obstacles to a just green transition (Bluedorn et al., 2022; Curtis et al., 2024; Sato et al., 2023).

These dynamics, together with the evidence of a wage premium associated with green employment, suggest that, although the green transition offers opportunities to improve the quality of employment, it also carries the risk of deepening pre-existing inequalities if specific interventions aimed at a just and inclusive transition are not implemented. Specifically, these findings underscore the need for targeted upskilling and reskilling programs to facilitate worker transitions into the green economy (Chen et al., 2020). Additionally, disparities related to informality and gender must be addressed to prevent labor market exclusion and ensure an inclusive and just transition.

The paper is structured as follows. Section 2 reviews the literature on green jobs and labor market dynamics within the green economy and provide empirical evidence on green employment. Section 3 outlines the synthetic panel methodology, data sources, and the development of the skills-based measure for identifying green jobs. Section 4 presents the main empirical findings, while Section 5 discusses final remarks. Section 6 presents the Appendices.

2 Literature review

2.1 Understanding labor market transformations

The impact of climate change on labor markets and its policy implications requires a clear understanding of the mechanisms driving this transformation. Climate change is expected to influence labor markets through both direct and indirect channels. On the one hand, direct impacts arise from extreme weather events, such as floods, heatwaves, and changing precipitation patterns, that disrupt economic activity, reduce agricultural productivity, and deteriorate public health conditions (Reckien et al., 2009; OIT, 2008). These disruptions can lead to job losses, particularly in high-emission and climate-sensitive sectors, as employers may reduce labor demand in response to environmental shocks (Bergant et al., 2022; OCDE, 2023).

On the other hand, indirect effects are driven by policies and initiatives aimed at accelerating the green transition. Investments in renewable energy, stricter environmental regulations, and financial incentives, such as tax credits, concessional interest rates for energy efficiency projects, and subsidies for sustainable development, reshape the demand for labor by altering production structures and occupational requirements (Martinez and Hinojosa, 2010; Westgard, 2009). These shifts require workers to acquire new skills and adapt to evolving labor market needs.

These changes in labor supply and demand, driven by environmental policies, are changing the occupational structure of the economy which can follow three distinct paths, each with implications for workers and policy design. According to Maczulskij (2024), first, at the intensive margin, existing workers shift from non-green to green jobs, reflecting an efficient reallocation of labor. Second, at the extensive margin, the occupational structure is gradually transformed as workers leave the labor market for polluting occupations and new workers enter green occupations. Third, both margins may interact, resulting in a combined transformation.

Those transformations will not occur all at once, but rather evolve over time, producing distinct effects at different stages. In the short term, green sectors, often more labor-intensive than traditional industries, are likely to generate new employment, particularly in infrastructure and renewable energy development (Martinez and Hinojosa, 2010). However, limited labor mobility and widespread skill mismatches may constrain these gains, potentially generating transitional frictions and even temporary structural unemployment (OCDE, 2023).

In the medium term, as climate policies are consolidated and diffused throughout the economy, broader restructuring of value chains is expected. This stage is likely to bring about both job creation and destruction, with heterogeneous impacts across sectors and regions (Vona, 2021). The net employment outcome will depend heavily on contextual factors such as energy prices, regulatory design, and the rate of technological adoption (Ferreira et al., 2015).

In the long term, if innovation and green investment continue to expand, they can become engines of productivity growth and job creation (Atkins, 2024). This may give rise to a virtuous cycle in which environmental sustainability and economic development reinforce one another—provided that inclusive institutional mechanisms are in place to support participation across all social groups (Rutzer et al., 2020).

A central feature of this transition is the growing demand for skilled labor in clean sectors such as solar energy, wind infrastructure, and sustainable construction (Consoli et al., 2016). However, without targeted investments in education and workforce training, skill mismatches and labor shortages could become significant barriers to progress (Maczulskij, 2024). Moreover, structural changes driven by environmental policy also influence consumer preferences, encouraging industries to adapt their production processes to meet sustainability standards. For these transformations to benefit workers equitably, labor market policies must be closely aligned with environmental objectives.

2.2 What does a green job mean?

The term green economy refers to a low-carbon, resource-efficient, and socially inclusive economy (UNEP, 2011; Sulich et al., 2020). Moreover, it involves a profound transformation that will require, among other things, the development of new knowledge and skills in both businesses and individuals (Fernández and Larrea, 2022). In this context, green jobs emerge, which, according to the International Labour Organization (ILO), are decent jobs that contribute to preserving and restoring the environment (OIT, 2021).

The definition of green jobs proposed by the ILO encompasses any job that contributes to environmental preservation and restoration (OIT, 2021). It includes both traditional sectors, such as manufacturing and construction, as well as emerging sectors like renewable energy and energy efficiency. Porto et al. (2024), Tsironis (2023) and Apostel and Barslund (2024) suggest four approaches to identifying a green job based on sector, production process, tasks, and skills.

The sector-based approach defines green jobs as those linked to economic activities classified as environmentally sustainable. The underlying methodology has the advantage of showing which specific economic activities are important in green transition and it creates the basis for strategic sectoral workforce planning (Abou-Ali and Amer, 2024). Under this definition, both solar panel installers and managers or secretaries in the energy sector would be considered green workers (Lobsiger and Rutzer, 2021). However, the same managerial or secretarial occupations in brown sectors would not necessarily align with the transition toward a carbon-neutral economy. The drawback is while it shows which sectors are needed for just transition, it does not provide information about the specific roles or tasks within those sectors that contribute to environmental sustainability and omit other sectors that do not typically fall within the green side, such as education, healthcare and retail (Urban et al., 2023).

When identifying green jobs based on production methods, bakers could be green workers by using organic flour, ecofriendly packaging, and energy-efficient ovens. Nevertheless, one limitation of this definition is that the use of environmentally sustainable production methods does not guarantee that the resulting products or services contribute to environmental protection and preservation (Lobsiger et al., 2021; Bohnenberger, 2022). Another drawback is that it does not strategically identify green jobs that are critical to the green transition or have specific green skilling needs. Additionally, there is an information challenge, as it is difficult to observe or measure the specific production processes of each productive unit.

In addition, there is a major information challenge, as it is often difficult to observe or measure the specific production processes of each productive unit. This lack of detailed data makes it difficult to accurately distinguish truly green jobs from others within the same occupational or industrial category.

The task-based definition evaluates how different job task profiles are impacted by this transition (Dierdorff et al., 2009). Unlike the industry-based classification, which groups jobs based on sector affiliation, the task-based approach focuses on the specific tasks performed within occupations (Vona, 2021). This framework identifies three main ways in which jobs are influenced by the green transition, resulting in distinct categories of green jobs: increased demand, enhanced skills, new and emerging jobs [1].

In this context, for example, electricians in the energy sector see increased demand in the green economy but do not experience changes in their task profile, placing them in the green increased demand category. In contrast, heating, air conditioning, and refrigeration mechanics and installers experience significant modifications to their task structure and require training, which categorizes them under green enhanced skills. Meanwhile, wind turbine service technicians represent green new emerging jobs, as they are entirely unique to the green economy. This task-based classification helps identify all occupations relevant to green workforce development, whether due to rising demand or shifts in task profiles.

A measure adopted for classifying a job as green involves the proportion of green tasks relative to the total tasks within an occupation. This method has been extensively discussed in the literature (Lobsiger and Rutzer, 2021;Porto et al., 2024; Sato et al., 2022). Although this approach captures the potential transformation of the labor market in response to the transition to a low-carbon economy, it focuses exclusively on the tasks performed and do not explore the skills or knowledge required to execute them. As a result, it fails to assess a worker's actual ability to perform green functions without the need for additional training.

Vona et al. (2018) argue that the skills necessary to perform green tasks must be taken into account when identifying green jobs. Under this approach, it is not sufficient for an occupation to include tasks related to the green transition; it is important to examine whether workers possess transferable skills that enable them to perform these tasks effectively. For this reason, Lobsiger et al. (2021) introduces the concept of green potential, which refers to occupations where workers already possess the skills, knowledge, and abilities required

[1]Green increased demand jobs are those that do not undergo modifications in their task structure but experience higher demand as a result of the green transition. These are considered indirect green jobs. Green enhanced skills jobs require notable adjustments to their task composition due to the green transition, classified as direct green jobs. Finally, green new emerging jobs are exclusively created within the green economy and require entirely new task profiles

to perform green tasks, even if their current roles are not officially classified as green.

In this study, we adopt the green potential concept following skill based approach of Vona et al. (2018) to assess the labor market in Colombia, as it provides a more comprehensive perspective on the country's ability to absorb and expand green employment. This metric identifies occupations that already contribute to the green economy and helps guide the strategic planning of training programs by highlighting roles with high green potential.

2.3 Empirical evidence on green jobs

The supply of green jobs has been analyzed using household surveys in both developed economies (Vona, 2021; Rutzer et al., 2020) and developing contexts (Porto et al., 2024; Ernst et al., 2019). The proportion of green jobs varies across different settings due to differences in methodological choices and the specific criteria employed to define green jobs. For instance, Ernst et al. (2019) estimates that in Argentina, between 4% and 7% of workers are employed in green jobs. Using a different approach Porto et al. (2024) find between 23% and 25% are green jobs in Argentina. Similarly, in Colombia, approximately 31% of workers are engaged in occupations with low and medium green potential[2] (LaboUR, 2023). On the other hand, Bowen et al. (2018) finds that 10.3% of current jobs in the United States fall into green jobs.

The evidence suggests that green potential is relatively higher among men, older adults, highly qualified workers, those in formal employment, and individuals in specific sectors such as construction, transportation, mining, and industry (Porto et al., 2024; Vona, 2021; LaboUR, 2023). Additionally, in terms of education, findings indicate that the demand for highly skilled workers with high green potential is particularly pronounced for managers and professionals, whereas it is lower for technicians and craft and related trades workers (Lobsiger and Rutzer, 2021).

Conversely, the demand for green jobs has not been studied as extensively, mainly due to data availability constraints. Online job postings have been the primary source for

[2]Low green potential is defined with a continuous index up to 0.30, medium potential as more than 0.30 up to 0.70, and high potential as above 0.70

quantifying the demand for green jobs (Song et al., 2021; Sato et al., 2022; Curtis and Marinescu, 2022; García-Suaza et al., 2023).

Specifically, according García-Suaza et al. (2023), in Colombia approximately 58% of job vacancies fall into the high or intermediate green potential category. This share highlights a mismatch between the supply and demand for green jobs and suggest that while employers seek workers with green-related skills, the availability of adequately trained professionals may not fully meet this demand.

The findings indicate that employers seek green jobs in industries such as oil and gas (Curtis and Marinescu, 2022) and fossil fuel extraction (Sato et al., 2023). Additionally, green jobs tend to be created in occupations that offer wages approximately 21% higher than the average (Curtis and Marinescu, 2022). Finally, low-carbon jobs need university education (García-Suaza et al., 2023) and have greater requirements in terms of technical, managerial, and social skills compared to other occupations (Sato et al., 2023).

While labor market transitions have been widely explored mainly in relation to informality (Maurizio et al., 2023) and poverty (Cruces et al., 2015), transitions to and from green jobs have only recently gained attention. For example, Curtis et al. (2024) and Duman and Ananian (2024), using longitudinal data from France and Vietnam analyze employment transitions between green and non-green workers. The results suggest that while there has been a significant increase in transitions from polluting to greener jobs, persistence in polluting jobs varies across local labor markets, and older workers and those without a university education are less likely to move into green employment.

Most existing studies on green economy focus on developed economies (Dierdorff et al., 2009;Janser, 2018; Rutzer et al., 2020; Vona, 2021;Sato et al., 2022;Vandeplas et al., 2022) while research on Latin American countries remains less explored (Ernst et al., 2019; Porto et al., 2024; Arias et al., 2023; García-Suaza et al., 2023). This study addresses this gap by analyzing labor transitions within a Latin American economy, providing new insights into how structural and institutional factors shape workers' mobility into green jobs in emerging markets.

2.4 The Green Wage Premium

The decarbonization process implies structural transformations in labor markets. While these transformations can generate aggregate benefits, the literature has emphasized that they also entail important distributional effects, generating winners and losers (Bergant et al., 2022). The green transition, therefore, is neither socially nor politically neutral. Evidence shows that phenomena such as automation or globalization have had adjustment costs that fall unequally on certain occupational groups, sectors and territories (Acemoglu and Autor, 2011; Autor and Dorn, 2013; Keese and Marcolin, 2023).

The study of wage differences between different groups of workers has always been an important topic of academic debate. Recently, along with the interest in climate change, the *wage greenium* has gained prominence when it comes to studying the wage differentials between workers in green and non-green jobs. A key element in understanding this distributive dimension is wage because it determines the well-being of workers and reflects the distribution of opportunities in the labor market.

Evidence suggests the wage gap between workers in green and non-green can vary according to the specific characteristics of the workers and contexts. Bluedorn et al. (2022) find that green jobs offer a wage premium of approximately 7% compared to polluting jobs studying 21 advanced countries, even after controlling for factors such as education, gender, and location. On the other hand, Curtis and Marinescu (2022) report that green jobs in the U.S. pay about 21% more than the average in other industries, with the premium being even greater for green jobs requiring lower educational qualifications.

Bone et al. (2025) found similar results for the UK labor market, where green job postings consistently offered higher average wages than non-green ones. However, their study also shows that the wage differences across educational levels in green jobs are relatively small. That is, the salary increases associated with holding a bachelor's or master's degree, compared to technical qualifications, are less pronounced than in other sectors. This suggests that practical and technical skills may be as valuable as academic credentials in many green occupations.

In the Global South, the pattern is different, Cerimelo et al. (2024) find that green jobs in Latin America (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Mexico, Peru and Uruguay) pay 20% more than non-green jobs and that this effect is increasing in the number of years of education. García-Suaza et al. (2023) study wage greeniums in Colombia, Ecuador, Mexico, and Peru. They find a positive relationship between green potential and wages and they mention that both, the share of highly educated workers and the experience required for each job, increases with the green potential. Complementary evidence from Chile, Ecuador, Mexico and Peru data confirms that green workers earn 18% more than their counterparts. These patterns could arise from supply side constraints, such as limited access to training and skill development, or from demand side where companies compete intensely for a limited pool of skilled workers, putting upward pressure on wages in these occupations. In either case, understanding who benefits and who is left behind in this wage structure is necessary to anticipate the social and political challenges of the green transition and to inform equitable labor market policies.

To ensure a just green transition, it is essential to explicitly incorporate compensation and protection mechanisms for the most vulnerable workers. An articulated combination of active policies for training, retraining and support for mobility is indispensable to accompany the structural change implied by the decarbonization of the economy. Only through a coordinated intervention between environmental, labor and social policies will it be possible to ensure that the green transition does not deepen existing inequalities, but rather opens up opportunities for a more inclusive and resilient economy.

3 Data sources and descriptive analysis

This section outlines the data sources used and the methodology employed to construct the General Green Skill Index (GGS henceforth), a measure for analyzing green jobs in the Colombian labor market.

3.1 Data

To identify the potential of green jobs in Colombia, this paper exploits various data sources. The primary data source for this paper is the Great Integrated Household Survey (GEIH, for its acronym in Spanish) from the Departamento Administrativo Nacional de Estadística [3] (DANE). The GEIH is a nationally representative household survey collected on a monthly basis. It provides detailed information on labor market characteristics, including occupation, employment status, and sociodemographic variables. In particular, data from 2021 and 2023 were used.

Since there is no information on the skill or knowledge composition of occupations for Colombia, this paper uses the O*NET dataset at the Standard Occupational Classification (SOC). The O*NET database includes importance scores for 35 skills, 32 knowledge areas, and 41 work activities across 912 occupations at the SOC 8-digit level.The importance scores range from 1 (low importance) to 5 (high importance)[4]. This source is the foundation for constructing the GGS following the methodology of Vona et al. (2018).

3.2 General Green Skill Index

The construction of the GGS index is based on identifying the skills, knowledge areas, and work activities on greener occupations. According to the methodology proposed by Vona et al. (2018), this identification is achieved using the following regression model:

$$\text{Imp}_k^l = \beta^l \times \text{Greenness}_k + \phi^{SOC\_3d} + \epsilon_k. \tag{1}$$

where Imp is the importance of knowledge, activity or skill l in occupation k and Greenness_k is an index that considers the ratio of green tasks to total tasks of an occupation k and ϕ^{SOC_3d} is a 3-digit SOC occupation dummy included to control for unobserved heterogeneity across related occupations, ensuring comparability among occupations with similar task content and skill requirements.

This expression allows the identification of skills that are more intensively utilized in greener occupations. The key parameter of interest is β^l, which captures the relationship between the greenness of an occupation and the importance of skill l within that occupation. A positive and statistically significant value of β^l indicates that the skill is more intensively

[3] https://microdatos.dane.gov.co/index.php/catalog/MERCLAB-Microdatos

[4] https://www.onetonline.org

used in greener occupations. Conversely, a negative coefficient would suggest that the skill is less relevant in green jobs.

After identifying green tasks, skills, and activities, the authors group the components into broader categories using Principal Component Analysis (PCA). PCA reduces dimensionality, highlights critical components, and explains the variance in skill profiles between green and non-green occupations. Four main categories were identified:

Table 1: Green General Skills identified from O*NET according to Vona et al. (2018)

Category	Code	Skill
Engineering and technical:	2C3b	Engineering and Technology
	2C3c	Design
	2C3d	Building and Construction
	2C3e	Mechanical
	4A3b2	Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment
	4A1b3	Estimating the Quantifiable Characteristics of Products, Events, or Information
Operation management:	2B4g	Systems Analysis
	2B4h	Systems Evaluation
	4A2b3	Updating and Using Relevant Knowledge
	4A4b6	Provide Consultation and Advice to Others
Monitoring:	2C8b	Law and Government
	4A2a3	Evaluating Information to Determine Compliance with Standards
Science:	2C4b	Physics
	2C4d	Biology

Notes: Author's elaboration based on Vona et al. (2018). In their methodology, Vona et al. (2018) select 14 out of 108 general skills and tasks, retaining those with a statistically significant coefficient computed in equation (1). These selected skills are then grouped into coherent categories using principal component analysis (PCA), keeping only those loading onto principal components with eigenvalues greater than 1.

Engineering and Technical group includes skills related to engineering, design, mechanics, and construction. These skills are important to the application of environmental technologies, which often involve adapting existing scientific knowledge to solve specific problems. In contrast to purely scientific tasks, engineering skills focus on application and adaptation in practical settings. This makes them essential in a wide range of occupations, from highly educated roles, such as architects and engineers, to those requiring less formal education, such as construction workers or maintenance technicians.

On the other hand, Operation Management skills involve the capacity to analyze systems, evaluate their performance, and facilitate effective decision-making. These skills are particularly important for roles that require identifying environmental needs, coordinating efforts across diverse stakeholder groups, and leading sustainability initiatives. Examples of occupations where these skills are critical include Chief Sustainability Officers and Supply Chain Managers, where managing complex environmental processes and ensuring alignment with sustainability goals is essential.

Similarly, the Monitoring group is related to ensure compliance with environmental, legal, and regulatory standards. These tasks often include administrative, legal, and technical activities that safeguard adherence to policies. Occupations that heavily utilize monitoring skills include: Environmental Compliance Inspectors, Government Property Inspectors, Emergency Management Directors and Legal Assistants. Finally, Science skills contribute to innovation and technological development and they are less narrowly focused on specific applications than engineering skills, making them relevant across a broader spectrum of occupations. Some examples of roles that rely on scientific group are: Environmental Scientists, Materials Scientists and Hydrologists, Biochemists and Biophysicists.

The GEIH uses the CUOC clasification (Clasificación Única de Ocupaciones para Colombia) which is an adaptation of International Standard Classification of Occupations (ISCO-08), while the ONET database is based on SOC 2010. In order to integrate both datasets, a conversion from SOC to ISCO was necessary. The conversion from SOC to ISCO was conducted using a crosswalk provided by the Bureau of Labor Statistics (BLS)[5]. The process involved two main steps, the fist one was the aggregation of SOC scores at the 6-digit level with the mean of the SOC scores and the second was mapping these scores to the corresponding ISCO 4-digit codes.

The main complication to be addressed during the crosswalking procedure is the many-to-many mapping between SOC and ISCO as a single SOC 6-digit code could correspond to multiple ISCO 4-digit codes, and vice versa. To address this challenge, it was assumed that the employment within each SOC 6-digit occupation was uniformly distributed among the corresponding ISCO codes. This assumption aligns with the methodology proposed by Scholl et al. (2023).

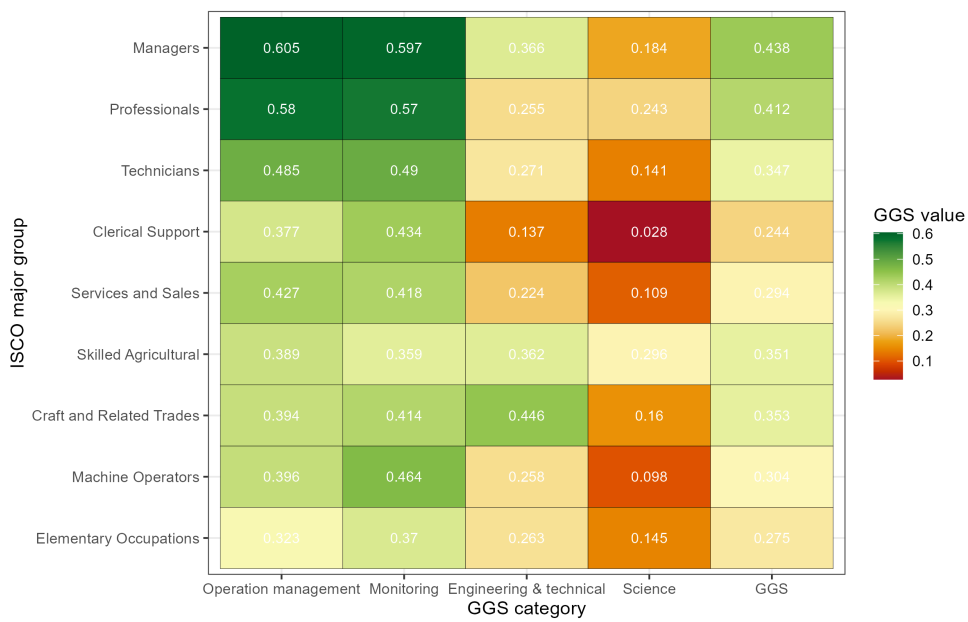
[5] Available at: https://www.bls.gov/soc/isco_soc_crosswalk.xls

After converting the data to the ISCO-08 classification, the GGS was derived by taking the simple average of the normalized scores for each of the four skill categories. The resulting index captures the green intensity of occupations at the ISCO-08 level and provides a robust measure of green skills in the Colombian labor market.

3.3 Descriptive analysis

This section explores the distribution of the GGS at the occupational level, analyzing its relationship with demographic and labor characteristics. Figure 1 presents the distribution of the GGS across major occupational groups (CUOC categories) and its four dimensions.

Figure 1: Green General Skill Index by ISCO major group



Notes: The numbers within each cell represent the average score for each combination of occupational group and category. The last column is the simple average of the four categories. Source: Author calculations based on GEIH (2021, 2023).

The results reveal a hierarchy in the distribution of GGS across occupational groups. Operation Management emerges as the most prominent dimension, particularly among high-skilled occupations such as Managers and Professionals. Managers, with the highest scores in this category, play a central role in organizing and coordinating sustainability strategies, overseeing systems, and integrating environmental goals into organizational practices. Similarly, Professionals show high values in Operation Management, which could be an indicator of their ability to analyze and implement green initiatives.

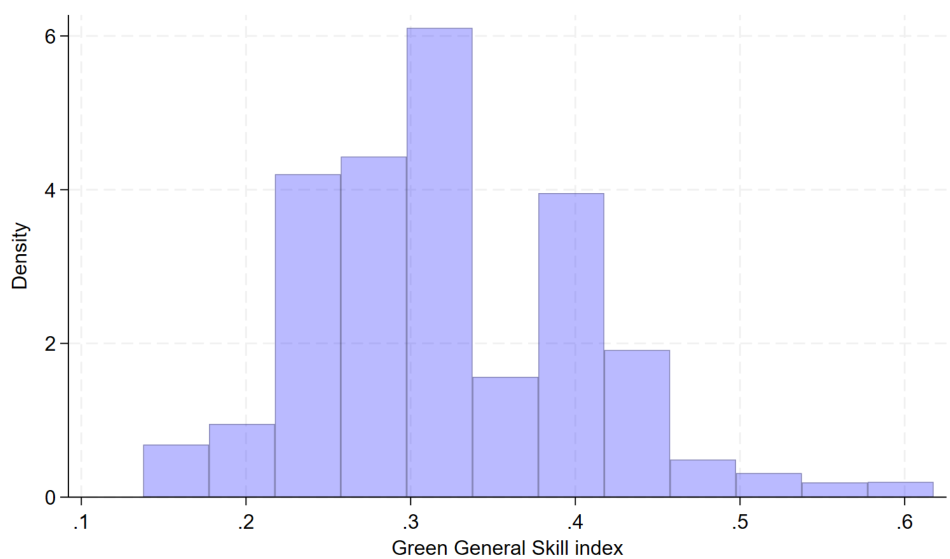
Monitoring stands out as an important group, particularly for occupations that require oversight and regulatory compliance. Managers and Professionals once again lead in this dimension. At the same time, moderate scores in Monitoring are observed for Machine Operators and Craft and Related Trades, highlighting the importance of compliance within technical and production roles. Engineering & Technical group reveals their importance among mid-level technical occupations such as Technicians and Craft and Related Trades. Craft workers contribute to the practical implementation of green technologies, focusing on tasks such as assembling, repairing, or modifying equipment to achieve sustainability standards. In contrast, technicians play a crucial role in translating technical plans into actionable solutions.

Science shows the lowest values across all occupational groups. Even among Professionals, where scientific knowledge might be expected to play a key role, the scores remain relatively low. This fact presents a characteristic of environmental technologies: they are often based on the application of existing scientific knowledge rather than the creation of new foundational research (Vona et al., 2018). In addition, according to the author, Science accounts for only 6.2% of the variance in their model, compared to 34.9% for Engineering and Technical skills. As a result, the green relevance of scientific knowledge tends to be diluted when occupations are aggregated into broader categories. Occupations such as Skilled Agricultural Workers display higher values in Science, given their need for biological and ecological expertise in managing natural processes. However, lower-skilled roles, including Clerical Support and Elementary Occupations, have minimal engagement with scientific tasks.

Finally, the GGS values highlight that Managers and Professionals lead with the highest scores (0.438 and 0.412, respectively), they reflect their important roles in the green economy. Technicians, with a score of 0.347, follow as key contributors in implementing green initiatives. In contrast, Elementary Occupations display the lowest GGS score (0.275), emphasizing their limited involvement in green tasks. This distribution underscores the need for targeted training programs to bridge the gap between high- and low-skilled workers, fostering a more equitable green transition.

Figure 2 presents the distribution of the GGS Index which peaks around 0.3, suggesting that most occupations possess moderate green skill intensity. The right-skewed distribution indicates that fewer occupations exhibit very high GGS values (above 0.4) and represents specialized green jobs, while some fall below 0.2 with limited green skill alignment. This pattern underscores disparities in green skill distribution, with a significant portion of occupations concentrated near the median.

Figure 2: Green General Skill Index distribution



Source: Author calculations based on GEIH (2021, 2023).

On the other side, Figure 3 presents the GGS score for occupations classified at the two-digit level according to the Colombian Classification of Occupations (CUOC). The results reveal that science, engineering, and specialized managerial roles have the highest GGS scores. Specifically, science and engineering professionals, production and specialized services managers, and health professionals show an alignment with green competencies. Conversely, occupations related to food preparation, cleaning, sales, and clerical support register the lowest scores with a weaker integration of green skills in these roles.

Another trend is the concentration of high-GGS occupations in STEM fields, particularly in engineering, electronics, and environmental sciences. This pattern highlights the role of technical expertise and innovation in fostering the green transition. Moreover, the presence of market-oriented skilled forestry, fishery, and agricultural occupations among mid-to-high scoring groups suggests that traditional sectors are undergoing a skill transformation driven by sustainability considerations.

Figure 3: Green General over ISCO 2-digit occupations

Notes: The circle size is the employment percentage for each category. Source: Author calculations based on GEIH (2021, 2023).

The dashed vertical line represents the mean GGS score, it serves as a benchmark to identify occupations above and below the average level of green skill intensity. Actually, the previous literature also defines green jobs based on specific thresholds. Studies by Elliott et al. (2021), Lobsiger and Rutzer (2021), as well as Porto et al. (2024), use the average score of their measure as a benchmark to classify occupations. Following this approach, we adopt the same methodology by setting the threshold for green jobs at the average GGS score.

Table 2 presents the distribution of green and non-green jobs in 2021 and 2023, based on the average of GGS index. The Colombian labor market has more non-green jobs, in 2021, green jobs accounted for 45% of total, while non-green jobs represented 55%. By 2023, the share of green jobs decreased to 43%, while non-green jobs increased to 57%. The decline in the share of green jobs suggests a slowing green transition in the Colombian labor market. This trend may reflect barriers to green job creation, slow adoption of sustainable technologies, or skill mismatches.

Table 2: Composition of Colombian labor market by green and non-green workes

	2021		2023	
Category	Number of workers	Share	Number of workers	Share
Non-green	11,220,033	55.0%	12,981,731	57.0%
Green	9,171,708	45.0%	9,806,662	43.0%
Total	20,391,741	100.0%	22,788,393	100.0%

Notes: The classification of jobs as green or non-green is based on the GGS index. The thresholds used to identify green jobs are determined by the mean values by year. Source: Author calculations based on GEIH (2021, 2023).

Finally, Table 3 highlights the distribution of green and non-green jobs across demographic and occupational characteristics for the years 2021 and 2023. Age is an important factor, with workers over 30 years old representing the majority in both green and non-green jobs, accounting for over 70% of total employment in both years. Gender disparities are present, as men dominate green jobs, comprising 71.97% in 2021 and decreasing to 68.91% in 2023, while women make up a smaller proportion, 28.03% in 2021 to 31.09% in 2023.

Green jobs are increasingly concentrated among workers with a university education, whose share rose from 31.08% in 2021 to 35.81% in 2023. In contrast, non-green jobs remain overwhelmingly dominated by workers without a university degree, whose share grew from 88.94% to 90.04% during the same period. In terms of formality, green jobs are more likely to be held by workers in the formal sector, with their share increasing from 46.19% in 2021 to 54.65% in 2023.

For occupational groups, salaried workers hold a slightly larger share of green jobs, increasing from 48.57% in 2021 to 53.53% in 2023. Self-employed workers remain a substantial group in non-green jobs and their representation in green jobs declined from 46.10% in 2021 to 43.52% in 2023. Overall, the data underscores persistent disparities in access to green jobs, which are more present for older, male, highly educated, and formally employed workers, while women, younger workers, and those in informal employment face greater challenges in entering the green economy.

Table 3: Characteristics of workers by green type

		2021			2023		
Variable	Category	Non-green	Green	Total per category	Non-green	Green	Total per category
Age	More than 30	71.39%	76.85%	73.84%	71.66%	78.58%	74.64%
	Less than 30	28.61%	23.15%	26.16%	28.34%	21.42%	25.36%
Sex	Men	51.74%	71.97%	60.84%	50.82%	68.91%	58.61%
	Women	48.26%	28.03%	39.16%	49.18%	31.09%	41.39%
Education	No University	88.94%	68.92%	79.94%	90.04%	64.19%	78.91%
	University	11.06%	31.08%	20.06%	9.96%	35.81%	21.09%
Informality	Formal	35.79%	46.19%	40.47%	35.26%	54.65%	43.60%
	Informal	64.21%	53.81%	59.53%	64.74%	45.35%	56.40%
Employment Status	Salaried workers	42.33%	48.57%	45.14%	42.83%	53.53%	47.44%
	Self-employed / Employed	46.56%	46.10%	46.35%	45.30%	43.52%	44.53%
	Others	11.11%	5.33%	8.51%	11.87%	2.95%	8.03%

Notes: The classification of jobs as green or non-green is based on the GGS index. The thresholds used to identify green jobs are determined by the mean values by year. Source: Author calculations based on GEIH (2021, 2023).

4 Methodology

This section outlines the methodology used to estimate labor market mobility between green and non-green jobs, incorporating a synthetic panel approach proposed by Dang and Lanjouw (2013) to address the absence of longitudinal data. The approach combines individual characteristics, mobility thresholds, and assumptions about error distributions to estimate the probability of labor transitions.

Let x_{ij} be a vector of individual characteristics observed in survey round j, $j = 1$ or 2, that are also observed in the other survey round for individual $i, i = \{1, \ldots, N\}$. Moreover, y_{ij} represents the outcome in survey round j. The linear projection of the outcome on individual characteristics for each survey round is given by:

$$y_{i1} = \beta_1' x_{i1} + \epsilon_{i1} \tag{2}$$

$$y_{i2} = \beta_2' x_{i2} + \epsilon_{i2}, \tag{3}$$

Let z_j be the threshold in period j that determines whether a worker is classified as green or non-green. Following the previous literature (Ernst et al., 2019; Lobsiger and Rutzer, 2021; Porto et al., 2024), individuals with a GGS equal to or above the average value in period j are considered green, while those below the average are classified as non-green. The focus is on understanding conditional probabilities such as:

$$P(y_{i2} \geq z_2 | y_{i1} \leq z_1) = \frac{P(y_{i2} \geq z_2 \cap y_{i1} \leq z_1)}{P(y_{i1} \leq z_1)}, \tag{4}$$

which represents the probability of being green worker in the in the second round, conditional on being non-green in the first round[6]. When panel data are available, equation (4) can be computed; otherwise, a synthetic panel approach must be applied (Dang and Lanjouw, 2013).

Dang and Lanjouw (2013) assume that in the underlying population the condition $x_{i1} = x_{i2}$ and $y_{i1}|x_{i1}$ and $y_{i1}|x_{i2}$ is satisfied. x_{ij} are used to predict the outcome in period 1 for individuals interviewed in period 2, and vice versa. Moreover, ϵ_{i1} and ϵ_{i2} have a bivariate normal distribution with correlation ρ and standard deviation $\sigma_{\epsilon 1}$ and $\sigma_{\epsilon 2}$, respectively.

If ρ is known, Dang and Lanjouw (2023) suggest calculate equation (4) by:

$$P(y_{i2} \geq z_2 \cap y_{i1} \leq z_1) = \Phi_2 \left(-\frac{z_2 - \beta_2' x_{i2}}{\sigma_{\epsilon_2}}, \frac{z_1 - \beta_1' x_{i2}}{\sigma_{\epsilon_1}}, -\rho \right) \tag{5}$$

where $\Phi_2(.)$ represents the standard bivariate normal cumulative distribution function and ρ denotes the correlation coeficient of errors. Since ρ is unknown, Dang and Lanjouw

[6]The other transition probabilities can be defined analogously by adjusting the conditions on y_{i1} and y_{i2}.

(2023) propose to estimate a lower bound and upper bound of mobility assuming that ρ is equal 0 or 1. In the context of green employment, ρ captures the degree of persistence that affect whether a worker remains in a green job or transitions to a different status over time. A high value of ρ (close to 1) shows strong persistence, the unobserved factors such as preferences for sustainability, skills, attitudes, among others, tend to remain stable across periods, making it much more likely that workers stay in the same type of job. On the other hand, a low value of ρ (close to 0) reflects low persistence allowing for greater mobility between green and non-green jobs.

The authors suggest that in absent any other information, one can start by assuming that ρ is either 0 or 1. However, by examining empirical estimates from actual panel data for other countries, they found a narrower range of this parameter.

4.1 Point estimates on mobility

Dang and Lanjouw (2013) explore the feasibility of producing point estimates of mobility instead of assuming bounds. The authors demonstrate that ρ can be derived from the simple intertemporal correlation coefficient $\rho_{y_{i1},y_{i2}}$:

$$\rho = \frac{\rho_{y_{i1},y_{i2}} \sqrt{\operatorname{var}(y_{i1})} \operatorname{var}(y_{i2}) - \beta_1' \operatorname{var}(x_i)\beta_2}{\sigma_{\epsilon_1}\sigma_{\epsilon_2}}, \tag{6}$$

where $\rho_{y_{i1},y_{i2}}$ is the simple intertemporal correlation coefficient of the dependent variable in each round. Since the intertemporal correlation of outcome cannot be directly observed without actual panel data, Dang and Lanjouw (2023) proxy $\rho_{y_{i1},y_{i2}}$ by working with the correlation between cohort-level average dependent variable across the two rounds. Calculating the intertemporal correlation of outcome at the cohort level is possible across the two cross-sectional surveys, even though the sampled households differ (Garcés-Urzainqui et al., 2021). Cohorts were constructed by birth year, sex and area.

Several validation exercises by the authors set that the cohort-level correlation approach does produce estimates of ρ that are quite close to their true value and thus point estimates of mobility that are correspondingly accurate.

The authors further generalize the framework to allow for point estimates of mobility between multiple groups over two periods. They show that the probability of an individual moving from group l in the first period to group m in the second period can be expressed as:

$$P(z_1^{l-1} \leq y_{i1} \leq z_1^l \cap z_2^{m-1} \leq y_{i2} \leq z_2^m) = \Phi_2 \left(\frac{z_1^l - \beta_1' x_{ij}}{\sigma_{\epsilon_1}}, \frac{z_2^m - \beta_2' x_{ij}}{\sigma_{\epsilon_2}}, \rho \right), \tag{7}$$

where z_1^{l-1} and z_1^l (respectively z_2^{m-1} and z_2^m) denote the lower and upper thresholds defining group l in period 1 (respectively group m in period 2). The estimation uses the cumulative distribution function of the standard bivariate normal, evaluated at the standardized thresholds determined by the estimated regression models for each period and adjusted by the estimated correlation ρ.

4.2 Measuring mobility

To complement the analysis of labor mobility between green and non-green occupations, this section presents a series of indicators commonly used to assess the magnitude and nature of mobility based on transition matrices. The following is a description of the five main indices that allow to characterize different dimensions of mobility building upon the framework established by Formby et al. (2004) (See Table 4). Let P a $n \times n$ Markovian matrix[7] where each entry p_{ij} represents the conditional probability of transitioning from occupational category i to j over the observation period. The diagonal elements of the matrix P correspond to individuals who remain in the same status (stayers), while the off-diagonal elements represent those who transition to a different class (movers). Let k the number of status or classes.

The Prais-Shorrocks index (M_1) provides a baseline measure of gross mobility through the normalization of matrix trace deviation from perfect immobility: $\frac{k-\text{tr}(P)}{k-1} \in [0, \frac{k}{k-1}]$. It reflects the average probability across all classes that an individual leave the initial status in the succeeding period; it is also interpreted as the normalized distance of P away from the identity matrix (Bartholomew, 1971).

[7] A $n \times n$ matrix is called a Markov matrix if all entries are nonnegative and the sum of each row is equal to 1 .

On the other hand, M_2, where λ_2 is the second largest eigenvalue of the transition matrix P. In the context of Markov chain theory, the magnitude of the second largest eigenvalue modulus, is used as a slowness of convergence measure (Sommers and Conlisk, 1979). A lower value of $|\lambda_2|$ indicates that the system rapidly loses memory of its initial conditions, while values close to 1 imply strong structural persistence. Therefore, higher values of M_2 denote faster convergence toward the stationary distribution and greater dynamic fluidity in the system. Conversely, lower values reflect a slow adjustment process, where occupational distributions remain close to their initial configuration over time.

The determinant based index M_3 use the absolute value of the determinant that reflects how rigid or fluid the system is. A determinant close to one implies that the matrix is near the identity, meaning most individuals remain in their original categories. Conversely, a determinant close to zero suggests mobility of individuals across categories. Therefore, higher values of M_3 indicate greater flexibility, while lower values point to persistence.

The previous indices captures the extent of mobility within the system but they remain insensitive to the weight of each state. The index M_4, proposed by Bartholomew (1971), captures structural immobility by weighting the diagonal elements of the transition matrix according to the marginal distribution π_i, that is, the share of the population initially located in each category. A low value of the index suggests that a large share of the population remains in the same occupational class, reflecting overall immobility. In contrast, a higher value indicates that transitions across classes are more common.

Finally, M_5 represents the average number of classes crossed by all individuals, as highlighted by Formby et al. (2004). Higher values show that mobility involves significant shifts between distant categories, while lower values reflect either immobility or transitions limited to adjacent states. Lower values indicate that transitions tend to happen between adjacent categories, while higher values suggest greater movement across the status, regardless of whether such transitions are upward or downward.

Table 4: Mobility indices for transition matrices

Indexes	Sources
$\mathrm{M}_1(P) = \dfrac{k - \mathrm{tr}(P)}{k-1}$	Prais (1955), Shorrocks (1978)
$\mathrm{M}_2(P) = 1 - \lvert\lambda_2\rvert$	Sommers and Conlisk (1979)
$\mathrm{M}_3(P) = 1 - \lvert\det(P)\rvert$	Shorrocks (1978)
$\mathrm{M}_4(P) = k - \sum_i \pi_i^* p_{ii}$	Bartholomew (1971)
$\mathrm{M}_5(P) = \dfrac{1}{k-1} \sum_i \pi_i^* \sum_j p_{ij} \lvert i-j\rvert$	Bartholomew (1971)

Notes: Source: Author's elaboration bases on Formby et al. (2004).

5 Results

5.1 Who's fit for the green transition in Colombia?

The results suggest that labor market is characterized by limited mobility, most individuals remain in their initial status over time (See Table 5). These probabilities are estimated using as threshold the mean value of GGS [8] and a correlation parameter of $\rho = 0.9519$ which explain that, among those who were in green jobs in 2021, 89.6% are expected to remain in green jobs in 2023. Similarly, among those who were in non-green jobs in the first year, 88.7% are expected to stay in non-green jobs in 2023. This overall stability suggests limited mobility across different skill profiles which is an indicator of structural barriers such as occupational specialization, mismatched skills, limited opportunities in green labor market and difficulties of changing occupations within a short time.

On the other hand, mobility rates are limited. The probability of becoming green worker conditional on being non-green is 11.3% (upward mobility) while the probability of moving from green to non-green jobs (downward mobility) is 10.4%. Although some level of persistence is expected, the relatively low rates of transition highlight the importance of examining who is effectively positioned to move into green jobs and who is not.

[8] As a robustness check, the classification was also performed using the sample median as the threshold (See Appendix A). The resulting transition probabilities and patterns remain consistent, and the main findings do not change substantially.

Data show differences between population groups. In terms of gender, men exhibit higher transition rates from non-green to green jobs and greater retention in green jobs. Women, in contrast, show lower transition rates and a higher probability of exits from green jobs. This result could be explained because of women are underrepresented in green-intensive occupations due to horizontal occupational segregation, limited access to technical education and STEM fields, and their higher concentration in service and care-related roles that are less aligned with green labor market (Organización Internacional del Trabajo y Comisión Europea, 2023; Alexander et al., 2024).

Educational attainment plays a decisive role as a predictor of green job mobility. Workers with university-level education are more likely to remain in green jobs (93.7%) in the last year and also show the highest rate of upward mobility (from non-green jobs to green jobs) (18.1%). Higher education increases access to green jobs and facilitates the development of technical skills required to remain in such positions, particularly through processes of upskilling and reskilling (Causa et al., 2024).

Regarding formality, results show that formal workers experience higher retention in green jobs (90.5%) and greater probability of upward mobility (11.9%), compared to informal (88.5% and 10.9%, respectively). In many developing economies, high rates of labor informality are linked to structural characteristics such as low productivity, limited access to technology, and weak institutional coverage that could limit the diffusion of green technologies and the development of green-related skills in informal segments of the labor market (International Labour Office, 2018). As a result, workers in informal employment may face greater obstacles to participating in the green transition due to the absence of institutional mechanisms that support training or the adoption of green practices. Increasing access to green jobs may require complementary strategies that promote both environmental transformation and labor formalization, particularly in sectors where informality is predominant.

Employment status and exposure to technological change also matter. Salaried workers and self-employed individuals exhibit similar stability in green jobs, however, the former have a slightly higher probability of remaining in green jobs (90%) compared to the latter

(89.35%). When considering exposure to technological change, such as artificial intelligence, the relationship with green job mobility appears limited. Workers in occupations with higher AI exposure show slightly higher green retention, but transition rates are not substantially different from those in low-exposure roles. These findings suggest that while both green and digital transitions involve shifts in skill demands, the degree of overlap in affected occupations remains modest in Colombia.

Exploring the groups of occupations under the ISCO-08 major classification further illustrates how green jobs is distributed across the occupational hierarchy. Occupations at the upper end of the skills spectrum, such as Managers, Professionals and Technicians show the highest levels of green persistence (92.1%, 93.3% and 90.3%, respectively). These groups also reveal higher upward transition probabilities (13.7%, 16.3% and 11.4%, respectively).

The sectoral transition patterns reveal two groups in green job dynamics (See Appendix B). The first includes sectors that combine high green job retention with upward mobility. This group is led by Information and Communication Technology (ICT), Financial and insurance services, Public administration, Education and health, and Agriculture and related. In these sectors, workers who begin in green occupations in 2021 are highly likely to remain in them in 2023, and non-green workers face comparatively higher chances of transitioning into green roles. According to OCDE (2023), many of these sectors have already been integrated into national strategies for mitigation and adaptation and are expected to benefit from increased investment and policy prioritization.

In contrast, the second group consists of sectors characterized by persistent non-green employment and higher rates of downward mobility. Arts, entertainment, recreation and others, Accommodation, Trade and Manufacturing form the core of this group. As noted in OCDE (2023), these sectors are characterized by high levels of informality and limited institutional support, which may reduce their capacity to incorporate green technologies or implement environmentally oriented practices.

Finally, geographic patterns present different scenarios of mobility across cities (See Appendix B). Cities such as Bogota, Bucaramanga and Ibague present the highest levels of green stability, these cities also exhibit higher upward mobility. In contrast, cities like Barranquilla, Cartagena and Cali show higher persistence in non-green employment (above 90%). While these differences are not extreme, they may reflect underlying sectoral composition, access to training, or local institutional dynamics. Overall, no city stands out as being disconnected from the green transition, but the slight differences in retention and mobility rates suggest that green job dynamics may be shaped by localized factors, such as the relative concentration of public sector jobs, infrastructure development, or sectoral composition.

Conversely, cities such as Barranquilla, Cartagena, and Cali show greater persistence in non-green employment paths. These patterns could reflect spatial differences in occupational structures and the availability of opportunities to access greener jobs. This pattern can be attributed to their economic structure, which is more concentrated in traditional sectors such as commerce, logistics, and other services less oriented toward sustainability. These activities are typically associated with conventional technologies and offer fewer opportunities for green jobs (Van Laake et al., 2021). In contrast,Bogotá's increased institutional capacity and the implementation of sustainability-oriented public policies, such as the expansion of electric public transport fleets (Cadena Monroy et al., 2022), have contributed to creating more favorable conditions for transitions to occupations with a higher green content.

Table 5: Transicion matrices by groups

Group	Variable		Green	Non-green
All	All	Green	89.57	10.43
		Non-green	11.34	88.66
Sex	Men	Green	91.38	8.62
		Non-green	14.75	85.25
	Women	Green	85.91	14.09
		Non-green	8.25	91.75
Age	More than 30	Green	89.59	10.41
		Non-green	11.37	88.63
	Less than 30	Green	89.36	10.64
		Non-green	11.10	88.90
Education	No university	Green	87.37	12.63
		Non-green	10.45	89.55
	University	Green	93.72	6.28
		Non-green	18.05	81.95
Informality	Formal	Green	90.55	9.45
		Non-green	11.86	88.14
	Informal	Green	88.47	11.53
		Non-green	10.94	89.06
Employment status	Self-employed and employers	Green	89.35	10.65
		Non-green	11.48	88.52
	Salaried workers	Green	90.00	10.00
		Non-green	11.48	88.52
AI exposure	High exposure	Green	90.42	9.58
		Non-green	11.02	88.98
	Low exposure	Green	88.87	11.13
		Non-green	11.55	88.45

Notes: Author's calculations based on GEIH (2021, 2023). Green workers are classified as those whose GGS values exceed the sample mean. The reported probabilities are calculated using a correlation parameter of $\rho = 0.9519$. Each row shows the probability of being in one of the two statuses in 2023, conditional on the worker's status in 2021.

5.2 From green or not to shades of green

The previous section analyzes labor market mobility using a dichotomous classification of green versus non-green jobs. This approach is consistent with recent frameworks adopted in the literature (Porto et al., 2024; Lobsiger and Rutzer, 2021; Ernst et al., 2019) and offers a clear overview of transition dynamics. Nevertheless, it simplifies the continuous nature of GGS. In fact, the degree of greenness of an occupation, captured through the GGS index, is not binary, but rather distributed along a spectrum.

To better capture this fact, the analysis was expanded to include a three-level classification of greenness: low, medium, and high, based on terciles of the GGS distribution across occupations (See Table 6). This stratification allows for a more detailed exploration of labor mobility across the green spectrum.

As in the previous results, overall persistence remains strong: workers tend to remain in their initial status. However, when the analysis distinguishes between low, medium, and high greenness, transitions toward greener jobs (from low to medium or from medium to high) are more common than downward cases. This asymmetric mobility suggests that, although limited, there are clear pathways of skill upgrading that are not captured when the green economy is viewed in binary terms.

This richer perspective also helps refine the understanding of group differences. Gender gaps persist, women remain concentrated in low green occupations, however the probability of stability in medium green jobs is slightly above that of men. Education continues to be a key enabler, with university educated workers showing both stronger retention in high-green roles and higher upward movement. Similarly, formality reinforces green job stability and supports upward transitions.

A few sectors emerge as hubs of high-green jobs and also as spaces where upward transitions from intermediate greenness levels are more likely (See Appendix C). This pattern is especially visible in ICT, Finance, Agriculture, and Professional Services, which appear to offer more dynamic pathways for green skill development. In contrast, sectors such as Accommodation, Trade, and the Arts remain concentrated in low greenness occupations, with limited upward mobility and some signs of downward mobility.

Occupational stratification is also more pronounced. Upward transitions are largely concentrated among high skill occupations, Professionals, Managers, and Technicians, while lower-skill groups, including Sales, Clerical, and Service workers, remain in the low greenness level. At the territorial level, cities such as Bogotá, Bucaramanga, and Ibagué retain a larger share of workers in high green jobs, but also exhibit more frequent upward transitions from intermediate positions (See Appendix C). This suggests stronger local ecosystems for skill development and alignment with green employment trajectories. Conversely, Barranquilla, Cartagena, and Cali show limited movement out of low greenness employment, suggesting more rigid labor structures and fewer channels for green transtion.

Table 6: Three-state transition matrix

Group	Variable		Low	Medium	High
All	All	Low	75.40	23.75	0.85
		Medium	12.63	61.31	26.06
		High	0.19	10.65	89.16
Sex	Men	Low	70.53	28.23	1.24
		Medium	10.36	61.15	28.49
		High	0.14	8.98	90.88
	Women	Low	79.07	20.38	0.55
		Medium	15.79	61.54	22.66
		High	0.30	14.19	85.51
Age	More than 30	Low	75.39	23.76	0.85
		Medium	12.58	61.31	26.11
		High	0.19	10.62	89.19
	Less than 30	Low	75.47	23.73	0.80
		Medium	13.02	61.34	25.64
		High	0.20	10.87	88.93
	No university	Low	76.49	22.73	0.78
		Medium	13.23	61.61	25.16
		High	0.24	12.89	86.87
	University	Low	64.74	33.82	1.44
		Medium	9.95	59.99	30.07
		High	0.10	6.79	93.11
Informality	Formal	Low	74.61	24.53	0.87
		Medium	12.43	61.14	26.43
		High	0.17	9.70	90.13
	Informal	Low	76.00	23.17	0.83
		Medium	12.80	61.46	25.75
		High	0.21	11.75	88.04
Employment status	Self-employed and employers	Low	75.30	23.83	0.88
		Medium	12.40	61.37	26.23
		High	0.19	10.88	88.92
	Salaried workers	Low	75.06	24.11	0.84
		Medium	12.70	61.24	26.07
		High	0.18	10.23	89.59
AI Exposure	High exposure	Low	75.80	23.43	0.77
		Medium	13.11	61.06	25.83
		High	0.18	9.76	90.06
	Low exposure	Low	75.14	23.97	0.89
		Medium	12.31	61.48	26.21
		High	0.20	11.40	88.40

Notes: Author's calculations based on GEIH (2021, 2023). Workers are classified into three groups (low, medium, and high) based on the tertiles of their GGS values. The reported probabilities are calculated using a correlation parameter of $\rho = 0.9519$. Each row shows the probability of being in one of the three statuses in 2023, conditional on the worker's status in 2021.

5.3 Mobility metrics of the green transition

Mobility indices provide a comprehensive view of how dynamic or rigid the labor market is in the context of green transition. Table 8 presents a set of mobility indices calculated for binary and three-level classification. M_1, M_2 and M_3 are numerically identical under binary approach (for an explanation see Appendix D), yet they capture distinct conceptual dimensions of labor market dynamics. M_1 reflects the average probability that an individual changes status; M_2 measures the speed at which the distribution converges to its stationary state; and M_3 quantifies overall system rigidity or fluidity by assessing the distance from perfect immobility. The values of these indices are low, ranging between 0.21 and 0.24, which is consistent with the previous persistence observed earlier.

Despite limited mobility, certain groups present a slightly greater propensity for transition. For instance, individuals with university education, and those employed in sectors such as Agriculture and related, Construction, Transportation, as well as people belong to occupation groups such as: Skilled Agricultural, Machine Operator and Craft and Related Trades register the highest values. This implies that these groups present more flexibility to move between status and faster convergence to stationary state.

On the other side, M_4 captures mobility by accounting for the degree of permanence within the same class and it reveals moderate labor mobility overall, but some groups stand out with higher values, suggesting more active transitions. Sectors such as Transportation, Agriculture and related activities, and Craft and related trades occupations as well as Machine Operators show the highest mobility. Similarly, male workers and individuals with no university education exhibit higher than average mobility. M_5 that captures the steps individuals move across classes shows the same pattern as M_4 indicating that these groups experience larger steps in transitions. However, the indices dos not distinguish whether these movements are upward or downward.

When a three classification is considered same groups show high mobility as in the binary structure. However, the more disaggregated analysis highlights new groups that were previously less visible. In the case of M_1 and M_2, university educated workers and professionals continue to show high values, but now shows the sector Energy, Water and Mining appears as a group with faster mobility to stationary state. M_3 places Barranquilla, Manizales and Villavicencio at the high end of the index distribution.

M_4 and M_5 identify Trade as well as workers in groups: Skilled Agricultural, Services and Sales, Technicians and informal workers with higher values in both indices, indicating more active and broader occupational shifts than previously captured. Although overall stability remains the dominant pattern, the results reveal signs of mobility. Introducing intermediate status into the analytical framework offers a more nuanced perspective on occupational trajectories, uncovering patterns of upward and downward transitions that are obscured in a binary view. This broadened perspective enhances the understanding of unequal mobility conditions and reveals the complex structure of opportunities and barriers within the emerging green labor market.

Table 7: Mobility indices

Group	Variable	2x2 transition matrix					3x3 transition matrix				
		M1	M2	M3	M4	M5	M1	M2	M3	M4	M5
All	All	0.218	0.218	0.218	1.110	0.110	0.371	0.194	0.635	2.240	0.122
Sex	Men	0.234	0.234	0.234	1.115	0.115	0.387	0.220	0.652	2.232	0.118
	Women	0.223	0.223	0.223	1.101	0.101	0.369	0.184	0.637	2.243	0.123
Age	More than 30	0.218	0.218	0.218	1.110	0.110	0.371	0.194	0.635	2.240	0.122
	Less than 30	0.217	0.217	0.217	1.109	0.109	0.371	0.193	0.637	2.246	0.125
Education	No university	0.231	0.231	0.231	1.112	0.112	0.375	0.197	0.641	2.258	0.131
	University	0.243	0.243	0.243	1.094	0.094	0.411	0.238	0.683	2.183	0.093
Informality	Formal	0.213	0.213	0.213	1.106	0.106	0.371	0.193	0.635	2.214	0.109
	Informal	0.225	0.225	0.225	1.111	0.111	0.373	0.195	0.638	2.262	0.133
Occupation group	Self-employed and employers	0.221	0.221	0.221	1.111	0.111	0.372	0.196	0.637	2.253	0.128
	Salaried workers	0.215	0.215	0.215	1.108	0.108	0.371	0.193	0.635	2.222	0.113
AI exposure	High exposure	0.206	0.206	0.206	1.104	0.104	0.365	0.185	0.630	2.243	0.123
	Low exposure	0.227	0.227	0.227	1.114	0.114	0.375	0.200	0.640	2.240	0.122
Sector	Agriculture and related	0.239	0.239	0.239	1.121	0.121	0.384	0.220	0.648	2.312	0.156
	Energy, Water and Mining	0.226	0.226	0.226	1.102	0.102	0.379	0.207	0.644	2.148	0.075
	Manufacturing	0.220	0.220	0.220	1.110	0.110	0.371	0.193	0.636	2.241	0.122
	Construction	0.236	0.236	0.236	1.104	0.104	0.386	0.216	0.652	2.130	0.066
	Trade	0.219	0.219	0.219	1.107	0.107	0.370	0.190	0.635	2.282	0.142
	Transportation	0.234	0.234	0.234	1.124	0.124	0.384	0.213	0.650	2.306	0.154
	Accommodation	0.225	0.225	0.225	1.093	0.093	0.370	0.186	0.637	2.215	0.110
	ICT	0.210	0.210	0.210	1.089	0.089	0.374	0.198	0.639	2.182	0.092

Notes: Source: Author calculations based on GEIH (2021, 2023). The indices are defined in Table 4. Under binary approach, M_1, M_2 and M_3 are equal (See details in Annex D for details.)

Table 8: Mobility indices (continuation)

Group	Variable	2x2 transition matrix					3x3 transition matrix				
		M1	M2	M3	M4	M5	M1	M2	M3	M4	M5
Sector	Financial and Insurance	0.209	0.209	0.209	1.099	0.099	0.373	0.195	0.639	2.238	0.121
	Real Estate	0.223	0.223	0.223	1.111	0.111	0.374	0.199	0.638	2.207	0.105
	Professional and Admin Services	0.203	0.203	0.203	1.102	0.102	0.362	0.181	0.626	2.198	0.101
	Public Admin, Education and Health	0.208	0.208	0.208	1.099	0.099	0.369	0.190	0.634	2.192	0.098
	Arts and others	0.221	0.221	0.221	1.095	0.095	0.368	0.183	0.634	2.253	0.128
Occupation major ISCO-08 group	Managers	0.215	0.215	0.215	1.079	0.079	0.375	0.202	0.640	2.083	0.042
	Professionals	0.230	0.230	0.230	1.069	0.069	0.395	0.222	0.665	2.124	0.063
	Technicians	0.211	0.211	0.211	1.103	0.103	0.369	0.190	0.633	2.257	0.130
	Clerical Support	0.214	0.214	0.214	1.099	0.099	0.368	0.186	0.634	2.230	0.119
	Services and Sales	0.225	0.225	0.225	1.097	0.097	0.371	0.188	0.637	2.299	0.151
	Skilled Agricultural	0.238	0.238	0.238	1.094	0.094	0.384	0.219	0.647	2.277	0.139
	Craft and Related Trades	0.234	0.234	0.234	1.116	0.116	0.381	0.209	0.647	2.192	0.098
	Machine Operators	0.234	0.234	0.234	1.121	0.121	0.382	0.210	0.648	2.309	0.155
	Elementary Occupations	0.228	0.228	0.228	1.109	0.109	0.373	0.195	0.638	2.250	0.128
Cities	Barranquilla	0.217	0.217	0.217	1.106	0.106	0.376	0.187	0.646	2.242	0.123
	Bogota	0.210	0.210	0.210	1.105	0.105	0.368	0.192	0.631	2.213	0.108
	Bucaramanga	0.215	0.215	0.215	1.109	0.109	0.364	0.193	0.625	2.227	0.116
	Cali	0.215	0.215	0.215	1.105	0.105	0.371	0.186	0.638	2.237	0.120
	Cartagena	0.218	0.218	0.218	1.106	0.106	0.374	0.188	0.642	2.247	0.125
	Cucuta	0.217	0.217	0.217	1.110	0.110	0.358	0.191	0.616	2.228	0.116
	Ibague	0.214	0.214	0.214	1.109	0.109	0.365	0.194	0.625	2.228	0.116
	Manizales	0.213	0.213	0.213	1.105	0.105	0.376	0.187	0.647	2.233	0.118
	Medellin	0.213	0.213	0.213	1.107	0.107	0.370	0.189	0.636	2.230	0.117
	Monteria	0.215	0.215	0.215	1.106	0.106	0.369	0.187	0.635	2.242	0.122
	Pasto	0.210	0.210	0.210	1.105	0.105	0.371	0.187	0.638	2.229	0.116
	Pereira	0.216	0.216	0.216	1.108	0.108	0.370	0.190	0.636	2.230	0.117
	Villavicencio	0.216	0.216	0.216	1.107	0.107	0.376	0.190	0.646	2.234	0.119

Notes: Source: Author calculations based on GEIH (2021, 2023). The indices are defined in Table 4. Under binary approach, M_1, M_2 and M_3 are equal (See details in Annex D for details.)

5.4 Green jobs: a path to better wages?

To further examine the wage differences between green and non-green workers jobs, Tables 9 and 10 present the regression results. The inclusion of the GGS in Model (1) reveals a positive association with wages, the higher green skill level, the higher wages. When a binary indicator of green jobs is included in Model (2), a wage premium of 10.6% is observed for green occupations relative to non-green counterpart.

Model (3) incorporates the O*NET classification of green jobs: New and Emerging, Green Enhanced Skills (reference), Green Increased Demand. The results show that workers in non-green and Green Increased Demand occupations earn 16.1% and 15.8% less, respectively. These differences reflect heterogeneity in wage returns within the green economy.

When the interaction between digital and green transitions is explored (Model 4), the results reveal that wage differentials are not uniformly distributed across categories. Workers in green occupations with high exposure to AI earn 16.5% more than those in high-exposure non-green occupations. These findings suggest that the green wage premium is amplified in occupations with high exposure to AI, suggesting a complementarity between digital and green transition in shaping wages.

Relative to formal non-green workers, those in green formal employment earn 13.8% more, while green informal workers face a wage penalty of approximately 29.9%. non-green informal workers exhibit the largest disadvantage, with wages 37.8% lower than the reference group. These results underscore the persistent relevance of informality as a key driver of wage disparities, even within green occupations.

Among individuals with university education, working in a green occupation is associated with a higher wage premium. While non-green university-educated workers earn 37.6% more than their counterparts, this premium rises to 80.7% for green university-educated workers. Green wage premium is concentrated among the more educated segments of the workforce.

Table 9: Wage regressions

Dependent variable: Log of wage	(1)	(2)	(3)	(4)	(5)	(6)
Age	0.038***	0.040***	0.040***	0.039***	0.039***	0.038***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age square	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rural (Base: Urban)	-0.172***	-0.188***	-0.178***	-0.166***	-0.187***	-0.183***
	(0.029)	(0.030)	(0.031)	(0.029)	(0.030)	(0.030)
Women (Base: Men)	-0.231***	-0.262***	-0.262***	-0.266***	-0.262***	-0.266***
	(0.030)	(0.028)	(0.024)	(0.026)	(0.028)	(0.025)
Salaried workers (Base: Self employed, employer)	-0.161***	-0.154***	-0.151***	-0.161***	-0.153***	-0.152***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.028)	(0.026)
Other workers (Base: Self employed, employer)	-0.223***	-0.242***	-0.253***	-0.242***	-0.247***	-0.257***
	(0.036)	(0.041)	(0.041)	(0.040)	(0.040)	(0.042)
University (Base: No University)	0.608***	0.649***	0.641***	0.616***	0.645***	
	(0.039)	(0.042)	(0.040)	(0.033)	(0.043)	
Informal (Base: Formal)	-0.397***	-0.410***	-0.411***	-0.406***		-0.410***
	(0.016)	(0.017)	(0.018)	(0.017)		(0.017)
Department fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	12.264***	12.602***	12.790***	12.609***	12.586***	12.655***
	(0.092)	(0.070)	(0.102)	(0.082)	(0.071)	(0.070)
Observations	652,603	659,756	659,756	653,430	659,756	659,756
R-squared	0.459	0.455	0.456	0.454	0.455	0.461

Notes: Source: Author's elaboration based on GEIH (2021,2023).
Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 10: Wage regressions (Continuation)

Dependent variable: Log of wage	(1)	(2)	(3)	(4)	(5)	(6)
Weekly working hours	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Green Skill Index	1.250***					
	(0.144)					
Green (Base: Non-green)		0.106***				
		(0.031)				
Increased Demand (Base: New enhanced skills)			-0.158*			
			(0.083)			
New and Emerging (Base: New enhanced skills)			0.089			
			(0.089)			
Non-green (Base: New enhanced skills)			-0.161**			
			(0.075)			
Non-green - Low exposure (Base: Non-green - High exposure)				-0.024		
				(0.038)		
Green - High exposure (Base: Non-green - High exposure)				0.165***		
				(0.057)		
Green - Low exposure (Base: Non-green - High exposure)				0.054		
				(0.052)		
Non-green - Informal (Base: Non-green -Formal)					-0.378***	
					(0.026)	
Green - Formal (Base: Non-green -Formal)					0.138***	
					(0.036)	
Green - Informal (Base: Non-green -Formal)					-0.299***	
					(0.032)	
Non-green - University (Base: Non-green - No University)						0.376***
						(0.042)
Green -No University (Base: Non-green - No University)						0.030
						(0.030)
Green - University (Base: Non-green - No University)						0.807***
						(0.057)
Department fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	12.264***	12.602***	12.790***	12.609***	12.586***	12.655***
	(0.092)	(0.070)	(0.102)	(0.082)	(0.071)	(0.070)
Observations	652,603	659,756	659,756	653,430	659,756	659,756
R-squared	0.459	0.455	0.456	0.454	0.455	0.461

Notes: Source: Author's elaboration based on GEIH (2021,2023).
Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Finally, the Oaxaca-Blinder (Oaxaca, 1973; Blinder, 1973) decomposition (See Annex E) sheds light on the sources of the observed wage differential between green and non-green occupations (Table 15). The average gap amounts to 0.36 log points in favor of green workers, more than 60% of this difference (0.218) is explained by observable characteristics, mainly education, formality, and working hours.

On the other side, almost 40% of the difference correspond to the unexplained component. This means that even if workers in green and non-green jobs had identical observable characteristics, green workers would still earn approximately 14.3% more. Results suggest that the green wage premium cannot be attributed solely to individual-level characteristics. The unexplained component may capture structural aspects associated with greener occupations, including differential returns to skills, institutional advantages, or selection into sectors better paid.

6 Concluding remarks

The transition to a low-carbon economy is an important condition for mitigating climate change. This process implies a structural change in the labor market, where polluting jobs can be progressively replaced by green occupations. This transformation affects the current composition of the labor force and redefines future employment trajectories. In terms of labor, such a transition can occur through three channels: at the intensive margin, through the mobility of workers from non-green jobs to green jobs; at the extensive margin, with the exit of workers from polluting occupations and the entry of new workers into green jobs; and finally, through changes in the organization of tasks that make the environmental content of existing work more sustainable. Understanding these dynamics facilitates the design of policies that promote efficient and equitable labor reallocation.

The results obtained show that the Colombian labor market presents limited mobility. Between 2021 and 2023, about 40% of workers were employed in green occupations. The probability of remaining in these jobs was 89.6% for those who were already in a green job in 2021, and 88.7% for those who remained in non-green occupations. Upward mobility, i.e., moving from a non-green job to a green job, was only 11.3 percent, while downward mobility stood at 10.4 percent. This rigidity can be explained by structural factors such as occupational specialization, skill mismatches, and high levels of informality, which restrict the capacity for occupational change in the short term.

Despite these limitations, certain groups show a slightly higher capacity to adapt to the green transition. Higher education emerges as a determinant; workers with university education have higher rates of permanence in green jobs and are also more likely to enter them from non-green occupations. This suggests that education increases the technical and environmental skills required and broadens the opportunities for mobility within the new production model.

From a sectoral perspective, two differentiated patterns are identified. Sectors such as technology, financial services, education, health and agriculture exhibit both high retention and greater mobility towards green jobs. In contrast, activities such as commerce, manufacturing, tourism and the arts show greater persistence in non-green occupations, reflecting structural barriers to joining the green economy. These differences are also manifested territorially, cities such as Bogota, Bucaramanga and Ibagué lead in stability and green mobility, while Barranquilla, Cartagena and Cali have higher levels of permanence in non-green jobs, probably due to a productive structure more concentrated in traditional sectors and with less institutional capacity.

In the institutional framework, labor formality also appears as a factor that promotes the green transition since it is positively associated with better results in terms of mobility and retention in green jobs. Formal workers have greater access to training opportunities, institutional protection mechanisms and green technologies, which facilitates their insertion and permanence in environmentally sustainable occupations.

From a sociodemographic approach, it is evident that gender is a critical dimension of inequality in the green transition. Women face multiple barriers to accessing and staying in green jobs, possibly attributable to occupational segregation and low female participation in STEM (Science, Technology, Engineering and Mathematics) disciplines, which are fundamental to many of these sectors. In addition, their high concentration in care and service activities, less aligned with the green economy, together with limited access to technical training, financing and support networks, restricts their full participation.

Beyond mobility, the study also reveals that green jobs are associated with a green wage premium. On average, workers in green occupations earn 10.6% more than their peers in non-green jobs. This premium is magnified when green jobs are combined with formal conditions or college education. However, an Oaxaca-Blinder decomposition shows that more than 60 percent of the wage differentials can be explained by observable characteristics, mainly education, formality and hours worked. This suggests that green jobs tend to be concentrated in structurally more advantageous sectors, with higher returns to skills, better working conditions and more robust institutional frameworks.

Given these findings, it is imperative that the green transition does not deepen existing inequalities. To achieve a sustainable and inclusive future, education systems need to promote more equitable learning in skills related to environmental sustainability, while addressing gender stereotypes and biases, especially in STEM areas.

Likewise, to promote a just transition in countries such as Colombia, it is crucial to address informality. More than half of the labor force operates in informal conditions according to DANE, which implies structural limitations such as low productivity, restricted access to technology and financing, and limited participation in decision-making processes. Informal workers are often more exposed to the effects of climate change and face greater decent work deficits. Therefore, any strategy toward a sustainable labor future must include mechanisms for progressive formalization and capacity building in the informal sector.

Taken together, these results suggest that the green transition has the potential to generate higher quality jobs and better incomes, but mobility to these more sustainable jobs is limited. Therefore, without targeted interventions, there is a risk of reproducing labor market inequalities. A just transition requires comprehensive efforts to reduce barriers to access to green jobs. This includes investments in workforce training and retraining, incentives for formalization, measures against occupational segregation, especially gender segregation, and regional strategies to strengthen sustainable labor ecosystems.

Ultimately, a green economy must be not only environmentally sustainable, but also socially equitable. Ensuring that all workers have the opportunity to benefit from the green transition is both a policy challenge and an imperative for inclusive social development.

Appendices

A Transition matrices using median as threshold

Table 11: Transition matrices

Group	Variable		Green	Nongreen
All	All	Green	88.39	11.61
		Nongreen	10.13	89.87
Sex	Men	Green	90.43	9.57
		Nongreen	13.27	86.73
	Women	Green	84.37	15.63
		Nongreen	7.37	92.63
Age	More than 30	Green	88.42	11.58
		Nongreen	10.16	89.84
	Less than 30	Green	88.18	11.82
		Nongreen	9.90	90.10
Education	No university	Green	85.98	14.02
		Nongreen	9.38	90.62
	University	Green	93.13	6.87
		Nongreen	16.12	83.88
Informality	Formal	Green	89.49	10.51
		Nongreen	10.56	89.44
	Informal	Green	87.18	12.82
		Nongreen	9.81	90.19
Employment status	Self-employed and employers	Green	88.14	11.86
		Nongreen	10.28	89.72
	Salaried workers	Green	88.88	11.12
		Nongreen	10.23	89.77
AI exposure	High exposure	Green	89.33	10.67
		Nongreen	9.78	90.22
	Low exposure	Green	87.63	12.37
		Nongreen	10.36	89.64
Sector	Agriculture and related	Green	89.61	10.39
		Nongreen	13.11	86.89
	Energy, Water and Mining	Green	89.52	10.48
		Nongreen	11.80	88.20
	Manufacturing	Green	87.70	12.30
		Nongreen	9.75	90.25
	Construction	Green	88.86	11.14
		Nongreen	12.16	87.84
	Trade	Green	87.01	12.99
		Nongreen	9.18	90.82
	Transportation	Green	88.48	11.52
		Nongreen	11.71	88.29
	Accommodation	Green	84.54	15.46
		Nongreen	7.72	92.28
	ICT	Green	91.85	8.15
		Nongreen	12.08	87.92
	Financial and Insurance Services	Green	90.95	9.05
		Nongreen	11.30	88.70

Notes: Author's calculations based on GEIH (2021, 2023). Green workers are classified as those whose GGS values exceed the sample median. The reported probabilities are calculated using a correlation parameter of $\rho = 0.9519$, and each row in the transition matrix sums to 100%.

Table 12: Transition matrices (continuation)

Group	Variable		Green	Nongreen
	Real Estate	Green	88.24	11.76
		Nongreen	10.46	89.54
	Professional and Admin. Services	Green	88.98	11.02
		Nongreen	9.29	90.71
	Public Admin, Education and Health	Green	90.19	9.81
		Nongreen	10.58	89.42
	Arts and others	Green	84.87	15.13
		Nongreen	7.61	92.39
Occupation major ISCO-08 group	Managers	Green	91.28	8.72
		Nongreen	12.18	87.82
	Professionals	Green	92.59	7.41
		Nongreen	14.46	85.54
	Technicians	Green	89.16	10.84
		Nongreen	10.15	89.85
	Clerical Support	Green	87.19	12.81
		Nongreen	8.79	91.21
	Services and Sales	Green	85.14	14.86
		Nongreen	8.15	91.85
	Skilled Agricultural	Green	89.51	10.49
		Nongreen	13.01	86.99
	Craft and Related Trades	Green	87.70	12.30
		Nongreen	11.03	88.97
	Machine Operators	Green	87.85	12.15
		Nongreen	11.21	88.79
	Elementary Occupations	Green	86.43	13.57
		Nongreen	9.49	90.51
Cities	Barranquilla	Green	86.11	13.89
		Nongreen	8.10	91.90
	Bogota	Green	89.88	10.12
		Nongreen	10.63	89.37
	Bucaramanga	Green	89.23	10.77
		Nongreen	10.63	89.37
	Cali	Green	86.58	13.42
		Nongreen	8.39	91.61
	Cartagena	Green	86.26	13.74
		Nongreen	8.36	91.64
	Cucuta	Green	88.62	11.38
		Nongreen	10.44	89.56
	Ibague	Green	89.62	10.38
		Nongreen	10.91	89.09
	Manizales	Green	87.25	12.75
		Nongreen	8.58	91.42
	Medellin	Green	88.08	11.92
		Nongreen	9.44	90.56
	Monteria	Green	87.27	12.73
		Nongreen	8.92	91.08
	Pasto	Green	88.36	11.64
		Nongreen	9.29	90.71
	Pereira	Green	87.61	12.39
		Nongreen	9.32	90.68
	Villavicencio	Green	87.28	12.72
		Nongreen	8.94	91.06

Notes: Author's calculations based on GEIH (2021, 2023). Green workers are classified as those whose GGS values exceed the sample median. The reported probabilities are calculated using a correlation parameter of $\rho = 0.9519$, and each row in the transition matrix sums to 100%.

B Transition 2×2 matrices by other groups

Table 13: Transition 2×2 matrices by economic sector and occupation group

Group	Variable		Green	Non-green
Sector	Agriculture and related	Green	90.7	9.3
		Non-green	14.5	85.5
	Energy, Water and Mining	Green	90.6	9.4
		Non-green	13.2	86.8
	Manufacturing	Green	88.9	11.1
		Non-green	10.9	89.1
	Construction	Green	89.9	10.1
		Non-green	13.5	86.5
	Trade	Green	88.3	11.7
		Non-green	10.3	89.7
	Transportation	Green	89.6	10.4
		Non-green	13.0	87.0
	Accommodation	Green	86.1	13.9
		Non-green	8.6	91.4
	ICT	Green	92.7	7.3
		Non-green	13.6	86.4
	Financial and Insurance	Green	91.8	8.2
		Non-green	12.8	87.2
	Real Estate	Green	89.4	10.6
		Non-green	11.7	88.3
	Professional and Admin Services	Green	90.1	9.9
		Non-green	10.5	89.5
	Public Admin, Education and Health	Green	91.2	8.8
		Non-green	11.9	88.1
	Arts and others	Green	86.4	13.6
		Non-green	8.5	91.5
Occupation major ISCO-08 group	Managers	Green	92.1	7.9
		Non-green	13.7	86.3
	Professionals	Green	93.3	6.7
		Non-green	16.3	83.7
	Technicians	Green	90.3	9.7
		Non-green	11.4	88.6
	Clerical Support	Green	88.5	11.5
		Non-green	9.9	90.1
	Services and Sales	Green	86.6	13.4
		Non-green	9.1	90.9

Notes: Author's calculations based on GEIH (2021, 2023). Workers are classified into three groups (low, medium, and high) based on the tertiles of their GGS values. The reported probabilities are calculated using a correlation parameter of $\rho = 0.9519$. Each row shows the probability of being in one of the two statuses in 2023, conditional on the worker's status in 2021

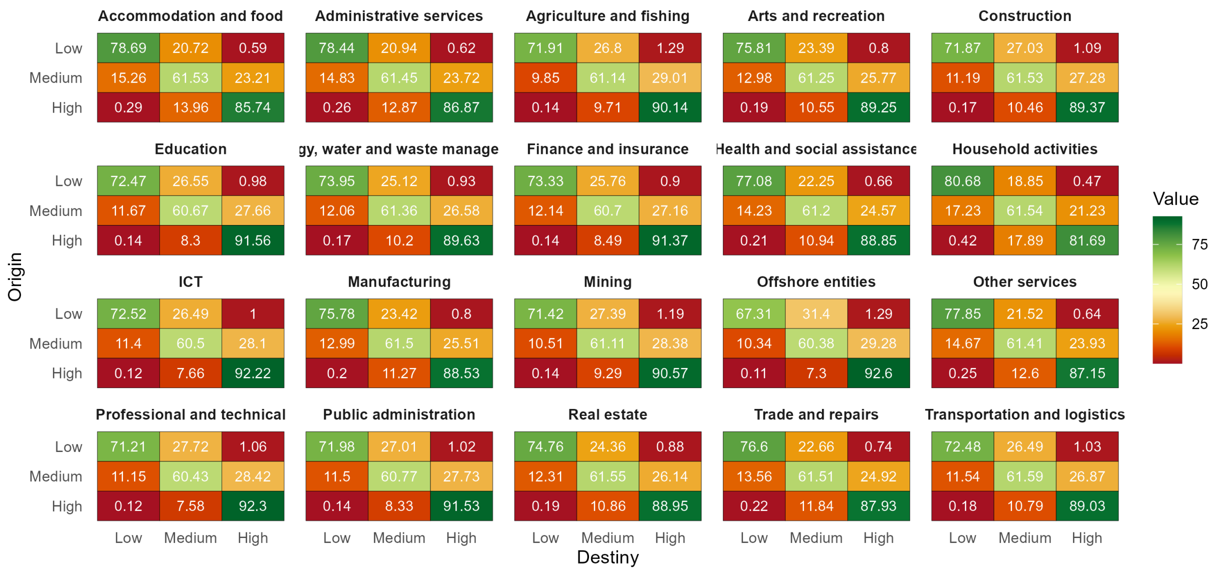
Table 14: Transition 2×2 matrices by occupation group and main cities

Group	Variable		Green	Nongreen
Occupation major ISCO-08 group	Skilled Agricultural	Green	90.6	9.4
		Nongreen	14.4	85.6
	Craft and Related Trades	Green	88.9	11.1
		Nongreen	12.3	87.7
	Machine Operators	Green	89.0	11.0
		Nongreen	12.5	87.5
	Elementary Occupations	Green	87.8	12.2
		Nongreen	10.6	89.4
Cities	Barranquilla	Green	87.4	12.6
		Nongreen	9.2	90.8
	Bogota	Green	90.9	9.1
		Nongreen	11.9	88.1
	Bucaramanga	Green	90.4	9.6
		Nongreen	11.9	88.1
	Cali	Green	87.9	12.1
		Nongreen	9.5	90.5
	Cartagena	Green	87.6	12.4
		Nongreen	9.4	90.6
	Cucuta	Green	89.9	10.1
		Nongreen	11.6	88.4
	Ibague	Green	90.7	9.3
		Nongreen	12.2	87.8
	Manizales	Green	88.5	11.5
		Nongreen	9.7	90.3
	Medellin	Green	89.3	10.7
		Nongreen	10.6	89.4
	Monteria	Green	88.5	11.5
		Nongreen	10.0	90.0
	Pasto	Green	89.5	10.5
		Nongreen	10.5	89.5
	Pereira	Green	88.8	11.2
		Nongreen	10.5	89.5
	Villavicencio	Green	88.5	11.5
		Nongreen	10.1	89.9

Notes: Author's calculations based on GEIH (2021, 2023). Workers are classified into three groups (low, medium, and high) based on the tertiles of their GGS values. The reported probabilities are calculated using a correlation parameter of $\rho = 0.9519$. Each row shows the probability of being in one of the two statuses in 2023, conditional on the worker's status in 2021.

C Transition 3×3 matrices

Figure 4: Transtion matrices by sector



Notes: Author's calculations based on GEIH (2021, 2023). Workers are classified into three groups (low, medium, and high) based on the tertiles of their GGS values. The reported probabilities are calculated using a correlation parameter of $\rho = 0.9519$. Each row shows the probability of being in one of the three statuses in 2023, conditional on the worker's status in 2021.

Figure 5: Transtion matrices by main cities

Notes: Author's calculations based on GEIH (2021, 2023). Workers are classified into three groups (low, medium, and high) based on the tertiles of their GGS values. The reported probabilities are calculated using a correlation parameter of $\rho = 0.9519$. Each row shows the probability of being in one of the three statuses in 2023, conditional on the worker's status in 2021.

Figure 6: Transtion matrices by occupation major ISCO-08 group

Notes: Author's calculations based on GEIH (2021, 2023). Workers are classified into three groups (low, medium, and high) based on the tertiles of their GGS values. The reported probabilities are calculated using a correlation parameter of $\rho = 0.9519$. Each row shows the probability of being in one of the three statuses in 2023, conditional on the worker's status in 2021.

D M_1, M_2 y M_3 indices under $2x2$ transition matrices

Corollary .1 *If M_1, M_2 and M_3 are computed as in Table 4 for a two-stage Markov matrix*

$$P = \begin{bmatrix} 1-p & p \\ q & 1-q \end{bmatrix},$$

where $1 - p - q \geq 0$ then M_1, M_2 and M_3 are equal.

Let M_1, M_2 and M_3 mobility indices defined by:

$$M_1(P) = \frac{k - \text{tr}(P)}{k-1}$$

$$M_2(P) = 1 - |\lambda_2|$$

$$M_3(P) = 1 - |\det(P)|$$

Then,

$$
\begin{aligned}
M_1 &= \frac{k - Tr(P)}{k-1} \\
&= \frac{2-(1-p+1-q)}{1} \\
&= \frac{2-(2-p-q)}{1} \\
&= p+q
\end{aligned} \tag{1}
$$

For a two-state Markov matrix, the second eigenvalue can be computed as $\lambda_2 = 1 - p - q$ (See Chen (2023)). So,

$$
\begin{aligned}
M_2 &= 1 - |\lambda_2| \\
&= 1 - |1-p-q| \\
&= 1 - (1-p-q) \quad \text{since } 1-p-q \geq 0 \\
&= p+q
\end{aligned} \tag{2}
$$

Finally, M_3

$$
\begin{aligned}
M_3 &= 1 - |det(P)| \\
&= 1 - |(1-p)(1-q) - pq| \\
&= 1 - |1-q-p+pq-pq| \\
&= 1 - |1-q-p| \\
&= 1 - (1-p-q) \quad \text{since } 1-p-q \\
&= p+q
\end{aligned} \tag{3}
$$

By (1), (2) and (3), M_1, M_2 and M_3 are the same for 2x2 Markov matrices.

E Oaxaca-Blinder decomposition

Table 15: Oaxaca-Blinder decomposition of wage disparities by green type

Variable	(1) Overall	(2) Explained	(3) Unexplained
Green	13.851***		
	(0.002)		
Nongreen	13.491***		
	(0.001)		
Difference	0.360***		
	(0.002)		
Explained	0.218***		
	(0.002)		
Unexplained	0.143***		
	(0.002)		
Age		0.001***	0.069***
		(0.000)	(0.005)
Weekly working hours		0.027***	-0.229***
		(0.001)	(0.005)
Women		0.017***	-0.015***
		(0.000)	(0.001)
University		0.035***	0.060***
		(0.000)	(0.001)
Formality		0.024***	0.008***
		(0.000)	(0.001)
Self employment / Employer		-0.001***	-0.028***
		(0.000)	(0.002)
Salaried		0.000	-0.027***
		(0.000)	(0.002)
Constant			0.394***
			(0.008)
Departament fixed effects	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes
Observations	659,450	659,450	659,450

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1 **Notes:**
Source: Author's elaboration.

References

Abou-Ali, H. and Amer, M. (2024). Analyzing labor market shifts in the transition to green jobs: Mapping egypt's green jobs. Economic Research Forum (ERF).

Acemoglu, D. and Autor, D. (2011). *Skills, tasks and technologies: Implications for employment and earnings*, volume 4. Elsevier Inc.

Alexander, N.-R., Cazzaniga, M., Fabrizio, S., Jaumotte, M. F., Li, L., Mondragon, J., Priano, S., and Tavares, M. M. (2024). Green jobs and the future of work for women and men. Technical report, International Monetary Fund.

Apostel, A. and Barslund, M. (2024). Measuring and characterising green jobs: A literature review. *Energy Research & Social Science*, 111:103477.

Arias, K., López, D., Camino-Mogro, S., Weiss, M., Walsh, D., Gomes, L. G., and Hallack, M. C. M. (2023). Green transition and gender bias: An analysis of renewable energy generation companies in Latin America. *Energy Research and Social Science*, 101(March).

Atkins, E. (2024). Green jobs, just transition, and the future of work. In *The Handbook for the Future of Work*, pages 375–387. Routledge.

Autor, D. H. (2014). Skills, education, and the rise of earnings inequality among the "other 99 percent". *Science*, 344(6186):843–851.

Autor, D. H. and Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US Labor Market. *American Economic Review*, 103(5):1553–1597.

Bartholomew, D. (1971). Stochastic models for social processes: A review and bibliography. *The Sociological Review*, 19(1):129–139.

Bergant, K., Mano, R., and Shibata, M. I. (2022). *From polluting to green jobs: A seamless transition in the US?* International Monetary Fund.

BID (2021). El papel de la transición energética en la recuperación sostenible de América Latina y el Caribe. *Banco Interamericano de Desarrollo (BID)*, page 50.

Blinder, A. S. (1973). Wage discrimination: reduced form and structural estimates. *Journal of Human resources*, pages 436–455.

Bluedorn, J., Hansen, N.-j., Noureldin, D., Shibata, I., and Tavares, M. M. (2022). Transitioning to a Greener Labor Market : Cross- Country Evidence from Microdata.

Bohnenberger, K. (2022). Is it a green or brown job? a taxonomy of sustainable employment. *Ecological Economics*, 200:107469.

Bone, M., González-Ehlinger, E., and Stephany, F. (2025). Skills or degree? the rise of skill-based hiring for ai and green jobs. *Technological Forecasting and Social Change*.

Bowen, A., Kuralbayeva, K., and Tipoe, E. L. (2018). Characterising green employment: The impacts of 'greening' on workforce composition. *Energy Economics*, 72:263–275.

Cadena Monroy, Á. I., Quijano Silva, N., and Espinosa Valderrama, M. (2022). *Ciudades sostenibles: un enfoque de modelaje urbano integrado para el análisis de política en Colombia*.

Causa, O., Nguyen, M., and Soldani, E. (2024). Lost in the green transition? Measurement and stylized facts. *Organisation for Economic Co-operation and Development*, (1796).

Cerimelo, M., De La Vega, P., Porto, N., and Vazquez, F. (2024). Beyond traditional wage premium: an analysis of wage greenium in latin america. *Documentos de Trabajo del CEDLAS*.

Chen, G. (2023). Introduction to basic properties of markov chain and its application in simple random walk. *Department of Mathematics, University of Chicago*, pages 1–8.

Chen, Z., Marin, G., Popp, D., and Vona, F. (2020). Green Stimulus in a Post-pandemic Recovery: the Role of Skills for a Resilient Recovery. *Environmental and Resource Economics*, 76(4):901–911.

Consoli, D., Marin, G., Marzucchi, A., and Vona, F. (2016). Do green jobs diffranciscor from non-green jobs in terms of skills and human capital? *Research Policy*, 45(5):1046–1060.

Cruces, G., Lanjouw, P., Lucchetti, L., Perova, E., Vakis, R., and Viollaz, M. (2015). Estimating poverty transitions using repeated cross-sections: a three-country validation exercise. *Journal of Economic Inequality*, 13(2):161–179.

Curtis, E. M. and Marinescu, I. (2022). Green Energy Jobs in the US.

Curtis, M., O'Kane, L., and Park, R. (2024). Workers and the green-energy transition: Evidence from 300 million job transitions. *Environmental and Energy Policy and the Economy. 5(1), 127-161.*

Dang, H.-A. H. and Lanjouw, P. (2013). Measuring Poverty Dynamics with Synthetic Panels Based on Repeated Cross-Sections. *SSRN Electronic Journal*, (December 2022).

Dang, H. A. H. and Lanjouw, P. F. (2023). Measuring Poverty Dynamics with Synthetic Panels Based on Repeated Cross Sections. *Oxford Bulletin of Economics and Statistics*, 85(3):599–622.

Dierdorff, E. C., Norton, J. J., Drewes, D. W., Kroustalis, C. M., Rivkin, D., and Lewis, P. (2009). Greening of the World of Work: Implications for O*NET-SOC and New and Emerging Occupations. Report for U.S. Department of Labor Employment and Training Administration, Washington, DC.

Duman, A. and Ananian, S. (2024). Labour market trajectories, social protection and the green. *ILO Working Paper*, (133).

Elliott, R. J. R., Kuai, W., Maddison, D., and Ozgen, C. (2021). Eco-Innovation and Employment: A Task-Based Analysis. *SSRN Electronic Journal*, (14028).

Ernst, C., Brizuela, A. S. R., and Epifanio, D. (2019). Green jobs in argentina: Opportunities to move forward with the environmental and social agenda. *Cepal Review*, 2019(129):51–71.

Fernández, J. and Larrea, M. (2022). Empleo y capacidades verdes en la CAPV. *CUADERNOS ORKESTRA*.

Ferreira, M., Rigolini, Jamele , L., Lugo,Maria Ana, and Vakis, Renos (2015). *La movilidad económica y crecimiento de la clase media en America Latina*, volume 3.

Formby, J. P., Smith, W. J., and Zheng, B. (2004). Mobility measurement, transition matrices and statistical inference. *Journal of Econometrics*, 120(1):181–205.

Garcés-Urzainqui, D., Lanjouw, P., and Rongen, G. (2021). Constructing synthetic panels for the purpose of studying poverty dynamics: A primer. *Review of Development Economics*, 25(4):1803–1815.

García-Suaza, A., Caiza-Guamán, P., Buitrago, C., Romero-Torres, B., and Sarango-Iturralde, A. (2023). Análisis de demanda de empleo verde a partir de información de vacantes para América Latina y el Caribe en el contexto de la transición energética. pages 0–32.

IMF (2022). A Greener Labor Market: Employment, Policies, and Economic Transformation, Chapter 3, World Economic Outlook, April 2022. *World Economic Outlook, April 2022*, (October 2020):67–86.

International Labour Office (2018). *Women and Men in the Informal Economy: A Statistical Picture*. International Labour Organization, Geneva, third edition.

Janser, M. (2018). The greening of jobs in Germany. *IAB-Discussion Paper*, (14).

Keese, M. and Marcolin, L. (2023). Labour and social policies for the green transition: A conceptual framework. *OECD Social, Employment, and Migration Working Papers*, (295):0_1–60.

LaboUR (2023). ¿Quiénes son los trabajadores verdes en Colombia?

Lobsiger, M. and Rutzer, C. (2021). Green potential of Europe ' s labour force : Relative share and possible skills imbalances Green potential of Europe ' s labour force : Relative share and possible skills imbalances . (January).

Lobsiger, M., Rutzer, C., Weder, R., Niggli, M., Kägi, W., and Huddleston, C. (2021). Jobs with green potential in Switzerland: Demand and possible skills shortages Jobs with green potential in Switzerland: Demand and possible skills shortages *. (January).

Maczulskij, T. (2024). How are green jobs created? a decomposition analysis. *Economics Letters*, 244:111950.

Martinez, C. and Hinojosa, C. (2010). Green jobs and skills : the local labour market implications of addressing climate change. *Oecd*, (franciscobruary):1–55.

Maurizio, R., Monsalvo, A. P., Catania, M. S., and Martinez, S. (2023). Short-term labour transitions and informality during the COVID-19 pandemic in Latin America. *Journal for Labour Market Research*, 57(1).

Oaxaca, R. (1973). Male-female wage differentials in urban labor markets. *International economic review*, pages 693–709.

OCDE (2023). Transición verde y formalización laboral en Colombia.

OIT (2008). Global Challenges for Sustainable Development: Strategies for Green Jobs. (Labour and Employment Ministers Conference).

OIT (2021). La bioeconomía y los empleos verdes en Colombia. pages 1–75.

Organización Internacional del Trabajo y Comisión Europea (2023). Empleos verdes: una oportunidad para las mujeres en América Latina. *Programa EUROCLIMA+*.

Porto, N., de la Vega, P., and Cerimelo, M. (2024). Going green: estimating the potential of green jobs in argentina. *Journal for Labour Market Research*, 58(1):1.

Prais, S. J. (1955). Measuring social mobility. *Journal of the Royal Statistical Society. Series A (General)*, 118(1):56–66.

Reckien, D., Grothmann, T., and Egli, T. (2009). Klimafolgen und anpassungsmassnahmen im verkehr und mobilität. In *KyotoPlus-Navigator Praxisleitfadenzur Förderung von Klimaschutz und Anpassung an den Klimawandel: Erfolgsfaktoren, Instrumente, Strategie*, pages 231–282.

Rutzer, C., Niggli, M., and Weder, R. (2020). Estimating the Green Potential of Occupations: A New Approach Applied to the U.S. Labor Market. (October).

Sato, M., Cass, L., Saussay, A., Vona, F., Mercer, L., and Kane, L. O. (2023). Skills and wage gaps in the low-carbon transition : comparing job vacancy data from the US and UK. (January).

Sato, M., Vona, F., and Kane, L. O. (2022). Who ' s fit for the low-carbon transition ? Emerging skills and wage gaps in job ad data. pages 1–62.

Scholl, N., Turban, S., and Gal, P. (2023). The green side of productivity An international classification of green and brown occupations. *OECD Productivity Working Papers*, (33).

Shorrocks, A. F. (1978). The measurement of mobility. *Econometrica*, 46(5):1013–1024.

Sommers, P. M. and Conlisk, J. (1979). Eigenvalue immobility measures for markov chains. *The Journal of Mathematical Sociology*, 6(2):253–276.

Song, K., Kim, H., Cha, J., and Lee, T. (2021). Matching and Mismatching of Green Jobs : A Big Data Analysis of Job Recruiting and Searching.

Sulich, A., Rutkowska, M., and Popławski (2020). Green jobs, definitional issues, and the employment of young people: An analysis of three European Union countries. *Journal of Environmental Management*, 262(December 2019).

Tsironis, A. (2023). Preparing the Workforce for the Low-Carbon Economy: A Closer Look at Green Jobs and Green Skills. 6(262):12.

UNEP (2011). Green Economy Report. 66(May):37–39.

Urban, P., Rizos, V., Ounnas, A., Kassab, A., and Kalantaryan, H. (2023). *Jobs for the green transition: definitions, classifications and emerging trends*. CEPS.

Van Laake, T., Lozano, C., and Gillod, A. (2021). Sustainable urban mobility, rural accessibility and interurban connectivity: Colombia's 21st century transport challenges THIS.

Vandeplas, A., Vanyolos, I., Vigani, M., and Vogel, L. (2022). *The possible implications of the green transition for the EU labour market.*, volume 8022.

Vona, F. (2021). *Labour Markets and the Green Transition: a practitioner's guide to the task-based approach.*

Vona, F., Marin, G., Consoli, D., and Popp, D. (2018). Environmental regulation and green skills: An empirical exploration. *Journal of the Association of Environmental and Resource Economists*, 5(4):713–753.

Westgard, R. E. (2009). Green jobs. *Oil and Gas Journal*, 107(34):12.