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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 incoming 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. In this context, the ability of workers to transition between green and non-green jobs will be crucial to ensure a just labor market adjustment. 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 to estimate the probability of labor transitions employs a skills-based green index. The results reveal a high degree of labor market persistence, explained by the role of skills in shaping mobility, and show a wage premium of 10.6% for green occupations compared to their non-green counterparts. 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.

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1 Introduction

The transition away from fossil fuels is expected to be one of the most significant forces shaping labor markets in the coming decades. As economies shift toward cleaner technologies and production processes, the demand for green jobs will increase, while employment in high-emission sectors may contract. However, the extent to which workers can move into green jobs depends critically on their ability to transfer or adapt existing skills to emerging labor market demands, as well as the availability of alternative employment opportunities for those displaced by the green transition (Curtis et al., 2024). While the expansion of green jobs is widely anticipated, the central challenge is to enable workers in traditional sectors to transition without exacerbating existing economic and social inequalities.

Understanding these transitions is critical not only for the design of a just transition, but also for fostering labor market dynamism, social mobility, and resilience (Vandeplas et al., 2022). Despite a growing body of research on 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), the green dimension remains comparatively underexplored, particularly in developing regions such as Latin America (Maurizio et al., 2023). Empirical work on the occupational mobility of workers into green jobs is scarce outside high-income economies (Bluedorn et al., 2022; Shibata et al., 2022; Vaccaro et al., 2022; Duman and Ananian, 2024), and few studies incorporate the structural inequalities—such as gender, formality status, and geographic location that shape adaptation to transitions.

Opportunities for successful transition is not uniform across the workforce. Workers with greater access to education and training are better positioned to adapt, while those in low-skilled, informal, or rural employment face steeper barriers IMF (2022). Age, gender, and skill level are known to significantly influence labor mobility (Duman and Ananian, 2024), and unequal access to reskilling opportunities risks deepening labor market polarization benefiting high-skilled workers while leaving low-skilled workers behind (Autor, 2014). This dynamic may widen wage disparities and reinforce structural disadvantages if not addressed proactively.

Colombia provides a compelling case to investigate these dynamics. Structural challenges such as low productivity growth, segmented labor trajectories, and territorial inequality intersect with emergent pressures like climate change, digitalization, and demographic shifts (DANE, 2023, 2024; Aristizábal-Ramírez et al., 2024). These dynamics are particularly salient in a country where the coexistence of high informality, limited social mobility, and uneven access to education and training constrains transition capacity for women, youth, rural workers, migrants and other vulnerable population groups (García-Suaza et al., 2023; PNUD, 2024; DANE, 2024; Galvis and Aponte, 2025). As a result, the green transition may reproduce existing inequalities unless it is accompanied by targeted policies that promote skills development, strengthen social protection, and create inclusive labor market pathways.

This paper addresses these gaps by applying a skills-based green index Vona et al. (2018) to Colombian household survey data from 2021 to 2023 and implementing a synthetic panel methodology to estimate individual mobility between green and non-green jobs. This study delivers a replicable approach for data-scarce contexts and offers actionable insights for policies that aim to foster an equitable and inclusive green transition.

Our findings reveal marked labor market rigidity: 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. Transition probability is highly uneven—university-educated workers, those in formal employment, and individuals in dynamic sectors and territories display significantly higher upward mobility, while women, informal workers, and those with lower education face persistent barriers to entry and retention. These results extend the literature on skill mismatches, structural barriers, and gender disparities in green transitions by providing novel evidence from a middle-income economy with high informality.

The remainder of the paper is organized as follows: Section 2 reviews the literature on green jobs, labor market transitions, and empirical evidence on green employment. Section 3 outlines the synthetic panel methodology, data sources, and construction of the green jobs classification. Section 4 presents the main empirical findings. Section 5 discusses the implications for policy design, and Section 6 concludes.

2 Literature review

The literature on green employment has expanded considerably in recent years, reflecting the growing relevance of aligning labor markets with the imperatives of climate transition. The concept of green jobs has evolved from early general definitions, such as this the provided by the OIT (2021)[1], towards more granular classifications that focus on the tasks and, increasingly, the skills required within occupations. While sectoral approaches remain influential for national reporting and workforce planning (Abou-Ali and Amer, 2024), they can obscure heterogeneity within industries and may misclassify jobs with limited environmental content (Lobsiger et al., 2021).

Task-based and process-oriented frameworks emerged as a response to these limitations, emphasizing how jobs contribute to environmental outcomes through specific work activities or production methods. However, these approaches often face operational constraints in developing countries due to limited availability of micro-level data on production inputs and technologies (Bohnenberger, 2022; Urban et al., 2023). A more recent and empirically tractable alternative centers on occupational skills, in particular, green skills, defined as a set of technical and cognitive competencies relevant to environmental sustainability. Pioneered by Vona et al. (2018), this methodology uses O*NET-based scores to estimate the green potential of occupations, identifying those with high demand for environmentally relevant skills. It enables cross-country comparability, occupational granularity, and application in contexts with limited firm-level data thus gaining traction across both advanced and middle-income countries.

Several recent studies have usually applied and refined green skills or task-based approach. Curtis et al. (2024) and Sato et al. (2022) examine supply and demand-side green premiums and classification schemes across the U.S. and U.K., while Urban et al. (2023) highlight the limitations of these frameworks in contexts of high informality and weak occupational traceability. In Latin America, Porto et al. (2024) and Cerimelo et al. (2024) adapt the green potential methodology to national labor force surveys, but note that its application can be gender-blind, underestimate informality, and misalign with local occupation

[1] OIT (2021) defines green jobs as decent jobs that contribute to preserving or restoring the environment.

codes—issues that stem both from the method's assumptions and from data limitations. Other authors (Bohnenberger, 2022; Shibata et al., 2022; Sulich et al., 2020) have similarly called for more flexible and inclusive taxonomies that better reflect the diversity of labor markets.

Beyond classification, a parallel strand of the literature explores the quality and distributional implications of green employment. While some studies document a green wage premium, particularly in formal and high-skilled occupations (Curtis and Marinescu, 2022; Bluedorn et al., 2022), others caution that this premium is uneven and may reinforce labor market segmentation. Evidence from Latin America (Cerimelo et al., 2024; García-Suaza et al., 2023) shows that wage advantages tend to concentrate among urban, male, and tertiary-educated workers. In many cases, compositional effects rather than structural improvements drive the observed premiums (Valero et al., 2021), raising equity concerns. Gendered occupational segregation is particularly persistent. Women remain underrepresented in green-intensive sectors, face barriers to entry and advancement, and often cluster in jobs with weaker environmental alignment and lower pay (Arias et al., 2023).

Empirical research on labor market transitions into green jobs remains limited, especially in developing countries. In high-income settings, studies by Shibata et al. (2022), Duman and Ananian (2024) and Curtis et al. (2024) examine mobility patterns, highlighting the role of education, technical skills, and exposure to environmental regulation. These findings are consistent with economic theories of skill-biased technological change and job polarization (Autor and Dorn, 2013; Acemoglu and Restrepo, 2019), suggesting that the green transition may also yield asymmetric labor market outcomes. However, in middle-income economies, where labor markets are more segmented and longitudinal data are scarce, analyses of occupational transitions are less common and often descriptive. Porto et al. (2024) and Arias et al. (2023) explore labor force heterogeneity in Latin America, finding strong disparities by gender, education, and formality. García-Suaza et al. (2023) report that green jobs are disproportionately held by high-skilled and better paid workers, underscoring the risk of exclusion.

Beyond individual characteristics, spatial dynamics also shape transition outcomes, Vandeplas et al. (2022) show that losses in “brown” jobs are geographically concentrated in the EU, creating risks of localized disruption. Complementarily, Janser (2018) highlights that the greenness of occupations varies significantly across regions in Germany, pointing to the role of local demand conditions in shaping opportunities for green employment growth. Informality and weak institutional systems compound these regional challenges, particularly in rural areas (Porto et al., 2024). The interaction between green and digital transitions introduces additional complexity, as overlapping skill demands may create synergies but also increase barriers to entry for vulnerable groups (Bowen et al., 2018). As a result, there is growing policy interest in the concept of a just transition—one that mitigates inequality while promoting environmental sustainability (Bohnenberger, 2022; Arias et al., 2023; Granata and Posadas, 2024).

A just transition cannot be addressed without considering the digital dimension. Technological change, particularly the diffusion of artificial intelligence (AI), is reshaping labor markets through both automation and complementarity effects (García-Suaza et al., 2025; Pizzinelli et al., 2023; Felten et al., 2021). Routine-intensive occupations face greater risks of automation, while high-skilled jobs benefit from productivity gains and task augmentation (Acemoglu et al., 2022). These dynamics reveal that green and digital transitions may reinforce each other in amplifying inequalities in the absence of adequate policy intervention.

Traditional analyses of mobility rely on longitudinal surveys, which are rare in Latin America. This has motivated the use of synthetic panel methods, an approach that uses repeated cross-sectional surveys to infer individual transitions. These methods have been applied in various domains, from poverty and youth employment (Alfani et al., 2023) to income mobility (Dang and Lanjouw, 2013) and intergenerational mobility (Formby et al., 2004). Pioneered by Dang and Lanjouw (2013), synthetic panels estimate outcome distributions over time under parametric assumptions, enabling the construction of transition matrices without tracking the same individuals. Colgan (2023); Garcés-Urzainqui et al. (2021) show that synthetic panels often outperform pseudo-panels, especially when samples are small or cohort structures are weak.

Taken together, this body of literature highlights four critical gaps. First, empirical research on green employment remains concentrated in high-income contexts, leaving emerging economies underrepresented. Second, there is limited use of synthetic panel methods to analyze labor transitions in the green economy, despite their relevance in data-constrained settings. Finally, there is no consensus on how to operationalize green job taxonomies for dynamic labor market analysis, particularly using microdata.

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

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 [2] (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). This source includes importance scores for 35 skills, 32 knowledge areas, and 41 work activities across 912 occupations at the SOC 8-digit level. Skills refer to developed abilities that support learning and the execution of job tasks, knowledge denotes organized sets of facts and principles within specific domains and work activities describe general types of behaviors performed across many jobs. Each of these elements is assigned an importance score ranging from 1 (low) to 5 (high)[3], which indicates how essential that

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

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

skill, knowledge area, or activity is for the performance of a given occupation.

Following Vona et al. (2018), we use this information to identify Green General Skills (GGS) and then adapt the index to the Colombian context by mapping O*NET measures onto national occupational classifications. This approach allows us to approximate the skill content of green jobs in Colombia despite the absence of data.

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. According to Vona et al. (2018) a positive and statistically significant value of β^l indicates that the skill is more intensively 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 by the authors: Engineering and Technical, Operation management, Monitoring and Science.

According to Vona et al. (2018), the four categories capture distinct but complementary dimensions of green competences. Engineering and Technical skills are related to engineering, design, mechanics, and construction and they focus on applying their knowledge in practical settings. Operation Management skills emphasize system analysis, coordination, and decision-making for sustainability initiatives. Monitoring skills ensure compliance with environmental and regulatory standards through legal, administrative, and technical oversight. Finally, Science skills underpin innovation and technological development, supporting a wide range of occupations in research and applied sciences.

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 bridge from SOC to ISCO was necessary. The linkage between SOC and ISCO was conducted using a crosswalk provided by the Bureau of Labor Statistics (BLS)[4]. 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 challenge 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).

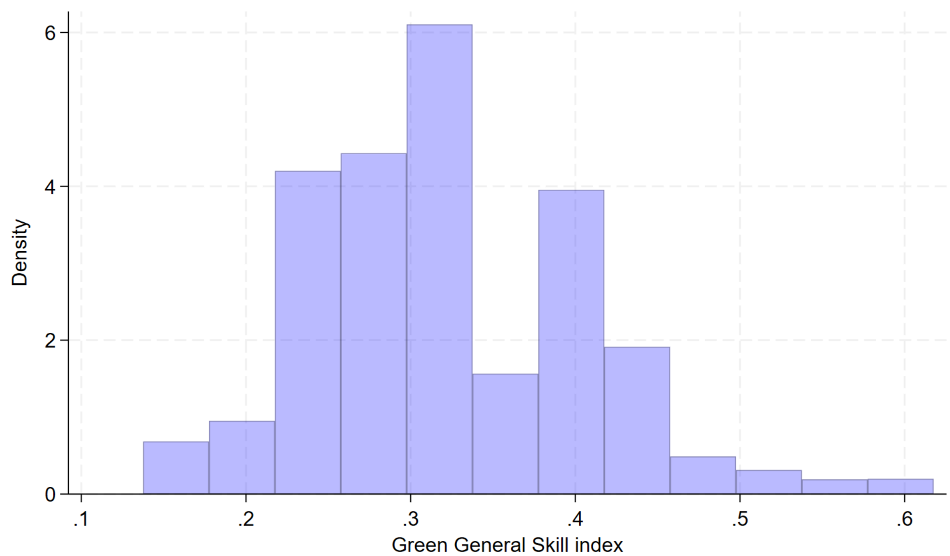
After adapting data to the ISCO-08 classification, the GGS was derived by taking the simple average of the normalized scores for each of the four skill categories. The resulting index captures the green intensity of occupations at the ISCO-08 level and provides a robust measure of green skills in the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

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

3.3 Descriptive analysis

This section explores the distribution of the GGS at the occupational groups, analyzing its relationship with demographic and labor characteristics. Figure 1 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 1: Green General Skill Index distribution

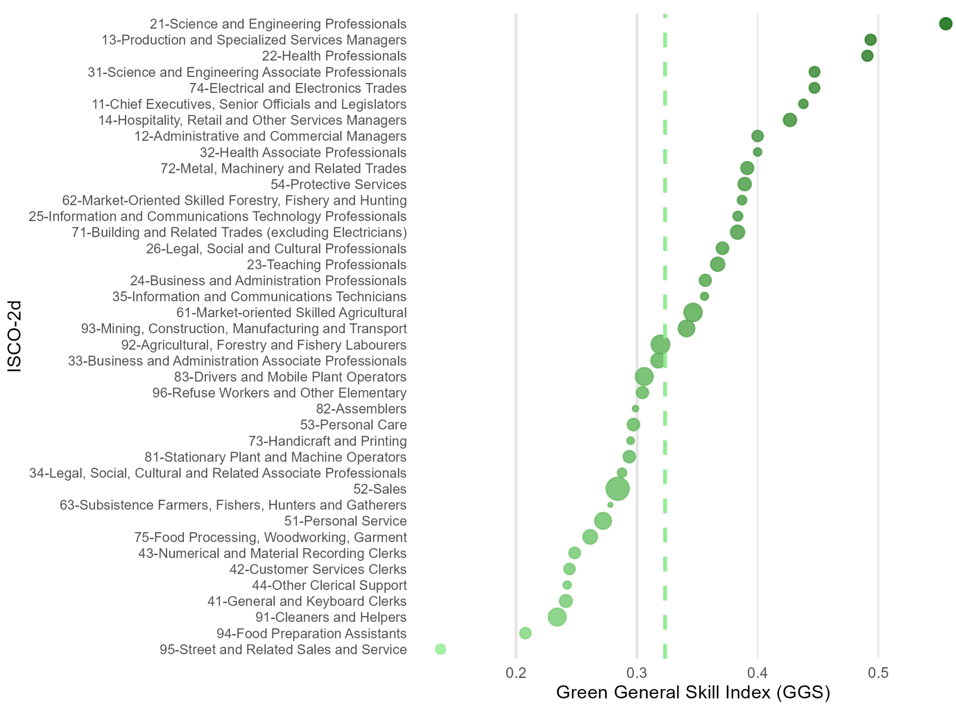


Source: Author calculations based on GEIH (2021, 2023).

On the other side, Figure 2 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 2: Green General over ISCO 2-digit occupations



Notes: The circle size is the employment share 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.

The dashed vertical line represents the mean GGS score and serves as a benchmark to identify occupations above and below the average level of green skill intensity. Previous studies (Elliott et al., 2021; Lobsiger and Rutzer, 2021; Porto et al., 2024) have similarly used the mean value of their measures to classify green jobs. Following this approach, we set the threshold for green jobs at the average GGS score, classifying occupations to the right of the line as green and those to the left as non-green. In general, green jobs correspond to professional, technical, and managerial roles that demand advanced skills and decision-making abilities, whereas non-green jobs are concentrated in services, clerical support, sales, and elementary occupations with lower skill requirements.

Table 1 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 according to Winkler et al. (2024), who find that the share of green occupations in Latin America has remained largely constant over the past decade.

Table 1: 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 2 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 2: 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 green status 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:

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

thus, equation (4) represents the probability of being green worker in the in the second round, conditional on being non-green in the first round[5]. When panel data are available, equation (4) can be computed; otherwise, a synthetic panel approach must be applied (Dang and Lanjouw, 2013).

Following Dang and Lanjouw (2013), the synthetic panel approach relies on a set of assumptions. First, it is assumed that the covariates used to predict outcomes are time-invariant and thus comparable across survey rounds, i.e. $x_{i1} = x_{i2}$. Second, the method relies on a

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

conditional stability assumption, the distribution of outcomes given the covariates is stable across periods, so that $y_{i1}|x_{i1}$ and $y_{i1}|x_{i2}$ (and vice versa) can be treated as having the same conditional distribution. Finally, the error terms ϵ_{i1} and ϵ_{i2} are assumed to follow a bivariate normal distribution with correlation ρ and standard deviations σ_{ϵ_1} and σ_{ϵ_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 (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 individual abilities or barriers to occupational mobility, 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 which implies that y_{i1} and y_{i2} are independent.

The authors suggest that in the absence of 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. To address this, Dang and Lanjouw (2023) explore the feasibility of producing point estimates of mobility instead of assuming bounds, they show that ρ can be computed by:

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

where $\rho_{y_{i1},y_{i2}}$ is the partial correlation of outcomes, derived from the correlation of cohort-level averages across two cross-sections, where cohorts are defined by time-invariant characteristics (e.g., birth year, sex, area). The authors found, through validation exercises, that this cohort-based approach yields estimates of ρ close to those from true panel data, and thus produces reliable point estimates of mobility. They further generalize the framework to model transitions between multiple groups, where the probability of moving from group l to group m is expressed as the bivariate normal cumulative distribution evaluated at group-specific thresholds[6].

4.1 Measuring mobility

To complement the analysis of labor mobility between green and non-green occupations, this section introduces a set of indicators based on transition matrices, following the framework of Formby et al. (2004). Let P be an $n \times n$ transition matrix where each entry p_{ij} represents the conditional probability of moving from category i to j, with diagonal elements corresponding to persistence in the same category and off-diagonal elements representing transitions. The indices can be grouped into those that capture higher mobility and those that emphasize immobility.

The first group includes three measures (See Table 3). The index M_1 evaluates gross mobility by normalizing the deviation of the trace of P from the identity matrix, reflecting the average probability that an individual exits the initial state in the subsequent period (Bartholomew, 1971). The index M_2 relies on the second largest eigenvalue of P; lower values of $|\lambda_2|$ imply faster convergence toward the stationary distribution, whereas values close to one reflect persistence in the initial configuration. The index M_3 is based on the determinant of P, where values near zero indicate mobility across categories and values close to one imply that individuals remain in their original states (Shorrocks, 1978).

The second group incorporates the relative weight of categories in measuring immobility. The index M_4, proposed by Bartholomew (1971), weights the diagonal elements of P by the marginal distribution π_i, thus accounting for the share of the population that remains in each category. Finally, M_5 measures the average number of categories crossed, capturing the extent of transitions across the distribution (Formby et al., 2004). Lower values of M_5 reflect persistence or short-range movements, while higher values denote mobility involving

[6]The probability can be computed by: $P(z_1^{l-1} \leq y_{i1} \leq z_1^l \cap z_2^{m-1} \leq y_{i2} \leq z_2^m) = \Phi_2\left(\frac{z_1^l - \beta_1' x_{ij}}{\sigma_{\epsilon_1}}, \frac{z_2^m - \beta_2' x_{ij}}{\sigma_{\epsilon_2}}, \rho\right)$

shifts across more distant categories.

Table 3: 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 4). These probabilities are estimated using as threshold the mean value of GGS [7] 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.

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. 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

[7] As a robustness exercise, 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.

year and also show the highest rate of upward mobility (from non-green jobs to green jobs) (18.1%). This pattern suggests that education not only facilitates entry into green occupations but also enhances the stability of employment within them, as it provides the foundational skills that enable workers to acquire new competences and adjust more effectively to the requirements of the transition.

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). 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 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.

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.

Table 4: Transition matrices by groups

Group	All		Sex				Age				Education			
Variable	All		Men		Women		More than 30		Less than 30		No university		University	
	G	NG	G	NG	G	NG	G	NG	G	NG	G	NG	G	NG
G	89.57	11.34	91.38	14.75	85.91	8.25	89.59	11.37	89.36	11.10	87.37	10.45	93.72	18.05
NG	10.43	88.66	8.62	85.25	14.09	91.75	10.41	88.63	10.64	88.90	12.63	89.55	6.28	81.95
Group	**Informality**				**Occupation group**						**AI exposure**			
Variable	**Formal**		**Informal**		**Self-emp./empl.**		**Others**		**Salaried workers**		**High exposure**		**Low exposure**	
	G	NG	G	NG	G	NG	G	NG	G	NG	G	NG	G	NG
G	90.55	11.86	88.47	10.94	89.35	11.48	87.31	9.87	90.00	11.48	90.42	11.02	88.87	11.55
NG	9.45	88.14	11.53	89.06	10.65	88.52	12.69	90.13	10.00	88.52	9.58	88.98	11.13	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. G means Green job and NG means Non-green jobs.

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 5). This classification 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 5: Three-state transition matrix

Group	All			Sex						Age			
Variable	All			Men			Women			More than 30			Less than 30
	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low
Low	75.40	12.63	0.19	70.53	10.36	0.14	79.07	15.79	0.30	75.39	12.58	0.19	75.47
Medium	23.75	61.31	10.65	28.23	61.15	8.98	20.38	61.54	14.19	23.76	61.31	10.62	23.73
High	0.85	26.06	89.16	1.24	28.49	90.88	0.55	22.66	85.51	0.85	26.11	89.19	0.80

Group	Age		University						Informality				
Variable	Less than 30		No university			University			Formal			Informal	
	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium
Low	13.02	0.20	76.49	13.23	0.24	64.74	9.95	0.10	74.61	12.43	0.17	76.00	12.80
Medium	61.34	10.87	22.73	61.61	12.89	33.82	59.99	6.79	24.53	61.14	9.70	23.17	61.46
High	25.64	88.93	0.78	25.16	86.87	1.44	30.07	93.11	0.87	26.43	90.13	0.83	25.75

Group	Informality	Occupation group						AI exposure					
Variable	Informal	Self-emp/ empl.			Salaried workers			High exposure			Low exposure		
	High	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High
Low	0.21	75.30	12.40	0.19	75.06	12.70	0.18	75.80	13.11	0.18	75.14	12.31	0.20
Medium	11.75	23.83	61.37	10.88	24.11	61.24	10.23	23.43	61.06	9.76	23.97	61.48	11.40
High	88.04	0.88	26.23	88.92	0.84	26.07	89.59	0.77	25.83	90.06	0.89	26.21	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 two statuses in 2023, conditional on the worker's status in 2021.

5.3 Mobility indices 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 7 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[8], although 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

[8] For 2×2 transition matrices, the three mobility indices (M_1, M_2, M_3) coincide. This happens because each index ultimately depends on the same underlying relationship among the transition probabilities. Therefore, once evaluated, they yield the same value, making the three measures equivalent in this case.

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 6: 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 3.

Table 7: 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 3.

5.4 Green jobs: a path to better wages?

To further examine the wage differences between green and non-green workers jobs, Table 8 present the regression results. we estimate the following regression model:

$$\log(w_i) = \alpha + X_i\beta + \varepsilon_i \tag{7}$$

where $\log(w_i)$ is the logarithm of monthly labor income and X_i is a vector of individual and job characteristics, including age, gender, education, informality status, occupationa group, economic sector, and department fixed effects. In additional specifications, we extend the analysis using re-centered influence function (RIF) regressions to study distributional statistics such as the median and the Gini coefficient, and apply Oaxaca–Blinder decompositions (Oaxaca, 1973; Blinder, 1973) to separate the explained and unexplained components of the green–nongreen wage gap.

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), results reveal that 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. Green formal workers 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.

Table 8: Wage regressions

Dependent variable: Log of wage	(1)	(2)	(3)	(4)	(5)	(6)
Informal (Base: Formal)	-0.397***	-0.410***	-0.411***	-0.406***		-0.410***
	(0.016)	(0.017)	(0.018)	(0.017)		(0.017)
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: Nongreen)		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)			
Nongreen - Low exposure (Base: Nongreen - High exposure)				-0.024		
				(0.038)		
Green - High exposure (Base: Nongreen - High exposure)				0.165***		
				(0.057)		
Green - Low exposure (Base: Nongreen - High exposure)				0.054		
				(0.052)		
Nongreen - Informal (Base: Nongreen -Formal)					-0.378***	
					(0.026)	
Green - Formal (Base: Nongreen -Formal)					0.138***	
					(0.036)	
Green - Informal (Base: Nongreen -Formal)					-0.299***	
					(0.032)	
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. All specifications include age, sex, education and occupation controls

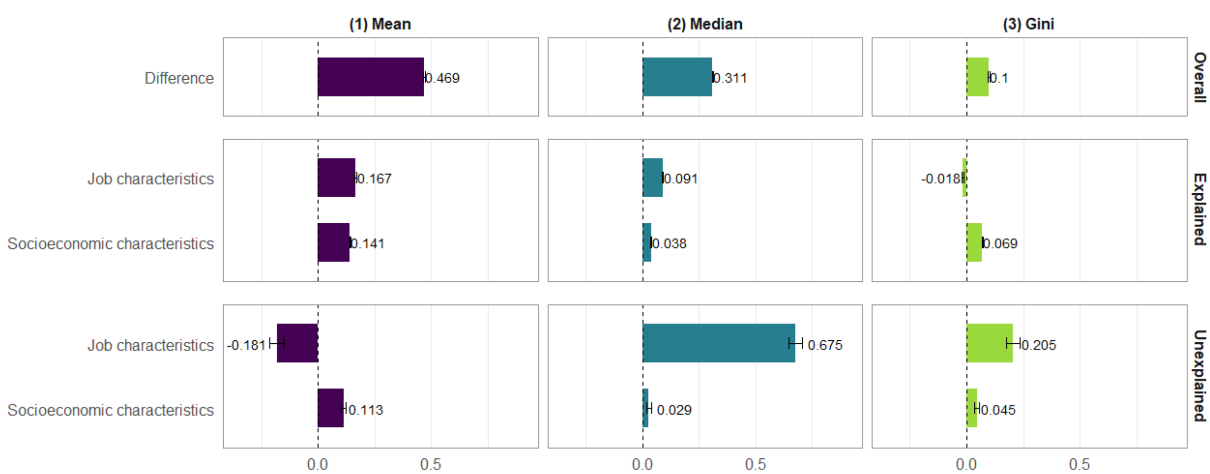
In order to understand the sources of the wage gap, we use the Oaxaca–Blinder decomposition. We extend the standard mean based approach by also performing decompositions at the median and for the Gini index, which allows us to capture average differences but also distributional aspects of the wage gap.

At the mean, the log wage gap between green and nongreen workers is 0.469, of which 65% (0.307) is explained by differences in observable characteristics and 35% percent remains unexplained (See Appendix 11). According to Figure 3, within the explained portion, both socioeconomic and job characteristics contribute positively, showing that differences in education, demographics, and occupational and sectoral structure widen the average wage differential. Socioeconomic characteristics also widen the gap while job characteristics reduce it within the unexplained component.

At the median, the observed wage difference is smaller, 0.311, but the relative importance of the components is reversed: only 42% is explained, while 58% is unexplained. The explained share arises from both socioeconomic and job characteristics, which widen the median gap, but the unexplained component is dominated by job characteristics with a large positive contribution, partially offset by a strongly negative constant.

In the Gini decomposition, overall inequality is higher among green workers, and the gap with nongreen workers is 0.100. Approximately half of this difference is explained by observable factors and half is unexplained. Within the explained component, socioeconomic characteristics increase the inequality gap, whereas job variables reduce it. The negative contribution of job characteristics implies that occupational and sectoral distributions among green workers attenuate inequality differences.

Figure 3: Oaxaca Blinder decomposition of wages



Notes: Author's calculations based on GEIH (2021, 2023).

The evidence shows that green jobs in Colombia are better paid. However, this advantage by itself does not capture the full picture. When workers face barriers of education, skills, or geography, the wage premium stops being an opportunity and instead becomes an exclusion factor. A proper assessment of the green transition must therefore look beyond wage gaps and consider whether workers can actually move into these jobs, as this is what determines whether the transition promotes upward mobility or increase existing inequalities.

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 9: Transition matrices

Group	All		Sex				Age			
Variable	All		Men		Women		More than 30		Less than 30	
	G	NG	G	NG	G	NG	G	NG	G	NG
G	88.39	10.13	90.43	13.27	84.37	7.37	88.42	10.16	88.18	9.90
NG	11.61	89.87	9.57	86.73	15.63	92.63	11.58	89.84	11.82	90.10

Group	Education				Informality				Occupation group	
	No university		University		Formal		Informal		Self-employed and employers	
	G	NG	G	NG	G	NG	G	NG	G	NG
G	85.98	9.38	93.13	16.12	89.49	10.56	87.18	9.81	88.14	10.28
NG	14.02	90.62	6.87	83.88	10.51	89.44	12.82	90.19	11.86	89.72

Group	Occupation group		AI exposure				Sector			
	Salaried workers		High exposure		Low exposure		Agriculture, Livestock, Hunting, Forestry and Fishing		Electricity, Gas, Water Supply, Waste Management and Mining	
	G	NG	G	NG	G	NG	G	NG	G	NG
G	88.88	10.23	89.33	9.78	87.63	10.36	89.61	13.11	89.52	11.80
NG	11.12	89.77	10.67	90.22	12.37	89.64	10.39	86.89	10.48	88.20

Group	Sector									
	Manufacturing		Construction		Trade		Transportation		Accommodation	
	G	NG	G	NG	G	NG	G	NG	G	NG
G	87.70	9.75	88.86	12.16	87.01	9.18	88.48	11.71	84.54	7.72
NG	12.30	90.25	11.14	87.84	12.99	90.82	11.52	88.29	15.46	92.28

Group	Sector									
	ICT		Financial and Insurance Services		Real Estate		Professional, Scientific, Technical and Administrative Services		Public Administration, Education and Health	
	G	NG	G	NG	G	NG	G	NG	G	NG
G	91.85	12.08	90.95	11.30	88.24	10.46	88.98	9.29	90.19	10.58
NG	8.15	87.92	9.05	88.70	11.76	89.54	11.02	90.71	9.81	89.42

Group	Sector		Occupation major ISCO-08 group							
	Arts, Entertainment, Recreation and Others		Managers		Professionals		Technicians		Clerical Support	
	G	NG	G	NG	G	NG	G	NG	G	NG
G	84.87	7.61	91.28	12.18	92.59	14.46	89.16	10.15	87.19	8.79
NG	15.13	92.39	8.72	87.82	7.41	85.54	10.84	89.85	12.81	91.21

Group	Occupation major ISCO-08 group									
	Services and Sales		Skilled Agricultural		Craft and Related Trades		Machine Operators		Elementary Occupations	
	G	NG	G	NG	G	NG	G	NG	G	NG
G	85.14	8.15	89.51	13.01	87.70	11.03	87.85	11.21	86.43	9.49
NG	14.86	91.85	10.49	86.99	12.30	88.97	12.15	88.79	13.57	90.51

Group	Cities									
	Barranquilla		Bogota		Bucaramanga		Cali		Cartagena	
	G	NG	G	NG	G	NG	G	NG	G	NG
G	86.11	8.10	89.88	10.63	89.23	10.63	86.58	8.39	86.26	8.36
NG	13.89	91.90	10.12	89.37	10.77	89.37	13.42	91.61	13.74	91.64

Group	Cities									
	Cucuta		Ibague		Manizales		Medellin		Monteria	
	G	NG	G	NG	G	NG	G	NG	G	NG
G	88.62	10.44	89.62	10.91	87.25	8.58	88.08	9.44	87.27	8.92
NG	11.38	89.56	10.38	89.09	12.75	91.42	11.92	90.56	12.73	91.08

Group	Cities					
	Pasto		Pereira		Villavicencio	
	G	NG	G	NG	G	NG
G	88.36	9.29	87.61	9.32	87.28	8.94
NG	11.64	90.71	12.39	90.68	12.72	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 $\rho = 0.9519$. Each row shows the probability of being in one of the two statuses in 2023, conditional on the worker's status in 2021. G means Green job and NG means Non-green jobs

B Transition 2×2 matrices by other groups

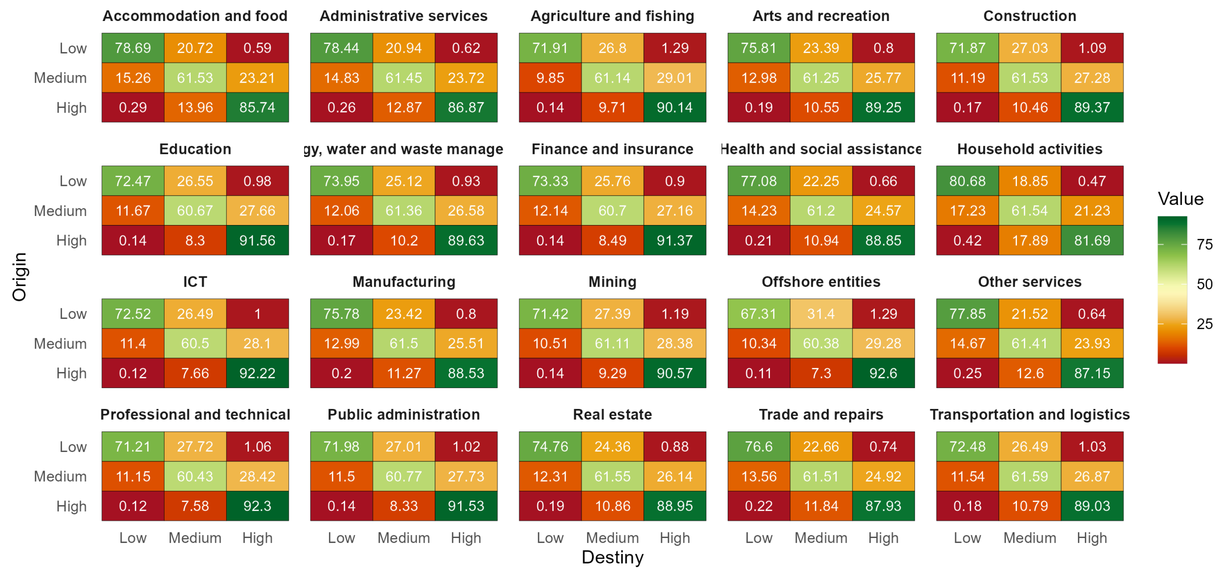
Table 10: Transition 2×2 matrices by economic sector and occupation group

Group	All		Sex				Age			
Variable	All		Men		Women		More than 30		Less than 30	
	G	NG	G	NG	G	NG	G	NG	G	NG
G	88.39	10.13	90.43	13.27	84.37	7.37	88.42	10.16	88.18	9.90
NG	11.61	89.87	9.57	86.73	15.63	92.63	11.58	89.84	11.82	90.10
Group	Education				Informality				Occupation group	
	No university		University		Formal		Informal		Self-employed and employers	
	G	NG	G	NG	G	NG	G	NG	G	NG
G	85.98	9.38	93.13	16.12	89.49	10.56	87.18	9.81	88.14	10.28
NG	14.02	90.62	6.87	83.88	10.51	89.44	12.82	90.19	11.86	89.72
Group	Occupation group		AI exposure				Sector			
	Salaried workers		High exposure		Low exposure		Agriculture, Livestock, Hunting, Forestry and Fishing		Electricity, Gas, Water Supply, Waste Management and Mining	
	G	NG	G	NG	G	NG	G	NG	G	NG
G	88.88	10.23	89.33	9.78	87.63	10.36	89.61	13.11	89.52	11.80
NG	11.12	89.77	10.67	90.22	12.37	89.64	10.39	86.89	10.48	88.20
Group	Sector									
	Manufacturing		Construction		Trade		Transportation		Accommodation	
	G	NG	G	NG	G	NG	G	NG	G	NG
G	87.70	9.75	88.86	12.16	87.01	9.18	88.48	11.71	84.54	7.72
NG	12.30	90.25	11.14	87.84	12.99	90.82	11.52	88.29	15.46	92.28
Group	Sector									
	ICT		Financial and Insurance Services		Real Estate		Professional, Scientific, Technical and Administrative Services		Public Administration, Education and Health	
	G	NG	G	NG	G	NG	G	NG	G	NG
G	91.85	12.08	90.95	11.30	88.24	10.46	88.98	9.29	90.19	10.58
NG	8.15	87.92	9.05	88.70	11.76	89.54	11.02	90.71	9.81	89.42
Group	Sector		Occupation major ISCO-08 group							
	Arts, Entertainment, Recreation and Others		Managers		Professionals		Technicians		Clerical Support	
	G	NG	G	NG	G	NG	G	NG	G	NG
G	84.87	7.61	91.28	12.18	92.59	14.46	89.16	10.15	87.19	8.79
NG	15.13	92.39	8.72	87.82	7.41	85.54	10.84	89.85	12.81	91.21
Group	Occupation major ISCO-08 group									
	Services and Sales		Skilled Agricultural		Craft and Related Trades		Machine Operators		Elementary Occupations	
	G	NG	G	NG	G	NG	G	NG	G	NG
G	85.14	8.15	89.51	13.01	87.70	11.03	87.85	11.21	86.43	9.49
NG	14.86	91.85	10.49	86.99	12.30	88.97	12.15	88.79	13.57	90.51
Group	Cities									
	Barranquilla		Bogota		Bucaramanga		Cali		Cartagena	
	G	NG	G	NG	G	NG	G	NG	G	NG
G	86.11	8.10	89.88	10.63	89.23	10.63	86.58	8.39	86.26	8.36
NG	13.89	91.90	10.12	89.37	10.77	89.37	13.42	91.61	13.74	91.64
Group	Cities									
	Cucuta		Ibague		Manizales		Medellin		Monteria	
	G	NG	G	NG	G	NG	G	NG	G	NG
G	88.62	10.44	89.62	10.91	87.25	8.58	88.08	9.44	87.27	8.92
NG	11.38	89.56	10.38	89.09	12.75	91.42	11.92	90.56	12.73	91.08
Group	Cities									
	Pasto		Pereira		Villavicencio					
	G	NG	G	NG	G	NG				
G	88.36	9.29	87.61	9.32	87.28	8.94				
NG	11.64	90.71	12.39	90.68	12.72	91.06				

Notes: Author's calculations based on GEIH (2021, 2023).. The reported probabilities are calculated using a correlation parameter of $\rho = 0.9519$. Green workers are classified as those whose GGS values exceed the sample mean. G means Green job and NG means Non-green jobs.

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 Oaxaca-Blinder decomposition

Table 11: Oaxaca Blinder decomposition over wages using mean, median and Gini coefficient

Variables	Mean	Median	Gini
Green worker	13.959***	13.958***	0.474***
	(0.002)	(0.002)	(0.001)
Nongreen worker	13.490***	13.647***	0.374***
	(0.001)	(0.001)	(0.001)
Difference	0.469***	0.311***	0.100***
	(0.002)	(0.002)	(0.002)
Explained	0.307***	0.129***	0.051***
	(0.002)	(0.001)	(0.002)
Unexplained	0.162***	0.182***	0.049***
	(0.002)	(0.002)	(0.002)
Explained			
Socioeconomic characteristics	0.141***	0.038***	0.069***
	(0.001)	(0.001)	(0.001)
Job characteristics	0.167***	0.091***	-0.018***
	(0.002)	(0.001)	(0.002)
Unexplained			
Socioeconomic characteristics	0.113***	0.029***	0.045***
	(0.005)	(0.005)	(0.005)
Job characteristics	-0.181***	0.675***	0.205***
	(0.016)	(0.015)	(0.016)
Constant	0.230***	-0.521***	-0.201***
	(0.017)	(0.016)	(0.016)
Observations	649,762	649,762	649,762

Notes: Author's calculations based on GEIH (2021, 2023). Workers are classified into green and nongreen according to the mean value of GGS score. Standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

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