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ABSTRACT

Exploring skills in the green transition: new insights from Italian data world

This paper investigates job transitions and skill alignment in Italy's green transition, using multiple datasets to analyse the role of skills in shaping occupational mobility. Building on previous studies, we identify 28 General Green Skills (GGS), primarily encompassing analytical, technical, and monitoring competencies, which overlap significantly with General Brown Skills (GBS), as 13 out of 18 GBS also appear among the GGS. Further, this paper offers a methodological overview of the construction of skill distance metrics, evaluating various alternatives. Selecting as a preferred alternative a skill distance metric derived from factor analysis and Manhattan distance, we find that it negatively correlates with occupational mobility. Preliminary correlations show that moving toward green occupations alleviates this negative correlation, while moving away from brown occupations does not interplay with skill distance.

KEYWORDS: green skills, brown skills, skill distance, job-to-job transitions, green jobs
JEL CODES: J24, J6, F64

Questo articolo, utilizzando più dataset, esamina le transizioni occupazionali e il ruolo che le competenze hanno nella transizione verde e nella mobilità occupazionale in Italia. A partire da studi passati, identifichiamo 28 General Green Skills (GGS), che comprendono principalmente competenze analitiche, tecniche e di monitoraggio, le quali si sovrappongono in modo significativo con le General Brown Skills (GBS), poiché 13 su 18 GBS sono presenti anche tra le GGS. L'articolo discute, inoltre, le diverse metodologie che possono essere adottate per costruire delle misure di distanza tra le competenze, valutando diverse alternative. La misura scelta, ottenuta dalla combinazione dell'analisi fattoriale con una distanza di Manhattan (non ponderata), risulta essere negativamente correlata con la mobilità occupazionale: la transizione verso occupazioni green attenua l'influenza della distanza delle competenze, mentre le competenze sembrano non avere un ruolo nelle transizioni tra le occupazioni brown.

PAROLE CHIAVE: *competenze green, competenze brown, skill distance, job-to-job transitions, green jobs*
CODICI JEL: J24, J6, F64

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1. Introduction

The European Green Deal (EGD) represents a transformative agenda aimed at achieving net-zero greenhouse gas emissions by 2050. To accomplish this, the initiative invests heavily in renewable energy, sustainable infrastructure, and the circular economy, seeking to reconcile economic growth with environmental sustainability. These investments are expected to significantly reshape labor markets, particularly in regions heavily reliant on fossil fuels or high-pollution industries. A key challenge lies in ensuring that the workforce possesses the skills required for emerging green technologies. Labour research demonstrates that reallocation costs are closely linked to the disparity in skill sets between “origin” and “destination” occupations (Gathmann and Schönberg 2010; Guvenen *et al.* 2020; Kambourov and Manovskii 2009). The success of the EGD depends significantly on the availability of workforce skills aligned with the demands of green technologies. Evidence from the American Recovery and Reinvestment Act (ARRA) reveals that regions with a higher concentration of engineering and technical skills experienced greater employment gains from green fiscal stimulus (Popp *et al.* 2021). Similarly, Vona *et al.* (2018) highlight that occupations requiring specialized expertise in areas such as renewable energy or environmental engineering saw notable growth, underlining the importance of targeted training programs to address skill mismatches. Regions with inadequate skill bases face heightened reallocation costs, which exacerbate disparities and limit the socioeconomic benefits of green investments. These findings align with broader evidence showing that local economies with strong skill endowments are better equipped to adapt to technological and organizational changes, including the green transition (Acemoglu and Autor 2012; Beaudry *et al.* 2010; Moretti 2004). Proactive skill development initiatives are therefore crucial to minimizing reallocation costs and enabling inclusive labor market transitions.

Assessing the labor market implications of green policies and technologies is complicated by the absence of consistent definitions for ‘green jobs’ and a lack of granular data on their characteristics. Conventional binary classifications, which categorize jobs as either green or non-green, are inadequate for capturing the complexities of roles that incorporate elements of both. For instance, occupations in construction or manufacturing may involve both traditional and environmentally beneficial practices, making it difficult to classify them unequivocally (Consoli *et al.* 2016). A solution proposed by the recent literature on the topic is to use the task-based approach as a flexible solution to build a continuous index of occupational greenness. The task-based approach (Autor 2013; Autor *et al.* 2003) has been widely applied in economics and environmental literature to address key labor market challenges during the green transition. It highlighted how climate change impacts productivity, with extreme weather events like heatwaves reducing outdoor workers’ efficiency and increasing reliance on capital-intensive technologies for cognitive tasks (Graff Zivin and Neidell 2012; Hsiang *et al.* 2018). Furhter, it examined how environmental policies raising the costs of polluting inputs, such as coal, drive labor and capital toward cleaner industries, often creating skill mismatches and reemployment challenges (Goulder *et al.* 2019; Rausch *et al.* 2011). Additionally, it identified emerging green tasks, like those tied to renewable energy systems or energy-efficient retrofitting, which demand specialized skills not always addressed by current training programs (Cedefop 2019; Vona *et al.* 2018). These insights make the task-based framework a vital tool for policymakers to develop inclusive strategies for the green transition.

This paper offers methodological insights and preliminary evidence in the examinations of job transitions and skill alignment in Italy's green transition. To achieve these objectives, we exploit several datasets. We derive a measure of occupational "greenness" using the task-based framework and the work of Vona *et al.* (2018). This method applies greenness scores from the O*NET database to the Italian CP2011 occupational classification system via ISCO crosswalks. We utilize the Italian Labour Force Survey (ILFS) to compute employment shares, which serve as occupation weights in the analysis, as well as to obtain descriptive statistics on the main characteristics of occupations. We exploit the *Indagine Campionaria delle Professioni* (ICP) a survey with the aim of investigating the characteristics of professional occupations, with reference to skills and knowledge requirements. Lastly, we incorporate the *Comunicazioni Obbligatorie* (CO), a detailed dataset tracking formal changes to employment contracts.
Methodologically, we adapt and extend the related literature on the topics of green jobs, skill measures, and job-to-job transitions. First, we adopt a task-based framework to analyze skill demands and job-to-job transitions in the context of the green transition. To identify skills associated with green and brown occupations, we adapt the methodology established by Vona *et al.* (2018). Specifically, we use regression analyses to estimate the relationship between task relevance scores and occupational greenness. In these models, we control for employment weights, occupational fixed effects, and other job characteristics. This allows us to identify a set of General Green Skills (GGS) that are consistently associated with greener jobs. Additionally, we compute pairwise skill distance metrics to quantify the barriers to transitioning between occupations. Among other possible choices (Gathmann and Schönberg 2010; Ingram and Neumann 2006; Macaluso2025), the favourite measure is a combination of factor analysis and Manhattan distance measures. This distance measure captures the degree of overlap in skill requirements between any two occupations, allowing us to evaluate how skill distance influences labor market mobility. Lastly, to model job-to-job transitions, we adopt and adapt the gravity-like framework proposed by Cortes and Gallipoli (2018), to examine how skill distance affects mobility patterns within the green transition. Specifically, we focus on transitions 'toward' green jobs and 'away' from brown jobs. To partially account for unobserved factors affecting the transitions, we incorporate fixed effects at both the origin and destination occupations. By analyzing these patterns, we aim to describe how skill mismatches and occupational characteristics affect the likelihood of transitioning into greener roles.
The results of this paper reveal critical topical and methodological insights into the skill requirements and labor market dynamics of the green transition. First, we identify 28 GGS that are pivotal for green occupations. These skills emphasize analytical capabilities, technical expertise, and monitoring functions, aligning closely with prior findings by Vona *et al.* (2018). The results suggest that these skills are not unique to specific countries (Italy and U.S.) but rather reflect a certain degree of 'universality' in the demand of green jobs. As a novelty, we explore the relevance of soft skills in the context of the green transition. Although these skills are often highlighted in public discourse, our analysis finds that they play a relatively minor role compared to hard, technical competencies. Using the same methodological approach for GGS, we identify the set of General Brown Skills (GBS), defined as the most relevant skills in brown occupations. Notably, 13 of the 18 GBS also appear among the 28 GGS, highlighting a significant overlap in the skills highly demanded by both green and brown occupations.
In our analysis of skill distances, the implementation of factor analysis allows us to identify four factors

identifying four broad skill categories: analytical intelligence (accounting for 28% of total variance); dexterity and motor skills (16%); monitoring (10%); managerial abilities (8%). The essence of these factors is aligned with works by Ingram and Neumann (2006) and Poletaev and Robinson (2008). When combining four factor analysis with Manhattan distance, we compute a distance metric that is unimodal, with a mean of 0.18, a standard deviation of 0.07, a minimum value of 0.004 and a maximum value of 0.584. Metrics computed using the alternative approaches positively correlate with our preferred metric, supporting the robustness of our choice. We find that occupations within the same macrogroup tend to exhibit greater similarity in skill requirements, while significant disparities emerge between occupations across different macrogroups.
When examining job-to-job transitions within the adapted framework of Cortes and Gallipoli (2018), we observe the following empirical facts. First, we observe a persistent negative correlation of the measure of skill distance on occupational mobility. Then, we interact the skill distance measure with a dummy that captures transitions 'toward' green occupations. The interaction mediates the negative correlation of the un-interacted skill distance. A possible, but tentative, interpretation is that workers, from non-green occupations, self-select into green ones where the skill set is as close as the origin occupation. Lastly, we interact the skill distance measure with a dummy that captures transitions 'away' from brown occupations. This interaction shows no statistical significance, suggesting that, for these transitions, there is no interplay with the skill distance between origin and destination occupations.
The rest of the elaborate is organized as follows. Section 2 describes the data being employed. Section 3 carefully details and explains the methodology employed in this paper. Section 4 shows the results associated with the methodology presented. The last section concludes.

2. Data

This section provides an overview of the data sources used in the analysis, detailing their characteristics, scope, and relevance.
Greenness measure. To identify green jobs, we follow Vona *et al.* (2018). In their paper, the authors measure the greenness of occupations using a task-based approach that leverages data from the O*NET database, which provides detailed descriptions of tasks performed across U.S. occupations. The methodology involves calculating a continuous greenness score for each occupation, defined as the ratio of green-specific tasks to the total number of tasks associated with the occupation. This measure ranges from 0, indicating no green tasks, to 1, where all tasks are explicitly related to environmental sustainability. This exercise provides a list of occupations in Standard Occupational Classification (SOC) by greenness of each occupation.
To identify green jobs within the Italian labour market, one can exploit this list and translate it to the *Classificazione delle Professioni* (CP2011), the Italian classification of jobs. Unfortunately, given that there is no straight crosswalk between SOC and CP2011, the best option is to exploit the International Standard Classification of Occupations (ISCO), which offers a crosswalk for both classifications. Besides others, the following main limitation should be kept in mind. SOC and ISCO differ in their levels of granularity. O*NET (SOC) data offers detailed occupational information at the six-digit level, while

ISCO is aggregated at the four-digit level. This discrepancy results in many-to-many mappings between occupations, where a single SOC occupation may correspond to multiple ISCO categories or vice versa. At the same time, the ISCO-CP2011 crosswalk takes place at the three- and five-digit, respectively. Such mismatches introduce measurement errors, particularly when analyzing task-level or skill-specific data. To alleviate these concerns, we manually match CP2011 and ISCO at the five- and four-digit level, using the three-digit-ISCO crosswalk only to ensure that such matches occur within the more aggregated categories indicated by the official crosswalk. This procedure allows us to have a SOC(6d)-ISCO(4d)-CP2011(5d) crosswalk. In some particular cases, the match is made directly between CP2011(5d) and SOC(6d), without passing through the intermediate aggregation of ISCO(4d). At the end of the process, we carry out some further 'manual' interventions to correct some obvious false positives/ false negatives resulting from the double crosswalk[1]. Once we are able to measure the greenness of an occupation within the CP2011 classification, we identify green jobs as those occupations with a greenness measure higher than zero.

Conversely, still following the approach by Vona *et al.* (2018), we identify brown jobs within the CP2011 classification via combining the identification of the most polluting intensive industries and the probability of a job being in one of these industries.

LFS. The Italian Labour Force Survey (LFS) is one of the principal surveys conducted on a quarterly basis across the national territory, providing detailed insights into the structure and evolution of the Italian labour market. In our analysis, we utilize the ILFS to compute employment shares, which serve as occupation weights in the analysis, as well as to obtain descriptive statistics on the main characteristics of occupations. These characteristics include, but are not limited to, the average age, the share of female workers, and the average years of education of individuals employed in each occupation.

Given that the focus of our study is based on the *Indagine Campionaria delle Professioni* (ICP), a survey which was last conducted in 2013, we draw on LFS data from the period 2011-2014 to ensure temporal relevance and alignment with the ICP. For both the computation of weights and the extraction of descriptive characteristics, we exclude from the sample individuals in the armed forces (identified by CP2011 codes starting with "9") as well as respondents who are either too young (aged 19 or younger) or too old (aged 65 or older). No additional restriction is imposed on the data.

The calculation of sampling weights is performed as follows. For each quarterly LFS database, we define cells based on occupation (3D), sector (2D), and region. The share of each cell is determined by dividing the number of individuals within it (weighted according to the sampling weights provided by the survey) by the total number of observations. By averaging the data across the four quarters, we create a dataset with distinct weights for each cell-year, which can then be used for region-, sector, or year-specific analyses. From this dataset, we estimate the relevant employment share for each occupation by collapsing the data to the occupation-year level and computing the simple average over the period from 2009 to 2013. This procedure, compared to the alternative of using employment shares

[1] The following are examples of the manual corrections: 1) SOC 11-1021.00 "General and Operations Managers" corresponds to ISCO 1112 "Senior Government Officials" with a greenness of 0.04. However, the corresponding CP2011 category is 11223 "Secretary Generals and Heads of Control and Management in Public Administration", which is then assigned a greenness of 0. 2) SOC 17-2161.00 "Nuclear Engineers" corresponds to ISCO 2149 "Engineering professionals not elsewhere classified", with a greenness of 0.14. However, the corresponding CP2011 category is 22114 "Energy and Nuclear Engineers", which is then assigned a greenness directly from the SOC correspondence of 0.83.

computed solely from 2013 data, minimizes the risk of weight volatility due to year-specific dynamics in the labor market or sampling errors. The average characteristics of occupations are computed using the same approach: first, averages are calculated at the occupation-sector-region-year level; then, depending on the specific needs of the analysis, these averages are further aggregated across one or more dimensions.

ICP. The ICP is a survey which has been carried out twice (in 2007 and 2013) by *Istituto nazionale per l'analisi delle politiche pubbliche* (INAPP) with the aim of investigating the characteristics of professional occupations, with particular reference to skills and knowledge requirements. The ICP refers to a theoretical model borrowed from the U.S.-based O*Net (Occupational Information Network), which defines occupations as a multidimensional concept that can be described by referring to multiple areas: skill and competencies requirements, workers characteristics that affect job performance, job characteristics and workplace conditions.

The survey employs Computer-Assisted Personal Interviewing (CAPI) to collect data from approximately 16,000 workers. The questionnaire closely mirrors the structure of the primary O*Net questionnaires, a similarity that, as discussed in Section 3.1, facilitates the application of the methodology proposed by Vona *et al.* (2018) to the Italian context for identifying skills critical to the green transition. Specifically, the questionnaire consists of a total of 255 questions, divided into thematic sections as follows:

- Section B - Knowledge requirements: refers to general knowledge (e.g., "knowledge of the principles and methods that govern business operations");
- Section C - Skills requirements: refers to general skills, such as "reading comprehension" or "negotiation";
- Section D - Abilities requirements: pertains to abilities, defined as individual attributes that tend to remain relatively stable over time and are not easily altered. While some overlap with Section C exists (e.g., D2: Comprehension of written communications; C1: Understanding of written texts), this Section also encompasses more physically oriented abilities (e.g., "multilimb coordination", "peripheral vision");
- Section E – Values requirements: refers to values required by the profession, such as moral integrity, or autonomy;
- Section F - Work Styles requirements: This section pertains to dimensions that could be classified as soft skills (e.g., "the job requires persistence in the face of obstacles"; "the job requires being approachable and cooperative with others at work");
- Section G - Work Activities: it refers to generalized work activities, understood as a set of actions, practices, or similar processes that underline the specific tasks (e.g., "reviewing and checking information from materials, events, or the environment to identify or assess problems");
- Section H - Working Conditions: It refers to working conditions (physical conditions, the ways in which the profession is performed, and the relationships it requires with other people).

Sections B, C, D, and G share a consistent structure: for each questionnaire item, both a "relevance" score and a "level" score are reported. These scores respectively indicate the importance of the item in performing the profession and the level at which the corresponding skill or task is required for the job[2].

[2] The questionnaire provides examples to guide respondents in assessing the level variable. For instance, for skill B1 (reading

Relevance is rated on a 1-to-5 scale, whereas level is rated on a 1-to-7 scale. Section F, focused on soft skills, follows a similar structure but reports only relevance scores. In contrast, Sections E and H adopt a different approach. Specifically, Section E assesses the extent to which respondents agree (on a 1-to-5 scale) with various statements (e.g., "workers in this occupation receive the right recognition for what they do") and does not provide information on the relevance of these items. Section H, unlike the other sections, focuses on work context characteristics rather than individual characteristic requirements. It records both the frequency and intensity of exposure to specific work setting conditions or hazards (e.g., "How often does your work require you to work outdoors, exposed to all weather conditions?"). In line with the work of Vona *et al.* (2018), the identification of skills critical to the green transition primarily relies on Sections B, C, and G – those most directly related to the concept of skills[3]. In total, these sections capture information on 161 dimensions of skill heterogeneity. Section F, which addresses soft skills (16 items), is also included in the analysis separately. For the construction of skill distance metrics, as detailed in Section 3.2, Section D on abilities is also considered[4]. To improve the interpretability of the results, all scores from the utilized sections are rescaled to a 0-1 scale.

COB. The Italian *Comunicazioni Obbligatorie* (CO) is an administrative dataset maintained by the Italian Ministry of Labour and Social Policies. This dataset is built on mandatory notifications that employers, since 2009, must submit whenever there is a new employment contract, a modification to an existing contract, or a termination. As this notification process is legally required, the CO dataset provides a comprehensive and detailed overview of formal employment relationships in Italy. The analysis exploits a randomized sample of individuals born on 48 specific dates (4 dates per month) in a given year, tracking employment-related events associated with these individuals over time.

CO includes rich information on employment contracts, individual worker characteristics, and firm attributes. Employment details such as contract start and end dates, type of contract (e.g., permanent, fixed-term, apprenticeship), and working hours are recorded alongside worker characteristics, including gender, age, nationality, and education level. Firm-related data cover economic sector classifications (based on the ATECO system), geographic location, and firm size, while occupations are categorized according to the ICP system. CO does not provide the salary and does not capture informal or undeclared work.

Our CO dataset contains data on individuals from 2009 to 2023, capturing their entire employment history during this period. This results in 4,508,786 unique individuals. We apply the following selection criteria to the data. We select only people aged between 15 and 64; we exclude the armed forces employees; contracts termination due to death or retirement; contracts that starts before 2012; and contracts shorter than 180 days. This selection leads us to have 2,793,904 unique individuals. Further,

comprehension), a low level is exemplified by "read step-by-step instructions for completing a form", while a high level is illustrated by "read a scientific journal article describing surgical procedures".

[3] One might argue that Section G refers to tasks rather than skills, potentially conflating different concepts. However, as suggested by the framework developed by Yamaguchi (2012), "observed tasks can be interpreted as a noisy signal of unobserved skills".

[4] The rationale for excluding Section D from the analysis of general green and brown skills lies in its focus on individual characteristics that are, by definition, "relatively stable over time and hard to modify." These attributes are less relevant to the type of skill adjustments and retraining central to this analysis. However, precisely because they are difficult to alter, these characteristics play a significant role in determining skill distances between occupations and in shaping the reallocation costs associated with job mobility, and hence are included in the construction of skill distance metrics.

in the case of overlapping contracts, to have a balanced individual-year panel, we select the most relevant contract of an individual in a year by applying the following hierarchical criteria:
1) we select the longest contract within the year; 2) we select full-time contracts over part-time ones; 3) we select permanent contracts over fixed-terms ones; 4) we select the longest contract through the whole period; 5) if we still have overlaps, we choose one of the overlapping contracts at random[5].

3. Methodology

This section outlines the methodological framework employed in the analysis, detailing the models, techniques, and assumptions that underpin the empirical approach.

3.1 General Green and Brown Skills

As highlighted by the literature (Curtis *et al.* 2024; Popp *et al.* 2021; Saussay *et al.* 2022; Vona *et al.* 2018), an in-depth investigation of the role of workplace *tasks* and *skills* provides a useful key to interpret and predict labor market dynamics in the context of the green transition. Particularly, it is crucial to identify which set of skills will gain relevance and significance as economies shift towards new low-carbon standards. Adapting it to the Italian context, we hence follow the data-driven methodology outlined by Vona *et al.* (2018) to identify the set of General Green Skills (GGS) demanded in the green economy.
Our analysis on general green and brown skills in the Italian labor market leverages mainly upon the ICP, described in Section 2, in which each 5-digit occupation is defined in terms of two vectors of *relevance* and of *level* scores across tasks and skills. In light of the high level of correlation between relevance and level scores[6], we restrict our analysis to relevance scores. We then restrict the analysis to Sections B, C, F and G of the ICP – thereby excluding Section D on attitudes, Section E on work values and Section H on work context and conditions[7]. Again, this choice is aligned with the previously cited works, the only novelty being the inclusion of Section F on work styles, which may be interpreted as reflecting the role of "soft skills".
To identify GGS we follow closely the empirical approach by Vona *et al.* (2018), adopting the Greenness indicator as a "search criterion". Thus, we regress the importance score of each general tasks (or skill) *l* in occupation *k* on the Grenness indicator plus a set of two-digit occupational dummies:

$$\text{Task Rel}_k^l = \beta^l \times \text{Greenness}_k + \phi^{CP2D} + \epsilon_k \qquad (1)$$

We include occupational dummies (ϕ^{CP2D}) to enhance the comparability of skill profiles of occupations with similar core characteristics[8]. We use only two-digit occupational macrogroups containing at

[5] This last step removes only 0.36% of the data.
[6] The Pearson correlation coefficient between these two variables, computed across all occupations, is equal to 0.833.
[7] We exclude Section H on "Work Context" as its items pertain to workplace characteristics rather than to specific skills applied within the workplace. Section D ("Individual Attitudes") is excluded because attitudes are defined as "relatively stable over time and hard to modify", making them inherently unsuitable for the type of skill adjustments that we are interested in analyzing. Lastly, Section E on "Work Values" is excluded as it pertains to opinions on the values associated with various professions, the inclusion of which would conflate distinct concepts.
[8] The choice of including 2-digits dummies differs slightly from the approach of Vona *et al.* (2018), in which 3-digits dummies are used. This adjustment reflects the less granular occupational coding in the Italian context, which uses 5-digit codes instead of 6-digit codes.

least one job with positive greenness, thus eliminating broad categories that bear no relevance with regards to green jobs, such as "unskilled professions in domestic, recreational and cultural activities" (CP2011 82)[9]. Thus, just as outlined by Vona *et al.* (2018), we identify GGS by comparing green and non-green occupations that are relatively similar in overall task content and skill profiles. Hence, a positive (negative) and significant β^l denotes that general task (or skill) l is used more (less) intensively in greener occupations. We label a general task or skill as green when the estimated β^l is positive and statistically significant at the 5% level[10]. All regressions are weighed using employment shares at the 5-digit level, derived from the labor force survey as outlined in Section 2. Results remain, however, largely unchanged when unweighted regressions are considered.

It is important to explicitly note that this empirical approach involves conducting l (in our case, $l=177$) distinct regressions. This raises concerns about the validity of hypothesis testing procedures and highlights the potential need for multiple-testing corrections to mitigate the risk of identifying "false-positive" green skills. On the other hand, the imperfect measurement of greenness – our primary regressor of interest – likely introduces attenuation bias in our estimates, which operates in the opposite direction, increasing the risk of "false-negatives." Accurately quantifying the extent of these biases in our analyses is challenging. To address and mitigate these concerns, we take an indirect approach, incorporating and comparing alternative regression specifications to strengthen the robustness of our results. Specifically, we consider the 4 following alternative specifications: (i) no occupational dummy: $T_k^l = \beta^l \times \text{Greenness}_k + \epsilon_k$; (ii) same as (i), but considering only occupations that belong to 2-digits macrogroup in which at least one occupation has positive greenness; (iii) 1-digit occupational dummies: $T_k^l = \beta^l \times \text{Greenness}_k + \theta_k^{CP\,1D} + \epsilon_k$; (iv) 3-digits occupational dummies: $T_k^l = \beta^l \times \text{Greenness}_k + \psi_k^{CP\,3D} + \epsilon_k$. From this pool of potential relevant green skills, we extract the list of GGS by imposing two key restrictions: firstly, the β parameter associated to them should not be significantly negative (at the 5% significance level) in any of the considered specifications; secondly, the β parameter should be positive and statistically significant in the majority (i.e. in 3 out of 5) of the specifications. All results are reported and discussed in detail in Section 4.1.

We then adapt this methodology to symmetrically investigate which skills play a prevalent role in brown occupations, thus extracting an equivalent list of "general brown skills". To the best of our knowledge, this represents a novel empirical contribution. Evidently, the key (and only) difference consists in changing the main explanatory variable in the regressions, replacing the greenness measure with an indicator of "brownness" of occupations[11]:

$$\text{Task Rel}_k^l = \gamma^l \times \text{Brownness}_k + \phi^{CP\,2D} + \epsilon_k \qquad (2)$$

[9] Table A1 in Appendix A reports the list of two-digit occupations that do not contribute to the selection of GGS. Similarly, Table A2 reports the occupations excluded for the selection of general *brown* skills. Overall we use, respectively, 543 and 364 and of the 796 5-digits occupations to obtain the list of general *green* and of general *brown* skills.

[10] Using a 5% significance level marks another slight difference from the approach of Vona *et al.* (2018), who adopt the more stringent 1% threshold. This adjustment addresses concerns about the imperfect crosswalk from SOC to CP2011, which leads to a less precise measurement of occupational greenness and may introduce a stronger attenuation bias in our regressions.

[11] As noted in Section 2, our indicator of brownness differs from our greenness measure in that it is of binary – rather than continuous – nature. This does not, however, substantially alter the interpretation of its parameter in the regression framework.

Finally, to analyze whether “soft skills” might also play a relevant role in shaping labor market dynamics during the green transition, we extend the exact same empirical approach (both for green and brown skills) to the set of 16 additional skills listed in Section F of the ICP. Again, all results will be discussed in Section 4.

3.2 Skill distance metrics

To investigate labor market dynamics within the green transition and the pivotal role of skills during this phase, it is essential to go beyond a simple characterization of occupational skill profiles. A comprehensive understanding requires examining how skill profiles differ across occupations, identifying which occupations are similar in terms of skill requirements, determining clusters of related occupations, and assessing the degree of dissimilarity between them.

A valuable tool in this context is the development and application of a *skill distance* metric. This metric assigns a quantitative measure of skill distance to each possible pair of occupations, enabling a systematic characterization of the occupational landscape based on pairwise distances. Beyond serving as a descriptive tool, the skill distance metric can also be interpreted as a preliminary assessment of the cost – expressed in terms of the skill adjustments required – of moving between occupations. Moreover, it may act as a potential predictor of the likelihood of transitioning between occupations, offering valuable insights into the dynamics of labor mobility in the context of the green economy.

The concept of characterizing the occupational landscape using pairwise skill distance measures is not entirely new. It has been successfully applied in various contexts, including the analysis of human capital specificity (Gathmann and Schönberg 2010) and the returns to skills (Ingram and Neumann 2006). More recently, this approach has contributed to advancing our understanding of occupational mobility (Cortes and Gallipoli 2018), multidimensional skill mismatches (Guvenen *et al.* 2020; Neffke *et al.* 2024), and job displacement costs (Macaluso 2025). Despite these contributions, the literature on measuring skill and task distances between occupations remains relatively nascent. Most studies have relied on U.S. data, and no widely accepted methodological “gold standard” has yet been established.

Robinson (2018) provides a concise review of the literature on skill distance measures, emphasizing the shared core features across different approaches. Specifically, constructing occupation distance measures always involves two key steps. The first is the “vector characterization” of each occupation “in terms of underlying information on tasks or skills”. The second step consists in choosing a “measure of distance between the vectors”. Different choices in these steps can yield a wide array of distance measures (potentially equally valid), each emphasizing different dimensions of occupational skills or tasks. This section builds on prior research to contextualize, detail and justify the approach used in this study to derive novel measures of skill distances between occupations in the Italian labor market.

Vector Chracterization: Regarding the first step, vector characterization, the literature has explored two main approaches. The first, exemplified by Cortes and Gallipoli (2018) and Gathmann and Schönberg (2010), employes raw scores to represent occupational characteristics. The second approach, followed by studies such as Ingram and Neumann (2006), Guvenen *et al.* (2020), Lise and Postel-Vinay (2020), and Poletaev and Robinson (2008) involves applying transformations to the underlying data, such as principal component analysis or factor analysis. The raw-score approach offers the advantage of minimizing data manipulation, thereby preserving the integrity of the original information. In contrast, the transformation-based approach can simplify computational demands and improve the interpretability of the results by condensing complex datasets into a manageable structure.

It is worth noting, however, that selecting between these two overarching approaches does not yield a definitive method for vector characterization. Each path entails a range of nested decisions that can significantly influence the outcome. For instance, within the raw-score approach, one must determine which dimensions of occupational characteristics to include: should all available skills be considered, or only a carefully selected subset? Similarly, the transformation-based approach involves numerous methodological choices, such as choosing between PCA and factor analysis, determining the number of dimensions or factors to retain, and selecting criteria for dimensionality reduction[12].

An additional, non-trivial, decision is the selection of the level of aggregation (in terms of occupational codes) at which to compute distance measures. The finest level is, of course, determined by the underlying data, which in our case is defined at the 5-digit level. However, the hierarchical structure of occupational codes allows for aggregation by averaging relevance scores within groups, creating skill-profile vector characterizations at the 3-digit and 4-digit levels[13]. Ultimately, the choice of the "right" aggregation level depends on the focus and goals of the analysis. For our study, which examines job-to-job transitions and occupational mobility in the green transition, choosing a level of granularity that is too fine may undermine the significance of worker flows between specific occupation pairs, as similarly noted by Cortes and Gallipoli (2018). Conversely, higher levels of aggregation may dilute information about the *green* and *brown* content of occupations. To maintain flexibility, we compute distance measures at the 3-digit, 4-digit, and 5-digit levels.

As further detailed in Section 4.2 and in Appendix B, we ultimately adopt factor analysis with four factors as our preferred metric for vector characterization of occupations, aggregating information on relevance scores at the 4-digit level. However, given the specific focus of our analysis on occupational mobility within the green transition, we also consider an alternative approach based on raw scores, which emphasizes skills that are most relevant in this context by restricting the computation of distance measures to the subset of "general green skills" (see Table A4). To assess the sensitivity of the resulting distance measures to this methodological choice, we also consider a range of alternatives, including varying the number of factors as well as using raw scores to preserve the original information conveyed by the data. Our analysis reveals that the distance measures are generally robust across these alternative specifications, reinforcing confidence in the validity of the chosen approach.

Distance Measures: With regard to the choice of a distance measure, the literature can again be divided into two main approaches. The first, exemplified by Gathmann and Schönberg (2010) and Cortes and Gallipoli (2018), relies on norm angular separation (commonly referred to as cosine similarity), a measure extensively used in the trade and innovation literature. The second approach employs some form of lp-norm metric, most commonly the Manhattan distance ($l1$-norm) or the Euclidean distance ($l2$-norm).

[12] Yet another approach, successfully employed by Guvenen *et al.* (2020) to account for the fact that the scale of factor scores is somewhat arbitrary, is to transform factor scores into percentile ranks.

[13] Ideally, the 4- and 3-digit levels would account for varying employment shares within a macrogroup, using weighted averages. However, due to LFS weights only being available at the 3-digit level, we rely on simple averages.

Angular separation is frequently chosen due to its focus on differences in relative scores. This property ensures that the distance between the two vectors is zero when their scores are proportional, regardless of their magnitudes. However, such a property may be undesirable in the context of occupational distances. For example, in a transition from a junior to a senior position, where all skill requirements increase proportionally, angular separation would register no distance despite the evident need for skill adjustment. When the goal is to characterize the distance between occupations in terms of the absolute differences in required skills, lp-norm metrics are better suited, as they preserve information about the magnitude of skill requirements.

Among lp-norms, the most common choices are the Manhattan (e.g. Fredriksson *et al.* 2018; Guvenen *et al.* 2020; Macaluso 2025, and Euclidean (e.g. Fedorets 2019; Robinson 2018) distances. While there is a conceptual distinction – Manhattan distance aggregates absolute deviations linearly, whereas Euclidean distance penalizes larger deviations more heavily – the practical differences in empirical results are often minor. Given the absence of strong theoretical arguments favoring the disproportionate penalization of larger deviations (as implied by the Euclidean distance), we adopt the Manhattan distance as the main specification[14].

Weighted Measures: In addition to the two key choices regarding the approach to vector characterization and the selection of a distance metric, a final methodological consideration involves the use of weights when computing distance measures. The simplest approach assigns equal weights to all the skills or tasks considered in the distance measure. This "agnostic" method is predominant in the literature, except in studies that employ factor analysis or PCA, where weights are often derived from factor loadings. Alternatively, researchers may assign greater weights to skills deemed more relevant for the destination occupation. For instance, Bechichi *et al.* (2018) propose weights that reflect the relative importance of skills in the target role. Another approach involves accounting for differences in the costs of acquiring specific skills. For example, Neffke *et al.* (2024) uses an estimate of the years of schooling required to acquire each skill as a proxy for its acquisition cost.

To maintain the transparency of the distance measure and minimize the influence of subjective or arbitrary decisions, we adopt the unweighted approach as our main specification. However, as detailed in Section 4.2, we also explore the use of factor loadings as weights when computing distances after applying factor analysis. Importantly, we find a reassuringly high correlation between the weighted and unweighted measures, supporting the robustness of our chosen methodology.

Preferred Metric: As the last few paragraphs have highlighted, many options exist when it comes to construct a measure of skill distances between occupations. After carefully reviewing the paths that have been explored and used in the literature, the best fit for the analysis of occupational mobility in the green transition appears to be to combine factor analysis for the step on vector characterization with an (unweighted) Manhattan distance to obtain the pairwise distances. The rational for using factor analysis, as motivated by Poletaev and Robinson (2008), is the reasonable assumptions that jobs can be differentiated based on their requirements for a relatively small number of underlying skills ("factors"), and that "the relatively large number of characteristic ratings are reflections of these

[14] We also computed distance metrics using the Euclidean distance and found high correlations with the Manhattan-based measures.

underlying skills". The Manhattan distance is preferred over the Euclidean distance due to the lack of strong theoretical justification for disproportionately penalizing larger deviations. It is also favored over the Angular Separation, as differences in absolute skill requirements do matter in the context of occupational mobility.

The first step to construct our metric hence requires characterizing each occupation j in terms of a vectors of factor scores $\mathbf{R}_j$, the elements of which (R_f^j , f =1,2,...F) represent the relevance score of factor f for the generic occupation j. Factor scores are then rescaled to span across the interval 0-1, to mimic the scale of raw scores[15]. Once this is done, we then construct the measure D_{jk} of skill distance between the two generic occupations j and k by computing the rectilinean norm between the two vectors of normalized factor scores:

$$D_{jk}=\frac{1}{F}\sum_{f=1}^{F}|\tilde{R}_f^j-\tilde{R}_f^k|\,, \qquad (3)$$

where F is the chosen number of factors[16]. This procedure yields a pairwise distance measure which is correctly defined for each possible occupation pair, is symmetric, and bounded in the interval 01, with 0 reflecting the case of two perfectly similar occupations (as in the case of the distance of an occupation j to itself, D_{jj}) and 1 the (unlikely) case of a pair of occupations with diametrically opposite skill requirements. These distance measures will provide the empirical cornerstone of our analysis on job-to-job transitions and occupational mobility, the theoretical background of which is explained in the next section.

3.3 Occupational mobility in the green transition

We draw from the framework and associated gravity-like model of Cortes and Gallipoli (2018) to examine occupational mobility associated with workers transitioning between occupations in the green transition.

Their model assumes a static, partial equilibrium setting where workers, differentiated by initial occupations and selected observable characteristics, make occupational choices based on expected payoffs. Transition costs depend on task dissimilarities and fixed occupation-specific barriers. The model introduces the concept of task distance as a metric for occupational similarity, where higher distances correspond to greater task dissimilarities and higher mobility costs. The framework also incorporates fixed costs for transitioning between major task categories (e.g., routine manual to non-routine cognitive) and occupation-specific entry costs unrelated to tasks, such as licensing requirements. The authors use a log-linear specification to estimate the gravity model, regressing worker flow ratios on task distance, switching costs between task groups, and fixed effects for source and destination occupations.

Then, we adapt the estimating equation of Cortes and Gallipoli (2018) to our setting according to the following estimating equation:

[15] Specifically, defining $R_j^{max}\equiv\max\{R_f^1,R_f^2,...,R_f^N\}$ and $R_j^{min}\equiv\min\{R_f^1,R_f^2,...,R_f^N\}$ as the maximum and minimum values, respectively, taken by the scores of factor f across occupations, each factor score R_f^j is normalized as follows:

$$\tilde{R}_f^j=\frac{R_f^j-R_f^{min}}{R_f^{max}-R_f^{min}}$$

[16] There is no clear a priori consensus on the optimal choice for F, although the literature favors 3 and 4 as the most common options. Ultimately, as discussed in Section 4.2, we adopt a 4-factor decomposition.

$$\frac{\mathrm{sw}_{k,j}}{\mathrm{st}_{k,k}} = \tau_k + \alpha_j + \beta_1 \,\mathrm{SkillDist}_{k,j} + \beta_2 \,\mathrm{Green}_{j,k} \notin \mathrm{Green} + \beta_3 \,\mathrm{SkillDist}_{k,j} \times \mathrm{Green}_{j,k} \notin \mathrm{Green} + \varepsilon_{k,j} \qquad (4)$$

where $\frac{\mathrm{sw}_{k,j}}{\mathrm{st}_{k,k}}$ is the ratio of the number of switchers from origin occupation k to destination occupation j over the number of stayers in occupation k. Specifically, we compute this ratio by summing the numbers of switchers (stayers) across the years in our sample (2012-2023) and take their ratio, that is $\frac{\mathrm{sw}_{k,j}}{\mathrm{st}_{k,k}} = \frac{\sum_t \mathrm{sw}_{k,j,t}}{\sum_t \mathrm{st}_{k,k,t}}$. For clarity purposes, we multiply $\frac{\mathrm{sw}_{k,j}}{\mathrm{st}_{k,k}}$ by 100. *SkillDist*$_{k,j}$ is the skill-distance measure as defined in the previous subsection. It is then interacted with a dummy, Greenj,k/∈Green which takes value 1 if and only if the destination occupation j is green, while the origin occupation is not. We restrict the origin occupations to be not green to capture transitions towards, rather than between, green occupations. The two additional terms, τk and αj, represent origin occupation and destination occupation fixed effects. Depending on the specification of Equation [4], we include also dummies that capture whether the destination occupation is within the same 1- or 2-digit occupational macrogroup of the origin one. An error term, ϵk,j, completes the specification. β3 is the coefficient of interest, which captures the mediating role that a green destination occupation has in a transition from k to j. The intuition is to see how difficult it is to move towards a green occupation, given the skill distance between k and j and a set of fixed effects.

Conversely, we estimate the following equation as well:

$$\frac{\mathrm{sw}_{k,j}}{\mathrm{st}_{k,k}} = \tau_k + \alpha_j + \beta_1 \,\mathrm{SkillDist}_{k,j} + \beta_2 \,\mathrm{Brown}_{j,k\notin\mathrm{Brown}} + \beta_3 \,\mathrm{SkillDist}_{k,j} \times \mathrm{Brown}_{j,k\notin\mathrm{Brown}} + \varepsilon_{k,j} \qquad (5)$$

where $\mathrm{Brown}_{j,k\notin\mathrm{Brown}}$ is a dummy which takes value 1 if and only if the origin occupation k is brown, while the destination occupation is not. Again, we restrict the destination occupations to be not brown to capture transitions *away from*, rather than between, brown occupations. β_3 is still the coefficient of interest, which captures the mediating role that a brown origin occupation has in a transition from k to j. In this equation, the intuition is to see how difficult it is to move *away* from a brown occupation, given the skill distance between k and j and a set of fixed effects.

4. Results

Having outlined the key methodological steps, this section turns to the empirical findings, illustrating the main results on dynamics shaping the green transition in the labor market in Italy. Specifically, Section 4.1 begins by presenting the results on general green skills, drawing comparisons to the findings of Vona *et al.* (2018) for the U.S. labor market and introducing novel insights into the role of soft skills and general brown skills. Section 4.1 then shifts to the measurement of skill distances, exploring how occupations differ in their skill requirements and the potential challenges this poses for workforce reallocation. Lastly, 4.3 presents preliminary evidence on occupational mobility and job-to-job transitions in the Italian labor market, offering insights into the pathways and obstacles workers may face during the transition.

4.1 General Green and Brown Skills

As detailed in Section 3.1, we identify skills likely to play a prominent role in the green transition within the Italian labor market by applying the methodological framework proposed by Vona *et al.* (2018). To ensure the robustness of our results, we consider several slightly different regression specifications. From these analyses, we retain skills associated with a positive and statistically significant parameter (at the 5% level), resulting in an initial list of 46 potential General Green Skills (GGS), as shown in Table A3. To refine this list, we first exclude skills that display a significantly negative coefficient in at least one specification[17]. This step reduces the list to 40 potential GGS. Next, we impose an additional requirement: skills must exhibit a significantly positive coefficient in the majority (at least 3 out of 5) of the specifications. This results in the final set of 28 GGS, reported in Table A4. Within this final set, 14 skills are associated with a significantly positive parameter in 4 out of 5 specifications. These skills form the subset of "core" General Green Skills, representing the most robust elements of the green skills framework[18]. The details of this core set, which we manually group into broad thematic groups, are presented in Table 1.

Table 1. Core general green skills

Engineering and Technical:		
	B10	Engineering & Technology
	B11	Design
	B13	Mechanical
	G05	Estimating the Quantifiable Characteristics of Products, Events, or Information
	G21	Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment
Monitoring:		
	B29	Public Safety and Security
	G03	Monitoring Processes, Materials, or Surroundings
	G07	Evaluating Information to Determine Compliance with Standards
Operations Management:		
	B33	Transportation
	G12	Updating and Using Relevant Knowledge
	G20	Operating Vehicles, Mechanized Devices, or Equipment
Science:		
	B15	Physics
	B16	Chemistry
	B17	Biology

Note: this table presents the list of *core* GGS, i.e., skills associated with a significantly positive β parameter for "greenness" in at least four of the five specifications. This list represents the most relevant and robust subset of GGS, with the thematic grouping done manually.

Source: Author's elaborations on COB-ICP dataset 2012-2023

Our results on general green skills display a significant similarity with those provided by Vona *et al.* (2018). Out of the 14 "core skills" that we identify, 9 are also part of the list of Vona. Moreover, 13 out of the 14 general green skills identified by Vona *et al.* (2018) are included in our more general list of 28

[17] The excluded skills based on this criterion are: C20 (Equipment Selection); C28 (Repairing); C31 (Judgment and Decision Making); G19 (Working with Computers); G22 (Repairing and Maintaining Mechanical Equipment); G23 (Repairing and Maintaining Electronic Equipment).

[18] Figure A2 in Appendix B provides an illustrative example of the "robustness" of the estimates associated with core general green skills, in contrast to those related to skills identified merely as potentially green.

GGS (see Table A4), the only exception being "Providing Consultation and Advice to Others" (G38). This preliminary finding provides valuable insight into the degree of similarity in the skills required for the green transition across countries. The observed alignment between the U.S. and Italian labor markets suggests a certain degree of "universality" in the demand for general green skills across national contexts. Moreover, the similarity of results can also be seen as evidence supporting the validity of the data-driven approach used to identify the list of general green skills. This reinforces the approach's potential to inform cross-country empirical analyses, offering a robust foundation for exploring both shared and context-specific aspects of skill demands in the green transition.

An element of empirical novelty in our analysis is the investigation of the potential role of *soft skills* in the context of the green transition. This suggestion is gaining traction in surveys conducted among industry stakeholders (Czako 2022) and forward-looking analyses of current European environmental policies (García Vaquero *et al.* 2021). Without delving too deeply into the often misused or ambiguous concept of 'soft skills,' or entering the quagmire linked to its definition, for the purpose of this analysis, we identify them with the skills discussed in Section F (on *Work Styles*) of the ICP. This section focuses on personal characteristics (16 in total) that can affect job performance, rather than specific skills or tasks. Examples include traits such as an attitude towards leadership (F4), cooperation (F5), and social orientation (F6).

Using the same methodological approach as for the general green skills, we identify potentially relevant soft green skills – defined as those associated with a statistically significant positive parameter in at least one specification. This process yields a set of 8 soft skills (see Table A5). However, none of these skills satisfies the criteria used to classify general green skills, as none shows significance across the majority of specifications. This null result may be interpreted in two ways: it could indicate that hard skills are the primary determinants of success in the green transition, or it may reflect limitations in the definition and measurement of soft skills' relevance in this context. In either case, this outcome highlights the need for further research to better understand the role of soft skills in the green transition, and to refine the measurement approaches used to assess their importance.

Lastly, as described in Section 3.1, we extend our empirical investigation by applying the same methodological approach to symmetrically identify the set of General Brown Skills (GBS), defined as the most relevant skills in brown occupations. Following the same steps, we initially identify a list of 32 potential GBS, presented in Table A6. From this preliminary set, 5 skills are excluded because they exhibit a significantly negative parameter in at least one specification. Finally, by requiring skills to show a significantly positive parameter in the majority of specifications, we obtain the final list of 18 General Brown Skills, as reported in Table A7.

The most notable finding emerges when comparing the lists of General Green Skills (GGS) and General Brown Skills: 13 out of the 18 GBS are also included in the list of 28 GGS. This indicates a substantial overlap between the general skills that are highly demanded in green and brown occupations. This novel result is consistent with the findings of Vona *et al.* (2018), who note that "skill requirements of brown jobs are closer to those of green jobs than the general skill requirements of other jobs". Such findings reinforce the idea that, from a skills perspective, green and brown occupations share more similarities than might be expected.

This overlap highlights the potential to leverage similarities in skill demands to facilitate transitions from brown to green occupations, thereby minimizing adjustment costs and mitigating potentially adverse distributional consequences of the green transition. Furthermore, the comparison between GGS and GBS offers a practical framework for identifying specific skill gaps that brown workers may need to address to transition into green occupations. For instance, these preliminary results suggest training efforts might have to focus on enhancing skills related to process monitoring, as well as understanding and ensuring compliance with regulations and standards. This dual insight underscores both the opportunities and challenges in aligning workforce development strategies with the goals of a just transition.

4.2 Skill distance measures

The analysis of general green and brown skills offers valuable insights into the role of skills and the dynamics of skill demand within the green transition. However, to fully understand the labor market dynamics associated with the green transition, it is not sufficient to simply identify the skillsets likely to play a prominent role or to characterize occupations individually. A deeper understanding requires information about the extent and nature of skill differences across occupations, particularly between green and brown occupations. Specifically, it is essential to measure the degree and dimensions of skill divergence between occupations to assess the potential challenges and costs associated with reallocating workers during the transition.

As outlined in Section 3.2, the literature on skill distance metrics is still relatively new, and no universally accepted methodology has yet emerged as the gold standard for constructing pairwise measures of skill differences. This section outlines the methodological steps employed to calculate the distances that will serve as basis for our analysis and presents the key empirical findings derived from these measures.

Factor Analysis: In line with other studies on skills and skill distances (e.g., Ingram and Neumann 2006; Poletaev and Robinson 2008), our preferred metric for assessing differences in occupational skill profiles is constructed using factor analysis. This method reduces the dimensionality of the vector of relevance scores characterizing each occupation. Since there is no clear a priori determination of the optimal number of factors to retain, we explore various possibilities and apply data-driven techniques to guide this selection, as detailed in Appendix B. Ultimately, we select four factors, which collectively account for approximately 63% of the total variance.

This choice is aligned with the work of Ingram and Neumann (2006) and Poletaev and Robinson (2008), who both also opt for a 4-factors characterization. The essence of the factors that we identify is also fairly aligned with their results: the factor that explains most of the variance (about 28%) relates to analytical intelligence; the second factor (about 16%) appears to capture dexterity and fine motor skills; the third factor (about 10%) seems linked with the ability to oversee, monitor and troubleshoot; the fourth factor (about 8%) is more related to managerial abilities, such as “Monitoring and Controlling Resources”, or “Administration and Management”. Table 2 reports, for each of the four factors, the 5 skills with highest loadings into each of them.

Table 2. Factor analysis - skills with highest loadings

F1 - Analytical Intelligence		**F2 - Dexterity**	
D9A	Inductive Reasoning	D39A	Gross Body Coordination
C7A	Critical Thinking	D40A	Gross Body Equilibrium
D8A	Deductive Reasoning	D38A	Dynamic Flexibility
C8A	Active Learning	D37A	Extent Flexibility
G1A	Getting Information	D26A	Multilimb Coordination
F3 - Supervisioning		**F4 - Managing**	
C27A	Troubleshooting	G41A	Monitoring and Controlling Resources
C25A	Operation and Control	B1A	Administration and Management
C23A	Quality Control Analysis	C33A	Management of Financial Resources
C19A	Technology Design	G40A	Staffing Organizational Units
C29A	Systems Analysis	B6A	Personnel and Human Resources

Note: this table reports, for each of the first four factors extracted through factor analysis, the skills with the highest loadings. Factor names are manually assigned, reflecting a subjective interpretation of the common features shared by the skills with the highest loadings.

Source: Author's elaborations on COB-ICP dataset 2012-2023

After these four, the remaining factors contribute relatively little to explaining the total variance, and their interpretability becomes increasingly tenuous[19]. As further detailed in the next paragraphs and in Appendix B, we however find that using different number of factors ultimately leads to largely consistent results in terms of the distance measures[20]. The use of factor analysis, which significantly reduces data dimensionality, offers the additional benefit of enhancing the interpretability of results. This approach enables the decomposition of skill distance measures into their principal dimensions and facilitates graphical representations of differences between occupational skill profiles. The decomposition of distance measures and the use of visual tools can yield valuable insights by not only quantifying the extent of occupational differences but also pinpointing the specific dimensions where these differences are most pronounced. Further empirical research in this area could enhance our understanding, as such analyses have the potential to be particularly effective in identifying skill gaps and mismatches, especially between green and brown occupations. This, in turn, could offer actionable information for addressing these disparities in the context of the green transition.

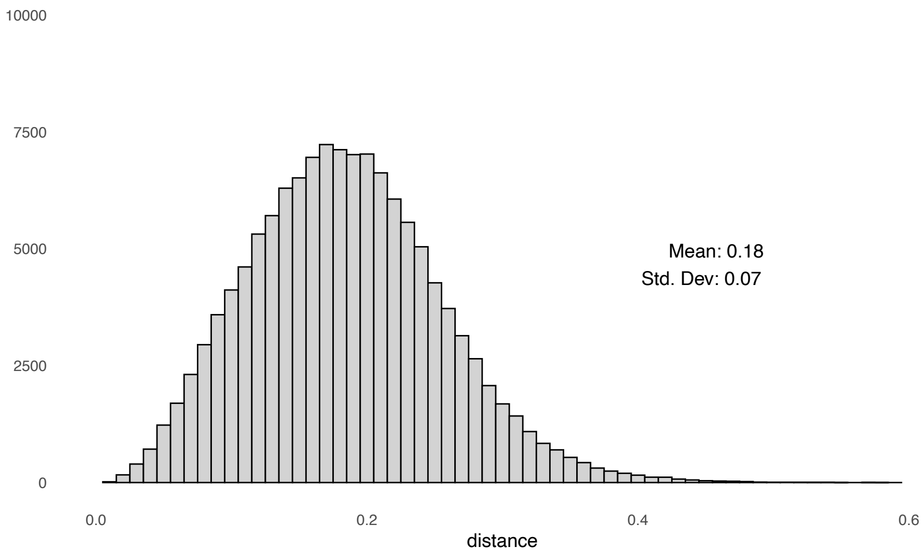
Distance Measures: Having characterized each occupation in terms of a vector of scores, we compute pairwise skill distance measures by taking the Manhattan distance (rectilinear norm) of each pair of vectors. These distances are computed at different aggregation levels (in terms of occupation codes). Since the main specification of the analysis on occupational mobility, discussed in Section 4.3, works on 4-digit occupational codes, this section will also mainly report results on skill distances computed

[19] At most, a fifth factor might be loosely interpreted as pertaining to creativity (e.g., "Thinking Creatively", "Originality"), while a sixth factor could be linked to teaching abilities (e.g., "Coaching and Developing Others", "Training and Teaching Others", "Instructing").

[20] As shown in Table B2, the correlations between distance measures obtained by varying the number of factors remain consistently high, even when considering the use of factor loadings as weights in the computation of the distance.

between 4-digit occupations. Appendix B, however, complements the discussion with results at the 5and 3-digits aggregation level. When working at the 4-digit level, the classification code for Italian occupations consists of 507 distinct occupations. Since our distance measure is symmetric (i.e. $Djk = Dkj$ for any k,j), we hence end up with a total of 128,271 pairwise skill distances – representing the distance in terms of skill profiles between each possible pair of 4-digit occupations. Figure 1 illustrates the empirical distribution of our preferred skill distance metric, which is bounded by construction between 0 (indicating perfect similarity) and 1 (indicating complete dissimilarity). The distribution is unimodal, with a mean of 0.18, a standard deviation of 0.07, a minimum value of 0.004, and a maximum value of 0.584. Metrics computed using the alternative approaches discussed in the previous sections exhibit relatively similar distributions (see Appendix B), and correlation analysis further supports the robustness of these measures to different methodological choices[21].

Figure 1. Empirical distribution of skill distance metric



Note: this histogram shows the distribution of the preferred skill distance metric, i.e., the Manhattan distances between occupations, each characterized through factor analysis as vectors of four factor scores.

Source: Author's elaborations on COB-ICP dataset 2012-2023

Nevertheless, two noteworthy patterns emerge when comparing distributions obtained adopting different approaches. First, when using raw scores, the "top-third" criterion – focusing on the most relevant skills for each occupation – yields, on average, higher skill distance values. This finding aligns with the intuition that incorporating irrelevant skills for both occupations can "dilute" the computed distances, leading to lower values under alternative methodologies. Second, skill distance metrics derived specifically from the vector of general green skills demonstrate the lowest correlations with other distance measures. This result is consistent with the green-specific focus of this metric, which

[21] See Table B1 and B2 in Appendix B. Specifically, correlations between different distance measures that rely on factor analysis are notably high, ranging from a minimum of 0.77 to 0.99. This suggests that the results are relatively robust to variations in the chosen number of factors and to whether or not the Manhattan distance is computed using factor scores as weights.

contrasts with the broader, more general perspective underpinning other measures. This finding suggests that tailoring distance metrics to the specific objectives of the analysis could be important, particularly in transition phases such as the green transition, where certain dimensions of skills may play a more prominent role in shaping occupational mobility.

A result which provides some reassuring evidence on the validity of these measures is that average distance between pairs of occupations that belong to the same 1-digit macrogroup (0.145) is significantly lower than that between pairs of occupations that belong to different macrogroups (0.192). This validity check is further confirmed by Table 3, which shows that – for each of the 8 macrogroups – distances to occupations *within* the macrogroup are always smaller that distance to occupations outside the group, and that average distances tend to be higher the further away from the diagonal – i.e. the least related the macrogroups are (as in the case, for example, of macrogroup 2 on “Professionals” and macrogroup 7, which contains “Unskilled Occupations”).

As illustrated in Appendix B, visual tools leveraging upon factor analysis and distance measures can provide valuable descriptive information on the relationship between green and brown occupations

Table 3. Average distances by macrogroups

	1	2	3	4	5	6	7	8
1	0.120							
2	0.156	0.160						
3	0.156	0.172	0.165					
4	0.148	0.170	0.161	0.096				
5	0.176	0.197	0.180	0.130	0.132			
6	0.207	0.219	0.193	0.204	0.184	0.139		
7	0.237	0.248	0.217	0.221	0.196	0.147	0.130	
8	0.224	0.239	*0.214*	0.168	0.152	0.180	0.178	0.138

Note: this table reports the average skill distances between occupations across all possible combinations of macrogroups. For example, the second row of the table shows that the average distance between occupations belonging to the first and the second macrogroups is 0.156, while the average distance within the second macrogroup is equal to 0.160. Average distances are here computed as simple averages, i.e. they are not weighted by the employment shares of occupations.

Source: Author’s elaborations on COB-ICP dataset 2012-2023

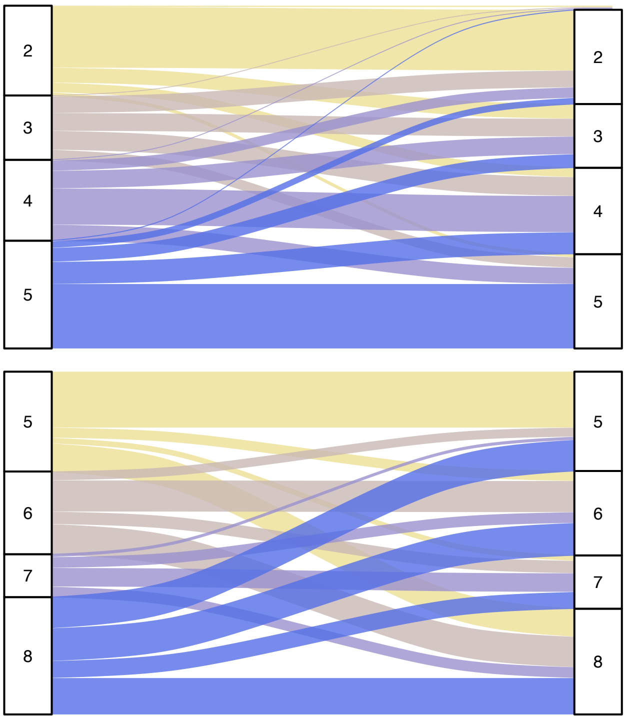
(within as well as across occupational macrogroups), for example, by providing a graphical representation of how different (similar) green jobs are to brown and to grey (i.e. neither green nor brown) jobs, and which are the dimensions along which these differences are largest (smallest). While valuable, this descriptive evidence needs to be complemented by a more analytical framework, a need which the next section addresses.

Overall, the results presented above suggest that, when combined, factor analysis and the corresponding skill distance metrics form a valuable toolset for characterizing occupations, understanding the features of occupational macrogroups, and investigating how skill gaps and overlaps along different dimensions may facilitate or impede occupational mobility within the green transition. Furthermore, the empirical findings indicate that the various distance measures employed – regardless of the specific choices made in terms of vector characterization – provide a robust and reliable framework for assessing occupational skill profiles and understanding the differences and similarities between them. This provides a solid foundation for a skill-based analysis of occupational mobility in the green transition, which is the focus of the next section.

4.3 Occupational mobility in the green transition

In the last part of the results section, we investigate occupational mobility both from a descriptive perspective and from a more formal estimation, applying Equation 4 and 5. We begin by a descriptive investigation. Specifically, Figure 2 reports two Sankey plots that visually represent the count of the job-to-job transitions between occupational macrogroups, with origin 1-digit occupation macrogroups on the left and destination ones on the right[22].

Figure 2. Job-to-job transitions between occupational macrogroups



Note: these two Sankey diagrams provide a visual representation of job-to-job transitions between occupational macrogroups. Nodes on the left and on the right represent "origin" and "destination" occupation, respectively. The bands connecting the nodes represent the flow of workers transitioning from one macrogroup to another. The width of each node is proportional to the employment share of the corresponding occupational group; the width of each band, instead, is proportional to the magnitude of the flow, indicating the volume of transitions between macrogroups. The transition counts are based on COB data from the 2009-2023 period, reflecting only workers who report a change in their 5-digit occupation codes, that is excluding workers who do not change occupations.

Source: Author's elaborations on COB-ICP dataset 2012-2023

[22] For clarity purposes, the graph has been split into two sub-plots. It is important to note that transitions also occur between macrogroups in the two separate sub-plots.

The following facts emerge. First, there is a quite high degree of mobility across macrogroups, including transitions between macrogroups quite distant from each other (i.e. from 2 to 5 and vice versa). Second, mobility across macrogroups seems higher in higher 1-digit macrogroups than lower ones (i.e. higher in 8 rather than in 2). Related to this point, it is worth remembering that the CP2011 classification is hierarchical in terms of skill requirements (i.e. classification 2 - Intellectual, scientific and highly specialized professions versus 8 - Unskilled professions).

Table 4. Skill distance and job-to-job transitions

	(1)	(2)	(3)	(4)
Skill dist.	-0.376***	-0.482***	-0.416***	-0.383***
	(0.020)	(0.020)	(0.019)	(0.018)
Num. Obs.	254,520	254,520	254,520	254,520
R2 Adj.	0.048	0.050	0.051	0.054
Dest. occ. FE	yes	yes	yes	yes
Orig. occ. FE		yes	yes	yes
Same 1D FE			yes	yes
Same 2D FE				yes

Note: the table presents the results resulting from equation 4 without including any interaction term. The skill distance measure corresponds to the one that is the combination of factor analysis with four factors and the Manhattan distance, as defined in Section 3.2. The dependent variable is the ratio of switchers over stayers for pairwise combinations of 4-digit occupations. Depending on the specification we include origin, destination, same 1- and 2-digit origin-destination occupation fixed effects. Origin occupation clustered SE. * = 0.1, ** = 0.05, *** = 0.01.

Source: Author's elaborations on COB-ICP dataset 2012-2023

Moving further, Table 4 reports the estimates associated to Equation 4 including only the skill distance measure. We use our preferred skill distance metric, that is the one resulting from the combination of factor analysis with four factors and the unweighted Manhattan distance[23]. In line with the labour economics literature that focuses on skill distance (Cortes and Gallipoli 2018; Gathmann and Schönberg 2010; Poletaev and Robinson 2008), we find that skill distance between occupations negatively correlates with the measure of occupational mobility, the ratio of switchers over stayers. Moreover, the coefficients are remarkably stable across columns, which include different sets of fixed effects.

[23] Appendix C reports the following tables with a skill distance measure that uses raw scores restricted to the subset of GGS skills.

Table 5. Skill distance and toward green job-to-job transitions

	(1)	(2)	(3)	(4)
Skill dist.	-0.386***	-0.489***	-0.423***	-0.389***
	(0.021)	(0.021)	(0.020)	(0.019)
Green	-0.038***	-0.043***	-0.043***	-0.037***
	(0.007)	(0.007)	(0.007)	(0.007)
Skill dist. * Green	0.091***	0.079***	0.078***	0.067**
	(0.028)	(0.028)	(0.028)	(0.027)
Num. Obs.	254,520	254,520	254,520	254,520
R2 Adj.	0.048	0.051	0.052	0.054
Dest. occ. FE	yes	yes	yes	yes
Orig. occ. FE		yes	yes	yes
Same 1D FE			yes	yes
Same 2D FE				yes

Note: the table presents the results resulting from equation 4. The skill distance measure corresponds to the one that is the combination of factor analysis with four factors and the Manhattan distance, as defined in Section 3.2. The green dummy takes value 1 for those transitions that go from non-green to green occupations. An occupation is defined as green if the greenness indicator, described in Section 2, is greater than zero. The dependent variable is the ratio of switchers over stayers for pairwise combinations of 4-digit occupations. Depending on the specification we include origin, destination, same 1- and 2-digit origin-destination occupation fixed effects. Origin occupation clustered SE. * = 0.1, ** = 0.05, *** = 0.01.

Source: Author's elaborations on COB-ICP dataset 2012-2023

Table 5 reports the estimation results related to Equation 4. Notably, the interaction between skill distance and the green dummy, which identifies job-to-job transitions with a non-green origin and a green destination occupation, is positive and statistically significant. This suggests that moving *toward* green occupations is relatively easier in terms of skills gap. Specifically, focusing on column (4), the coefficient of the interaction term is equal to 17.22% of the coefficient associated with the skill distance variable, indicating a non-negligible mediation effect. This correlation is net of origin and destination occupations fixed effects, as well as fixed effects that capture whether the origin and destination occupations are within the same macrogroup at the 1- and 2-digit. This correlation offers itself to, at least, the following interpretation. The interaction term between the skill distance measure and the *toward* green occupations dummy may suggest that workers, when transtitioning into green occupations, self-select into those occupations that, while green, are also less skill-distant to the destination occupation. However, this framework, *per se*, does not offer any insights into the validity of this interpretation. These are preliminary results and expanding and elaborating them represent an avenue for future research.

Table 6. Skill distance and away from brown job-to-job transitions

	(1)	(2)	(3)	(4)
Skill dist.	-0.378***	-0.485***	-0.419***	-0.385***
	(0.020)	(0.021)	(0.020)	(0.019)
Brown	-0.012	-0.035***	-0.031***	-0.020**
	(0.012)	(0.010)	(0.010)	(0.010)
Skill dist. * Brown	0.020	0.061	0.065	0.049
	(0.051)	(0.052)	(0.051)	(0.052)
Num. Obs.	254,520	254,520	254,520	254,520
R2 Adj.	0.048	0.050	0.051	0.054
Dest. occ. FE	yes	yes	yes	yes
Orig. occ. FE		yes	yes	yes
Same 1D FE			yes	yes
Same 2D FE				yes

Note: the table presents the results resulting from equation 5. The skill distance measure corresponds to the one that is the combination of factor analysis with four factors and the Manhattan distance, as defined in Section 3.2. The brown dummy takes value 1 for those transitions that go from brown to non-brown occupations. An occupation is defined as brown as described in Section 2. The dependent variable is the ratio of switchers over stayers for pairwise combinations of 4-digit occupations. Depending on the specification we include origin, destination, same 1- and 2-digit origin destination occupation fixed effects. Origin occupation clustered SE. * = 0.1, ** = 0.05, *** = 0.01.

Source: Author's elaborations on COB-ICP dataset 2012-2023

Table 6 reports the estimation results related to Equation 5. The interaction between skill distance and the brown dummy, which identifies job-to-job transitions with a brown origin and a non-brown destination occupation, is positive but not statistically significant. This suggests that moving *away* from brown occupations does not interplay with the occupation's skill distance.

5. Conclusions

This paper provides a methodological framework to investigate occupational mobility within the green transition exploiting Italian task, skills and transitions data. We identify Green General Skills within the Italian context, investigate the interplay of these and soft skills, finding a null result, and identify Brown General Skills as well. Further, we provide a detailed overview over the various possibilities a researcher faces when wants to employ a measure of skill distance. Lastly, we descriptively investigate the role of skill distance in occupational mobility, focusing on the green transition. Preliminary correlations suggest that moving *toward* green occupations alleviates the role of skill distance. A clear next step for this paper is to develop more the investigation of occupational mobility within the green transition. Why are green occupations relatively easier to access? How big is skill distance as barrier when compared to occupation specific barriers and other barriers not captured by fixed effects, such as access to cognitive occupations? These questions are left for future research.

Appendix A

General Green and Brown Skills

Table A1. Occupational groups without green occupations

CP (2D)	Occupation
11	Members of legislative and government bodies
24	Health specialists
26	Education and research specialists
41	Clerks and office machine operators
42	Money-handling and customer service clerks
44	Documentation collection, control, preservation, and delivery clerks
51	Skilled occupations in commercial activities
52	Skilled occupations in hospitality and food services
53	Skilled occupations in healthcare and social services
54	Skilled occupations in cultural services
63	Craftsmen and specialized workers in precision mechanics and artistic craftsmanship
65	Craftsmen and specialized workers in food processing, wood, textiles and clothing
82	Unskilled occupations in domestic, recreational, and cultural activities

Note: this table lists 2-digit occupational groups that do not include any occupations with a greenness score greater than zero. These groups are hence excluded from the main regression specification on general 'green' skills, which employs 2-digit occupational dummies.

Source: Author's elaborations on COB-ICP dataset 2012-2023

Table A2. Occupational groups without brown occupations

CP (2D)	Occupation
11	Members of legislative and government bodies
24	Health specialists
26	Education and research specialists
41	Clerks and office machine operators
42	Money-handling and customer service clerks
44	Documentation collection, control, preservation, and delivery clerks
51	Skilled occupations in commercial activities
52	Skilled occupations in hospitality and food services
53	Skilled occupations in healthcare and social services
54	Skilled occupations in cultural services
63	Craftsmen and specialized workers in precision mechanics and artistic craftsmanship
65	Craftsmen and specialized workers in food processing, wood, textiles and clothing
82	Unskilled occupations in domestic, recreational, and cultural activities
63	Craftsmen and specialized workers in precision mechanics and artistic craftsmanship
65	Craftsmen and specialized workers in food processing, wood, textiles and clothing
82	Unskilled occupations in domestic, recreational, and cultural activities
63	Craftsmen and specialized workers in precision mechanics and artistic craftsmanship
65	Craftsmen and specialized workers in food processing, wood, textiles and clothing
82	Unskilled occupations in domestic, recreational, and cultural activities
65	Craftsmen and specialized workers in food processing, wood, textiles and clothing
82	Unskilled occupations in domestic, recreational, and cultural activities

Note: this table lists 2-digit occupational groups that do not include any occupations with a positive brownness. These groups are hence excluded from the main regression specification on general 'brown' skills, which employs 2-digit occupational dummies.

Table A3. List of potential general green skills

Code	Skill Name
B02	Clerical
B10	Engineering and Technology
B11	Design
B12	Building and Construction
B13	Mechanical
B14	Mathematics
B15	Physics
B16	Chemistry
B17	Biology
B20	Geography
B29	Public Safety and Security
B30	Law and Government
B33	Transportation
C01	Written Comprehension
C03	Writing
C05	Mathematics
C06	Science
C17	Complex Problem Solving
C18	Operations Analysis
C19	Technology Design
C20	Equipment Selection
C21	Installation
C24	Operations Monitoring
C25	Operation and Control
C26	Equipment Maintenance
C27	Troubleshooting
C28	Repairing
C29	Systems Analysis
C30	Systems Evaluation
C31	Judgment and Decision Making
G01	Getting Information
G03	Monitoring Processes, Materials, or Surroundings
G04	Inspecting Equipment, Structures, or Materials
G05	Estimating the Quantifiable Characteristics of Products, Events, or Information
G07	Evaluating Information to Determine Compliance with Standards
G08	Processing Information
G09	Analyzing Data or Information
G10	Making Decisions and Solving Problems
G12	Updating and Using Relevant Knowledge
G19	Working with Computers
G20	Operating Vehicles, Mechanized Devices, or Equipment
G21	Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment
G22	Repairing and Maintaining Mechanical Equipment
G23	Repairing and Maintaining Electronic Equipment
G24	Documenting/Recording Information
G31	Resolving Conflicts and Negotiating with Others

Note: this table reports all skills ‘potentially’ identified as general green skills, meaning those associated with a significantly positive β parameter for “greenness” in at least one of the five considered specifications.

Source: Author’s elaborations on COB-ICP dataset 2012-2023

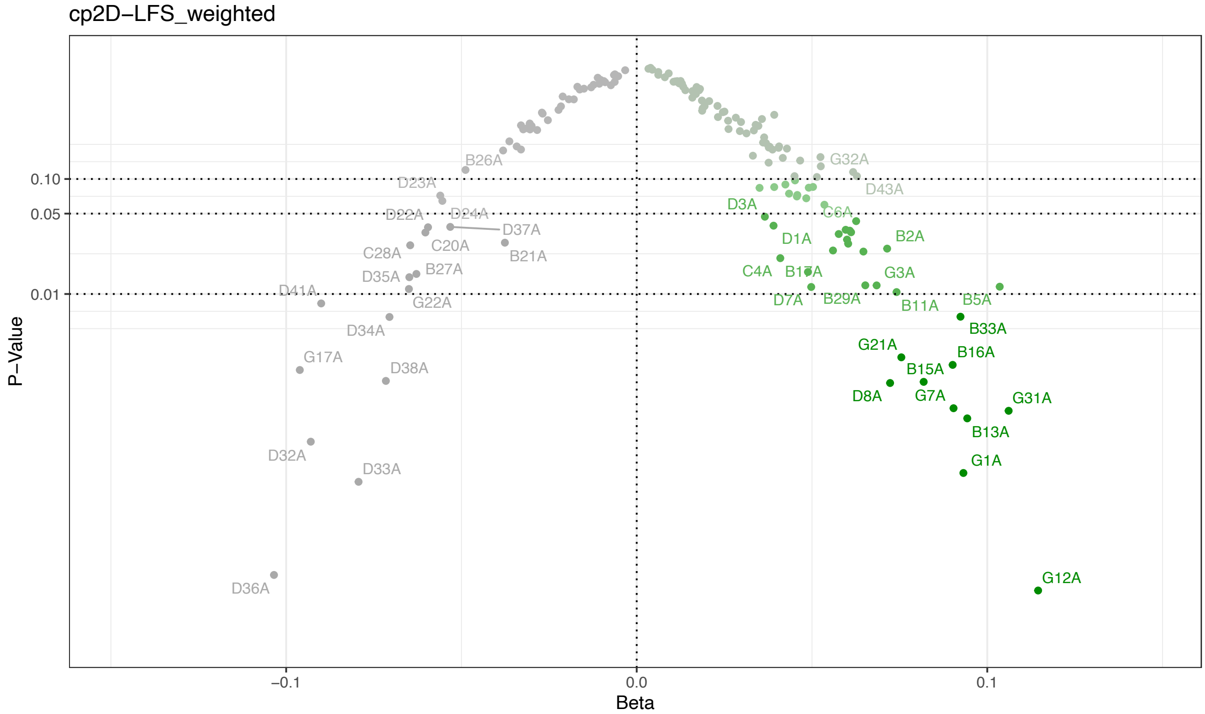
Table A4. List of general green skills

Code	Skill Name
B10	Engineering and Technology
B11	Design
B13	Mechanical
B15	Physics
B16	Chemistry
B17	Biology
B20	Geography
B29	Public Safety and Security
B33	Transportation
C01	Written Comprehension
C03	Writing
C19	Technology Design
C24	Operations Monitoring
C25	Operation and Control
C26	Equipment Maintenance
C27	Troubleshooting
C29	Systems Analysis
C30	Systems Evaluation
G01	Getting Information
G02	Identifying Objects, Actions and Events
G03	Monitoring Processes, Materials, or Surroundings
G04	Inspecting Equipment, Structures, or Materials
G05	Estimating the Quantifiable Characteristics of Products, Events, or Information
G07	Evaluating Information to Determine Compliance with Standards
G12	Updating and Using Relevant Knowledge
G20	Operating Vehicles, Mechanized Devices, or Equipment
G21	Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment
G31	Resolving Conflicts and Negotiating with Others

Note: this table presents the list of skills identified as “General Green Skills”, based on the approach outlined in Section 3.1.

Source: Author’s elaborations on COB-ICP dataset 2012-2023

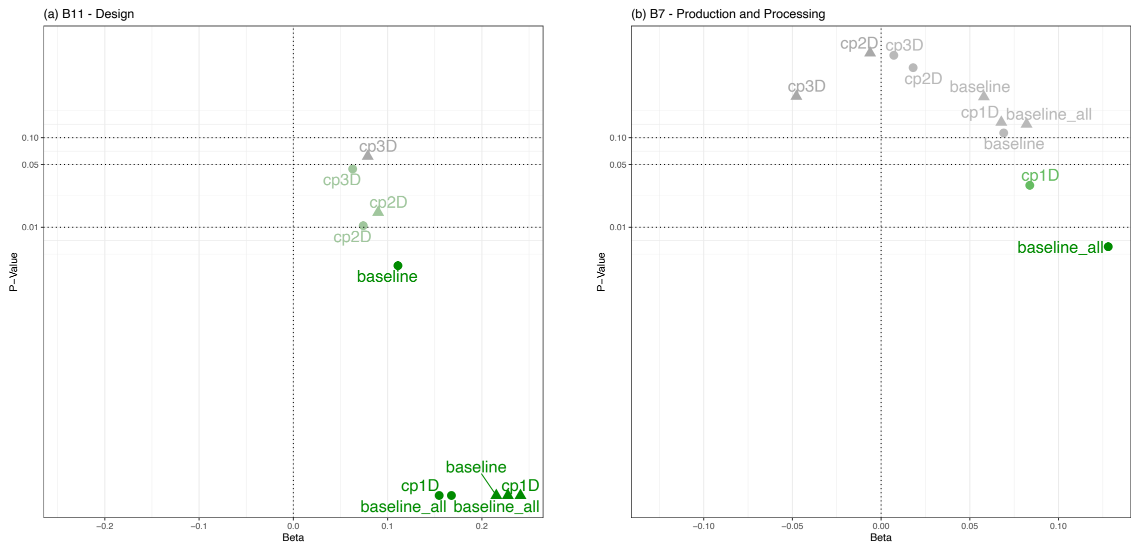
Figure A1. Point-estimate and statistical significance of β parameters



Note: this figure presents the point estimates of the Beta parameters (x-axis) and their corresponding p-values (y-axis) for the main specification. Skills associated with higher intensity of use in greener occupations (i.e., β > 0) are highlighted in green, with increasingly darker shades representing higher levels of statistical significance.

Source: Author's elaborations on COB-ICP dataset 2012-2023

Figure A2. Beta parameters for a "Core" and a "Potential" General Green Skill



Note: this figure illustrates a comparison of the distributions of the point estimates (x-axis) and p-values (y-axis) of the Beta parameters across various specifications for Skill B11 (Design), categorized within the "Core Green Skills," and Skill B7 (Production and Processing), initially identified as a potential green skill but subsequently excluded based on the criteria outlined in Section 3.1. The figure reports results from both weighted and unweighted regressions, which are depicted using circles and triangles, respectively.

Source: Author's elaborations on COB-ICP dataset 2012-2023

Table A5. List of potential soft green skills

Code	Skill Name
F01	Achievement/Effort
F03	Initiative
F04	Leadership
F12	Attention to Detail
F13	Integrity
F14	Independence
F15	Innovation
F16	Analytical Thinking

Note: this table reports all soft skills identified as "potentially" relevant for the green transition. However, as illustrated in Section 4.1, none of these skills meets the main criteria to ultimately be classified as a general green skill.

Source: Author's elaborations on COB-ICP dataset 2012-2023

Table A6. List of potential general brown skills

Code	Skill Name
B06	Personnel and Human Resources
B07	Production and Processing
B10	Engineering and Technology
B11	Design
B12	Building and Construction
B13	Mechanical
B15	Physics
B16	Chemistry
C06	Science
C10	Monitoring
C18	Operations Analysis
C19	Technology Design
C20	Equipment Selection
C21	Installation
C23	Quality Control Analysis
C24	Operations Monitoring
C25	Operation and Control
C26	Equipment Maintenance
C27	Troubleshooting
C28	Repairing
C29	Systems Analysis
C30	Systems Evaluation
C34	Management of Material Resources
C35	Management of Personnel Resources
G03	Monitoring Processes, Materials, or Surroundings
G04	Inspecting Equipment, Structures, or Materials
G05	Estimating the Quantifiable Characteristics of Products, Events, or Information
G18	Controlling Machines and Processes
G20	Operating Vehicles, Mechanized Devices, or Equipment
G21	Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment
G22	Repairing and Maintaining Mechanical Equipment
G36	Guiding, Directing, and Motivating Subordinates

Note: this table reports all skills "potentially" identified as general browns skills, meaning those associated with a significantly positive β parameter for "brownness" in at least one of the five considered specifications.

Source: Author's elaborations on COB-ICP dataset 2012-2023

Table A7. List of general brown skills

Code	Skill Name
B06	Personnel and Human Resources
B07	Production and Processing
B10	Engineering and Technology
B11	Design
B12	Building and Construction
B13	Mechanical
B15	Physics
B16	Chemistry
G20	Operating Vehicles, Mechanized Devices, or Equipment
G21	Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment
G22	Repairing and Maintaining Mechanical Equipment
G36	Guiding, Directing, and Motivating Subordinates
G20	Operating Vehicles, Mechanized Devices, or Equipment
G21	Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment
G22	Repairing and Maintaining Mechanical Equipment
G36	Guiding, Directing, and Motivating Subordinates
G22	Repairing and Maintaining Mechanical Equipment
G36	Guiding, Directing, and Motivating Subordinates

Note: this table presents the list of skills identified as “General Brown Skills”, based on the methodological approach outlined in Section 3.1.

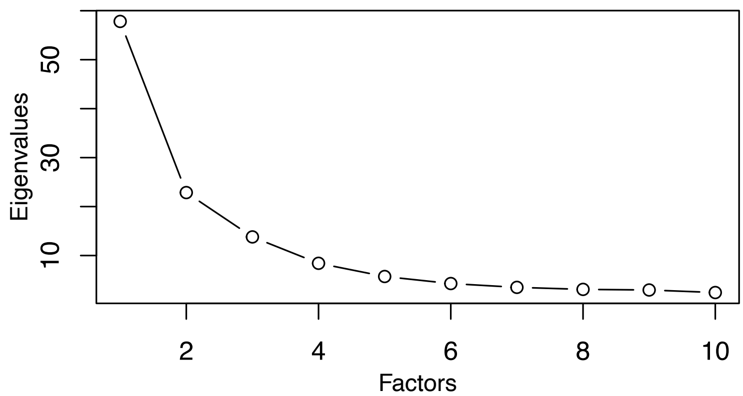
Source: Author’s elaborations on COB-ICP dataset 2012-2023

Appendix B

Skill distance measures

For the computation of skill distance measures, as mentioned in Section 2, we start by the raw scores measuring relevance scores across all items listed in Section B, C, D and G of the ICP. Section D, which covers individual characteristics that are stable over time and difficult to modify, is excluded from the analysis of general green and brown skills, as these traits are less relevant to skill adjustments and retraining. However, precisely because these traits are hard to change, they significantly impact adjustment costs and can act as barriers to occupational transitions and are therefore included in the computation of skill distance measures. Section G - which formally refers to tasks and activites rather than skills - is also included because, as suggested by the framework developed by Yamaguchi (2012), "observed tasks can be interpreted as a noisy signal of unobserved skills".
In total, these sections report scores on 161 skill dimensions. As noted by Ingram and Neumann (2006), it is unlikely that each dimension corresponds to a distinct worker skill trait. Therefore, we apply factor analysis to reduce the dimensions. Since there is no clear a priori guidance on the number of factors to extract, we determine this ex-post in a data-driven manner. Due also to the large number of variables (161 traits for 796 occupations), the factor analysis yields many potentially relevant factors. Specifically, applying the standard Kaiser criterion (retaining factors with eigenvalues > 1) would suggest retaining 17 factors, leading to a complex structure with many minor and likely uninterpretable factors. Even with a higher eigenvalue threshold ($\lambda > 2$), we would retain 12 factors. Therefore, we rely on the Scree Plot, a somewhat subjective but generally accepted approach, to determine the most appropriate number of factors.

Figure B1. Scree Plot

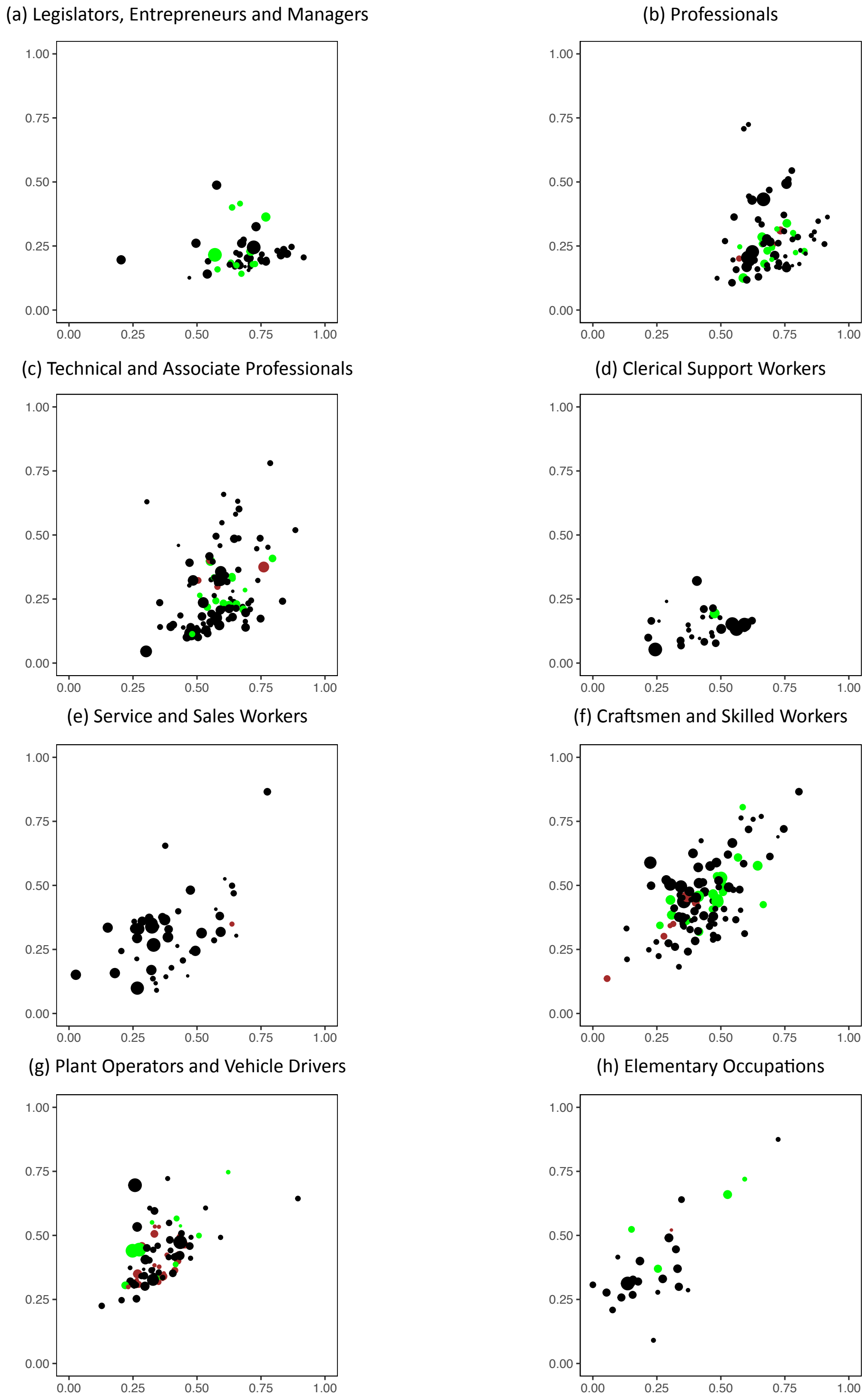


Note: the Scree plot displays the eigenvalues of the factors, ordered from largest to smallest.

Source: Author's elaborations on COB-ICP dataset 2012-2023

While no distinct "elbow" is evident in the graph, two inflection points can be observed: one at $F = 2$ and a more subtle one at $F = 4$. Retaining only two factors to explain skill heterogeneities appears too parsimonious and would likely result in the loss of important information. In line with the literature on skill distances, we hence choose $F = 4$ as our preferred specification.

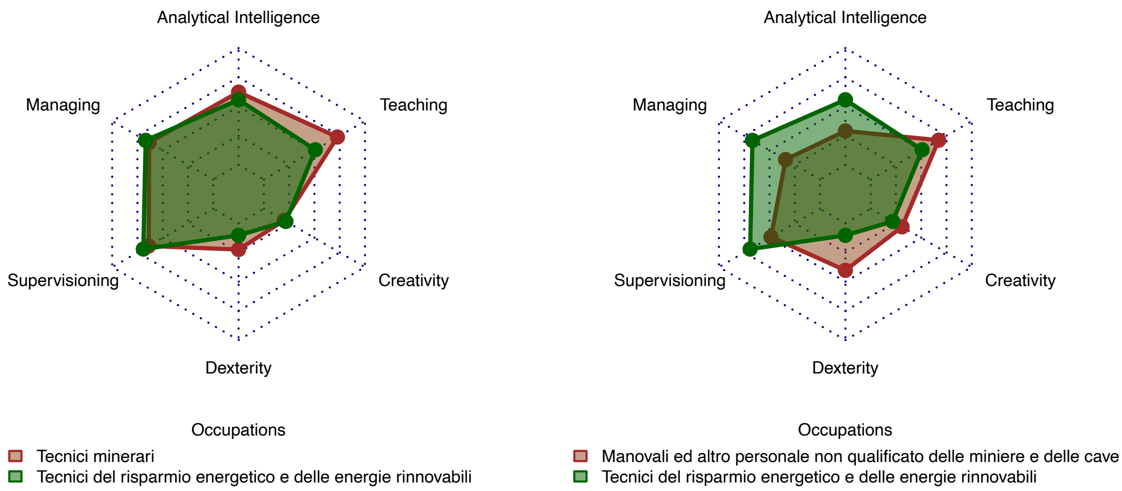
Figure B2. Distribution of factor scores across occupational groups



Note: this figure displays the distribution of scores for the first two principal factors: Factor 1 (related to analytical intelligence, shown on the x-axis) and Factor 2 (associated with dexterity and physical skills, shown on the y-axis) across the 8 broad 1-digit occupational macrogroups. Each dot represents an occupation, with dot sizes proportional to the relative share of the occupation within its respective macrogroup. Occupations classified as green 8 (i.e. greenness> 0) or brown are highlighted using their respective colors.

Source: Author's elaborations on COB-ICP dataset 2012-2023

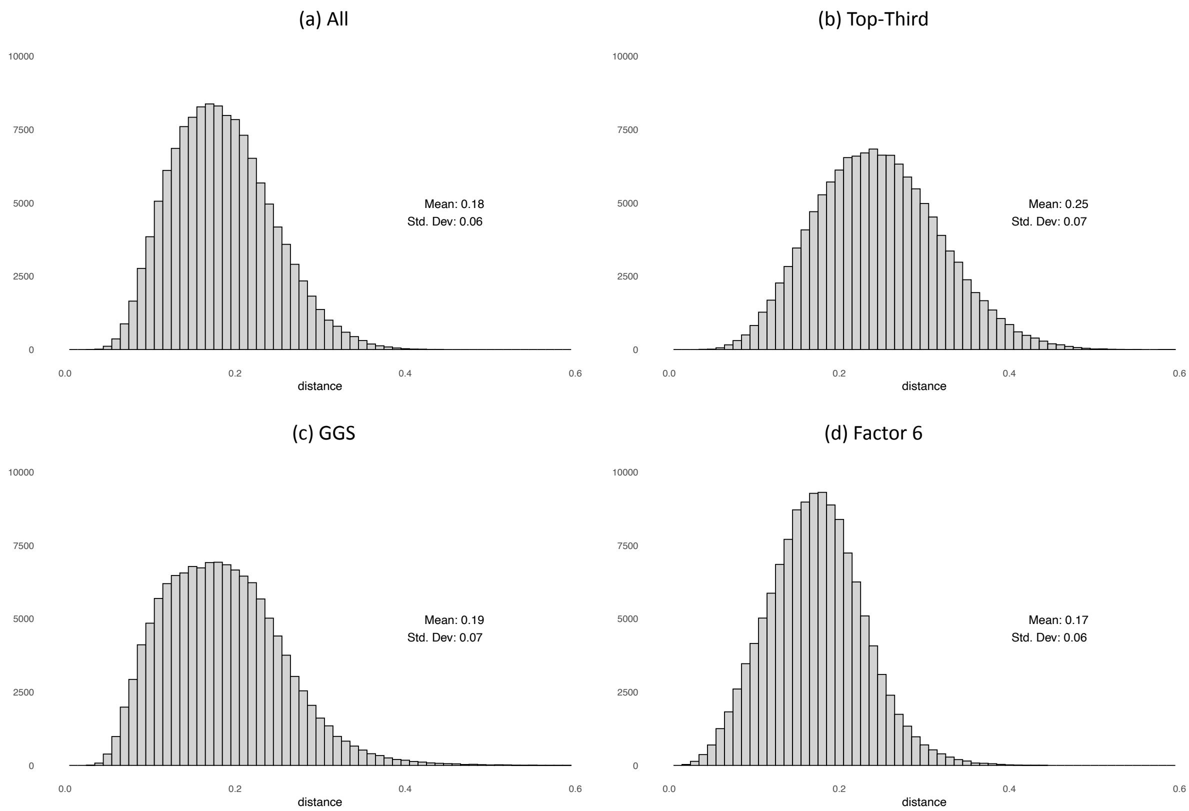
Figure B3. Example of radar charts for skill profiles comparison



Note: these two radar charts serve as a graphical tool to visualize the differences and similarities in skill profiles. The figure on the left compares the skill profile of a green occupation (Energy-saving and Renewable-Energy Technician) to a brown occupation (Mining Technician), which appears relatively similar in terms of skills. The figure on the right, in contrast, compares the same green occupation to another brown occupation (Unqualified Personnel in Mines and Quarries), highlighting the key dimensions where their skill requirements differ.

Source: Author's elaborations on COB-ICP dataset 2012-2023

Figure B4. Empirical distributions of skill distances



Note: this figure presents the histograms referring to the empirical distribution of skill distance measures under the four main alternative specifications we examine to test the robustness of our preferred metric.

Source: Author's elaborations on COB-ICP dataset 2012-2023

Table B1. Correlation between skill distance measures

	all	top33	GGS	F4	F5	F6
all	1	0.89	0.76	0.85	0.82	0.78
top33	0.89	1	0.63	0.77	0.75	0.72
GGS	0.76	0.63	1	0.66	0.61	0.57
F4	0.85	0.77	0.66	1	0.92	0.86
F5	0.82	0.75	0.61	0.92	1	0.93
F6	0.78	0.72	0.57	0.86	0.93	1

Note: this table reports the Pearson correlation coefficient between pairwise skill distance measures (for 4-digit occupations), computed using different approaches for vector characterization. The "all," "top33," and "GGS" criteria use raw scores: "all" considers all skill dimensions, "top33" dynamic all select – for each pair of occupations – only skills that are most relevant (i.e. in the top tertile of the distribution), and "GGS" restricts the analysis to the list of "General Green Skills". The remaining columns rely on factor analysis, with the only difference being the number of factors used: F4, F5, and F6 represent specifications with 4, 5, and 6 factors, respectively.

Source: Author's elaborations on COB-ICP dataset 2012-2023

Table B2. Correlation between skill distances based on factor analysis

	4F	5F	6F	4F-W	5F-W	6F-W
4F	1	0.92	0.85	0.90	0.88	0.89
5F	0.92	1	0.93	0.84	0.86	0.87
6F	0.85	0.93	1	0.77	0.79	0.83
4F-W	0.90	0.84	0.77	1	0.99	0.98
5F-W	0.88	0.86	0.79	0.99	1	0.98
6F-W	0.89	0.87	0.83	0.98	0.98	1

Note: this table reports the Pearson correlation coefficient between pairwise skill distance measures computed using slightly different approaches for factor analysis. Specifically, the columns represent distance measures obtained with varying numbers of factors (4, 5, or 6) and whether factor loadings are used as weights to compute the Manhattan distance (with columns labeled "W" indicating weighted distance measures).

Source: Author's elaborations on COB-ICP dataset 2012-2023

Table B3. Most similar occupation pairs

Occupation 1	Occupation 2
Systems Designers and Administrators	Software Analysts and Designers
Researchers and Graduates in Engineering Sciences	University Professors in Engineering Sciences
Furriers and Fur Modelers	Tailors, Modelers, and Milliners
Reinforced Concrete Bricklayers	Stone and Brick Masons
General Managers in Trade Companies	Managers of Large Companies in Logistics
Executives in Central Administrations	General and Departmental Directors
Travel Agency Clerks	Travel Agents
University Professors in Law and Social Sciences	University Professors in History & Philosophy
Managers of Small Companies in Social Assistance	Managers of Large Companies in Social Assistance
Managers of Large Companies in Logistics	Managers of Large Trade Companies

Note: this table reports the 10 most similar 4-digit occupation pairs in ascending distance order (i.e., starting with the lowest distance) based on our distance metric.

Source: Author's elaborations on COB-ICP dataset 2012-2023

Table B4. Most different occupation pairs

Occupation 1	Occupation 2
Animal-drawn Vehicle Operators	University Professors in Engineering Sciences
Boiler and Nautical Equipment Operators	Ambassadors, Ministers, and Senior Diplomats
Steam Boiler and Thermal Engine Operators	Retail Sales Clerks
Street Vendors	Steam Boiler and Thermal Engine Operators
Dairy Product Preparation Workers	Divers and Underwater Workers
Unskilled Fishing and Aquaculture Workers	Protocol and Document Sorting Clerks
Retail Sales Clerks	Aircraft Commanders and Pilots
Stage Machinists and Technicians	Dairy Product Preparation Workers
Switchboard Operators	University Professors in Life and Earth Sciences
Electronic Device Maintenance Workers	Athletes

Note: this table reports the 10 most different 4-digit occupation pairs in descending distance order (i.e., starting with the highest distance) based on our distance metric.

Source: Author's elaborations on COB-ICP dataset 2012-2023

Appendix C

Job-to-Job Mobility

Table C1. Skill distance and job-to-job transitions. GGS

	(1)	(2)	(3)	(4)
Skill dist.	-0.378***	-0.514***	-0.445***	-0.411***
	(0.020)	(0.021)	(0.020)	(0.020)
Num. Obs.	254,520	254,520	254,520	254,520
R2 Adj.	0.048	0.051	0.052	0.054
Dest. occ. FE	yes	yes	yes	yes
Orig. occ. FE		yes	yes	yes
Same 1D FE			yes	yes
Same 2D FE				yes

Note: the table presents the results resulting from equation 4 without including any interaction term. The skill distance measure corresponds to the one that is the combination of raw scores based on GGS and the Manhattan distance, as defined in Section 3.2. The dependent variable is the ratio of switchers over stayers for pairwise combinations of 4-digit occupations. Depending on the specification we include origin, destination, same 1- and 2-digit origin-destination occupation fixed effects. Origin occupation clustered SE. * = 0.1, ** = 0.05, *** = 0.01.

Source: Author's elaborations on COB-ICP dataset 2012-2023

Table C2. Skill distance and toward green job-to-job transitions. GGS

	(1)	(2)	(3)	(4)
Skill dist.	-0.380***	-0.519***	-0.449***	-0.415***
	(0.020)	(0.022)	(0.021)	(0.020)
Green	-0.029***	-0.035***	-0.036***	-0.030***
	(0.008)	(0.008)	(0.008)	(0.008)
Skill dist. * Green	0.026	0.069**	0.066**	0.057*
	(0.033)	(0.030)	(0.030)	(0.029)
Num. Obs.	254,520	254,520	254,520	254,520
R2 Adj.	0.048	0.051	0.052	0.054
Dest. occ. FE	yes	yes	yes	yes
Orig. occ. FE		yes	yes	yes
Same 1D FE			yes	yes
Same 2D FE				yes

Note: the table presents the results resulting from equation 4. The skill distance measure corresponds to the one that is the combination of raw scores based on GGS and the Manhattan distance, as defined in Section 3.2. The green dummy takes value 1 for those transition that go from non-green to green occupations. An occupation is defined as green if the greenness indicator, described in Section 2, is greater than zero. The dependent variable is the ratio of switchers over stayers for pairwise combinations of 4digit occupations. Depending on the specification we include origin, destination, same 1- and 2-digit origin-destination occupation fixed effects. Origin occupation clustered SE. * = 0.1, ** = 0.05, *** = 0.01.

Source: Author's elaborations on COB-ICP dataset 2012-2023

Table C3. Skill distance and away from brown job-to-job transitions GGS.

	(1)	(2)	(3)	(4)
Skill dist.	-0.378***	-0.515***	-0.447***	-0.412***
	(0.020)	(0.022)	(0.021)	(0.020)
Brown	-0.001	-0.027**	-0.023**	-0.013
	(0.013)	(0.011)	(0.011)	(0.012)
Skill dist. * Brown	0.000	0.041	0.042	0.025
	(0.054)	(0.052)	(0.052)	(0.053)
Num. Obs.	254,520	254,520	254,520	254,520
R2 Adj.	0.048	0.051	0.052	0.054
Dest. occ. FE	yes	yes	yes	yes
Orig. occ. FE		yes	yes	yes
Same 1D FE			yes	yes
Same 2D FE				yes

Note: the table presents the results resulting from equation 5. The skill distance measure corresponds to the one that is the combination of raw scores based on GGS and the Manhattan distance, as defined in Section 3.2. The brown dummy takes value 1 for those transitions that go from brown to non-brown occupations. An occupation is defined as brown as described in Section 2. The dependent variable is the ratio of switchers over stayers for pairwise combinations of 4-digit occupations. Depending on the specification we include origin, destination, same 1- and 2-digit origin-destination occupation fixed effects. Origin occupation clustered SE. * = 0.1, ** = 0.05, *** =0.01.

Source: Author’s elaborations on COB-ICP dataset 2012-2023

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INAPP
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