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Lost in the green transition? Measurement and stylized facts

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ABSTRACT/RÉSUMÉ

Greening the economy entails jobs contracting in “high-polluting” economic activities and expanding in environment-friendly activities. Minimizing the corresponding transition costs is crucial to accelerate decarbonisation and reduce displacement costs for affected workers. Using individual-level labour force data for a large sample of European countries, this paper finds that the shares of green and high-polluting jobs remained approximately stable between 2009 and 2019, hinting at a slow or yet-to-come green transition in labour markets. Green and high-polluting jobs are unequally distributed across socioeconomic groups: women are under-represented in both green and high-polluting jobs, while green jobs are associated with higher educational attainment, and high-polluting jobs with lower educational attainment. Equally important from a policy perspective, the results show that high-polluting jobs are concentrated in rural areas. These results are confirmed by analyzing labour market transitions: for instance, while women are more likely to transition from study to job, they are significantly less likely to get a green job. Overall, the results suggest that well designed and targeted policies are needed to support efficient and inclusive labour market transitions in the greening economy: to minimize scarring effects for displaced workers, help individuals’ upskilling and reskilling, and support the matching between workers and jobs in higher demand.

JEL: H12, H23, I3, Q41, Q48

Keywords: green transition, labour markets, policy analysis.

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La transition climatique nécessite une contraction des emplois dans les activités plus polluantes et une expansion des emplois dans l’économie dite « verte ». Il est essentiel de minimiser les coûts de cette transition pour accélérer la décarbonation et réduire son impact pour les populations et territoires concernés. En utilisant des données individuelles par travailleur pour un large échantillon de pays européens, cet article constate une stabilité de la part des emplois verts et très-polluants entre 2009 et 2019, ce qui laisse présager une transition verte lente ou encore à venir sur le marché du travail. L’analyse des données individuelles montre que les emplois très polluants et verts sont très inégalement répartis au sein de la population: par exemple, les femmes sont sous-représentées dans les emplois verts et très polluants, tandis que les emplois verts sont associés à un niveau d'éducation plus élevé et les emplois très polluants à un niveau d'éducation plus faible. En outre, les emplois très polluants sont concentrés dans les zones rurales. Ces résultats sont confirmés par une analyse fine des transitions vers une économie plus verte sur le marché du travail: par exemple, alors que les femmes sont généralement plus susceptibles d’obtenir un emploi à la fin de leurs études, elles sont nettement moins susceptibles d'obtenir un emploi vert. Les résultats de cette étude suggèrent que les politiques publiques ont un rôle crucial à jouer pour accompagner une transition climatique efficace et inclusive: pour minimiser les couts auprès des populations et territoires les plus exposés, pour encourager les qualifications et le redéploiement des travailleurs, notamment des plus fragiles, vers les métiers verts en croissance.

JEL: H12, H23, I3, Q41, Q48

Mots clés: Transition écologique, marché du travail, analyse des politiques.

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Orsetta Causa, Emilia Soldani, and Maxime Nguyen[1]

Introduction

Climate change is a major threat to economic growth and wellbeing: its recognition and the desire to mitigate its consequences are progressively inducing consumers, producers and policy makers to shift behaviour, in an effort to build more sustainable and environmentally friendly societies and economies. Such shift, generally indicated as *green transition,* will require ambitious policies and a move away from polluting activities towards more sustainable and environmentally friendly ones. As a consequence, labour demand will likely increase for certain occupations, referred to as "green jobs", and decrease for others, referred to as "brown" or "high-polluting". While the economic impacts of the transition will vary depending on country-specific context, challenges and policies implemented, significant shifts in employment and reallocations are likely to be necessary.[2]

Well-designed polices can and should mitigate transition costs, to pursue environmental objectives while anticipating and addressing possible risks of exacerbating economic, territorial, and social inequalities. One major area of policy concern pertains to the labour market implications of the green transition. This requires a careful assessment of exposure among different categories of workers, for instance to identify those facing the highest risk of dismissal, and how their likelihood of re-employment can be improved, minimising potential scarring effects. A pre-condition for this assessment is the existence of a transparent and methodologically robust definition of green and high-polluting jobs, which is currently hindered by important gaps in statistics and data sources. These "technical" issues can have a significant impact on the overall assessment and therefore the policy implications of the green transition on labour markets.

This paper develops a coherent characterization of "green" and "high-polluting" jobs across a large sample of European countries, providing an empirically robust basis to elaborate appropriate policy strategies for "fair" transition away from high-polluting production models. To ease the exposition, green jobs indicate the occupations that, irrespective of their actual impact on the environment, involve green tasks and are hence expected to face increased demand as a result of the green transition. Similarly, high-polluting jobs indicate the occupations that are over-represented in economic sectors producing large shares of air

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[2] See OECD work by e.g. Borgonovi et al. (2023) and Bibas et al. (2018) for ex-ante simulations of the likely effect of the transition under alternative scenarios.

polluting emissions.[3] Applying a mix of well established and novel data-driven definitions, the first step is to characterize green and high polluting jobs in terms of their prevalence over time and across different categories of workers, identified by characteristics such as gender, age, education, and place of residence. The second step is to zoom in on workers' transitions from non-employment to green jobs and from high-polluting jobs to unemployment, including possible displacement-driven scarring effects.

In a literature characterized by country-specific definitions and analysis, an important contribution of this study is the adoption of a cross-country view, which requires an harmonized definition of green and high-polluting jobs beyond national borders.[4] The characterization of high-polluting jobs applies a new methodology, developed in Causa et al. (2024 forthcoming), which delivers a country-specific list of high-polluting industries and occupations. In the absence of EU-specific definitions of green tasks and occupations, the analysis of green jobs follows the standard approach in the literature, which consists in cross-walking a well-established US-based taxonomy of green jobs to international data. The current paper however proposes a revised and improved cross-walk to map the US-based taxonomy to EU labour force data.

Sections 1 and 2 elaborate the approach to measure green and high-polluting jobs. Section 3 briefly presents the data exploited in the analysis. Section 4 provides stylized facts about green and high-polluting jobs: across countries. over time, and across socio-economic groups. Section 5 zooms in on workers' transitions from non-employment to green jobs and from high-polluting jobs to unemployment. Section 6 wraps-up the evidence and concludes the paper with policy considerations.

1. Green jobs

The measurement framework to assess the "greenness" of jobs has developed at a fast pace over the recent years. Despite the progress achieved, there is not yet an official and uncontroversial international definition of what "green" jobs are, let alone how many of those jobs there are and may be in the future.

The most commonly used definition draws on pioneering work by the U.S. O*NET Green Task Development Project (O*NET , 2010). O*NET classifies occupations affected by the green transition in three categories based on the required changes in their tasks: 1) Green new and emerging: new occupations with unique tasks and worker requirements (e.g., wind energy engineers or solar photovoltaic installers, for whom all tasks are 'green'); 2) Green-enhanced skills: existing occupations requiring new tasks, skills and knowledge (e.g., general and operations managers for whom new green tasks relate to managing the sustainability of operations); 3) Green increased demand: existing occupations in increased demand due to the green transition but with no significant changes in tasks or worker requirements. While the first two categories can be considered directly green as they explicitly involve green tasks, the third is

[3] Both concepts are defined in greater detail below. The literature alternatively refers to these categories as green-task or green-driven and brown jobs.

[4] On the US, inter alia, see Vona et al. (2018), Bowen et al. (2018), Bergant et al. (2022), Saussay et al. (2022) and more recently Hanson (2023). There is also a relevant literature on the United Kingdom, for example Valero et al. (2021) and Office for National Statistics ongoing work ONS (2023); as well as papers on other countries such as Germany (in particular forthcoming work in this area for the next Economic Survey of Germany (Barreto Sanchez, Krill, & Grundke, 2023), France on the manufacturing sector (Dussaux, 2020) and the Netherlands on eco-innovation and employment (Elliott, Kuai, Maddison, & Ozgen, 2021). A few studies used aggregate labour force statistics to provide cross-country evidence: see Dechezlepretre et al. (2020) for a study on the manufacturing sector, Tyros et al. (2023) and more recently, related cross-industry work Frohm et al. (2023). These studies are insightful, but relatively limited in scope, due to the aggregate nature of the data. The main micro-based cross-country analysis today is Bluedorn et al. (2022).

considered indirectly green according to O*NET (e.g., chemists and materials scientists) and is therefore not considered in the taxonomy developed here.[5] In addition, O*NET also compiles a detailed list of all tasks involved in each green occupation and indicates which tasks are green (green tasks are defined as aimed at reducing the environmental impact of human activities). Based on this list, it is possible to further define the list of green occupations, by only considering as green those for which at least 10% of all tasks are green (as in Tyros et al. (2023)and OECD (2023)). This taxonomy has been widely applied in the literature, starting with seminal work by Vona et al. (2018).

The European Commission is working on a similar taxonomy of green occupations for E.U. member countries, which in the near future may result in a list of jobs which, based on the characteristics of E.U.-labour markets, can be considered green.[6] In the absence of such E.U.-based taxonomy, the present analysis follows the common approach in the literature, applying the U.S.-based O*NET taxonomy to other countries ((IMF, 2022), (Scholl, Turban, & Gal, 2023), (Tyros, Andrews, & De Serres, 2023)). This requires appropriate crosswalks and adjustments, since O*NET uses U.S. Standard Occupational Classification (SOC) at the 8-digit level, while labour force survey data for European countries report workers' occupations according to the International Standard Classification of Occupations (ISCO) at the more aggregated 3-digit level. The difference in classification and granularity raises mapping, weighting, and aggregation issues. The mapping is notably complex due to the 'many to many' correspondences – i.e., SOC occupations tend to be mapped to more than one ISCO occupation and vice versa, raising a "double counting" risk.[7]

The current analysis develops a methodology to neutralise the risk of double counting and reducing measurement errors when mapping O*NET's U.S.-based green jobs taxonomy to EU labour force data. In a nutshell, it builds on a crosswalk and weighting exercise from SOC 8-digit to ISCO 3-digit to assign to each ISCO 3-digit occupation a green score between zero and one, based on the employment share of green occupations among the underlying SOC 8-digit ones. The score takes the value 1 if all underlying SOC 8-digit occupations are green and zero if none of them is. The logic and key steps of the exercise are presented in Figure 1 and can be summarised as follows. The starting point is a list of (directly) green SOC 8-digit occupations with a non-negligible share of green tasks, based on O*NET classification. This is aggregated to U.S. SOC 6-digit by computing the share of green 8-digit occupations in each SOC 6-digit.[8] At this point, an official crosswalk from U.S. SOC 6-digit to ISCO 4-digit occupations, prepared by the Bureau of Labour Statistics, is applied.[9] The idea is to assign to each 4-digit ISCO occupation the average of the green scores of the corresponding SOC 6-digit occupations. However, the crosswalk features several many-to-many correspondences. To deal with these, in taking the average each SOC 6-digit occupation is weighted by its share of employed workers over the total number of workers in all occupations

[5] For an application of a broad definition of green jobs, i.e., that focuses on all three categories, including green increased demand jobs that do not involve green tasks, see (Valero, et al., 2021).

[6] More details on the ongoing work from the European Commissions can be found on the official webpage: https://ec.europa.eu/newsroom/empl/items/741088/en.

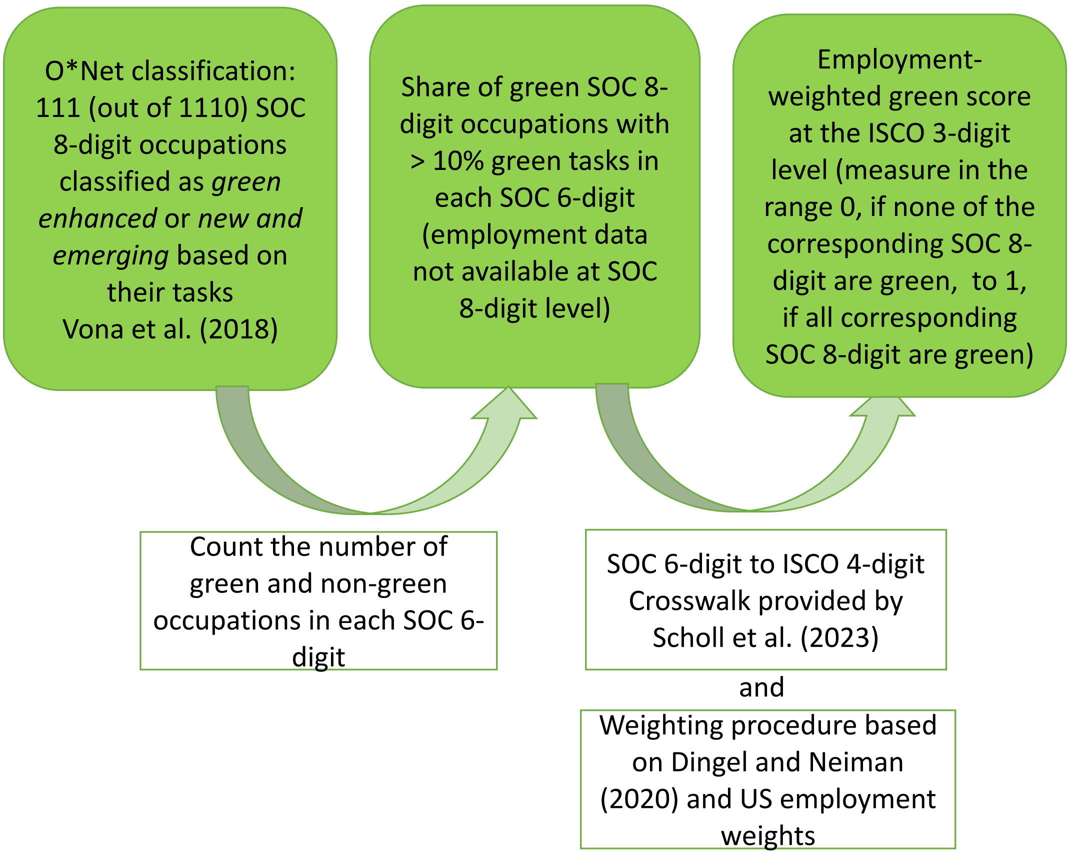
[7] This issue has been discussed by Vona himself in (JRC, 2021) and in few papers e.g., (Valero, et al., 2021).

[8] Starting from O*NET initial list of SOC 8-digit green occupation, all those with over 90% non-green tasks are considered as not green. Going from 8 to SOC 6-digit is necessary because this is the most granular level of available US employment data. Employment-weighted metrics cannot be computed because employment data at SOC 8-digit level are not available. In each in each SOC 6-digit occupation, the share of green occupations is therefore computed as the number of green SOC 8-digit divided by the total number of SOC 8-digit occupations.

[9] This official crosswalk can be accessed at https://www.bls.gov/soc/soccrosswalks.htm. To reflect changes in the economy and the nature of work, the SOC system is periodically revised. The O*NET taxonomy of green occupations used in this analysis uses the SOC 2010 classification. In 2018, a new SOC classification (referred to as SOC 2020) was introduced, which can be mapped to ISCO through a new cross-walk, released in 2020 (https://www.bls.gov/soc/2018/#crosswalks). Applying the 2022 cross-walk to O*NET list of green occupations is possible, but requires an additional step to convert SOC 2010 occupations into SOC 2018. At the ISCO 3-digit level, the two alternative cross-walks yield widely comparable results.

mapped into the same ISCO 4-digit, based on US employment data by SOC 6-digit. This method, outlined in Scholl et al. (Scholl, Turban, & Gal, The green side of productivity: An international classification of green and brown occupations, 2023), builds on the methodological intuition developed by Dingel and Neiman (2020), who applied it to cross-walk the O*NET taxonomy of "teleworkable" jobs to non-US data.[10] Given the complexity of the mapping, an example may be useful (see Figure 2 below): The ISCO 4-digit occupation "Senior government officials" corresponds to three different SOC 6-digit occupations, two of which contain a positive share of green occupations. To assess the green score of "Senior government officials", an employment-weighted average across the corresponding SOC 6-digit occupations is computed, because a simple average would result in overweighting the SOC occupations mapping into multiple ISCO occupations.

Figure 1. Building green scores for European occupations: an overview



Source: Secretariat elaborations based on (Vona F. , Marin, Consoli, & Popp, 2018), (Scholl, Turban, & Gal, GFP Methodological Note "Green Side of Productivity": Classifying Green, Brown, and Grey occupations in the International Standard Classification of Occupations (ISCO) Version 08., 2023) and (Dingel & Neiman, 2020).

Alternative relevant definitions of green jobs are worth flagging, including:

[10] The original mapping exercise in Dingel and Neiman (2020) links the U.S.-based O*NET taxonomy to ILO labour force data for 85 countries, using country-specific employment weights, rather than U.S.-based employment weights. The choice to apply the same employment weights to each country, as in the current analysis, can facilitate the cross-country comparisons of the share of green jobs.

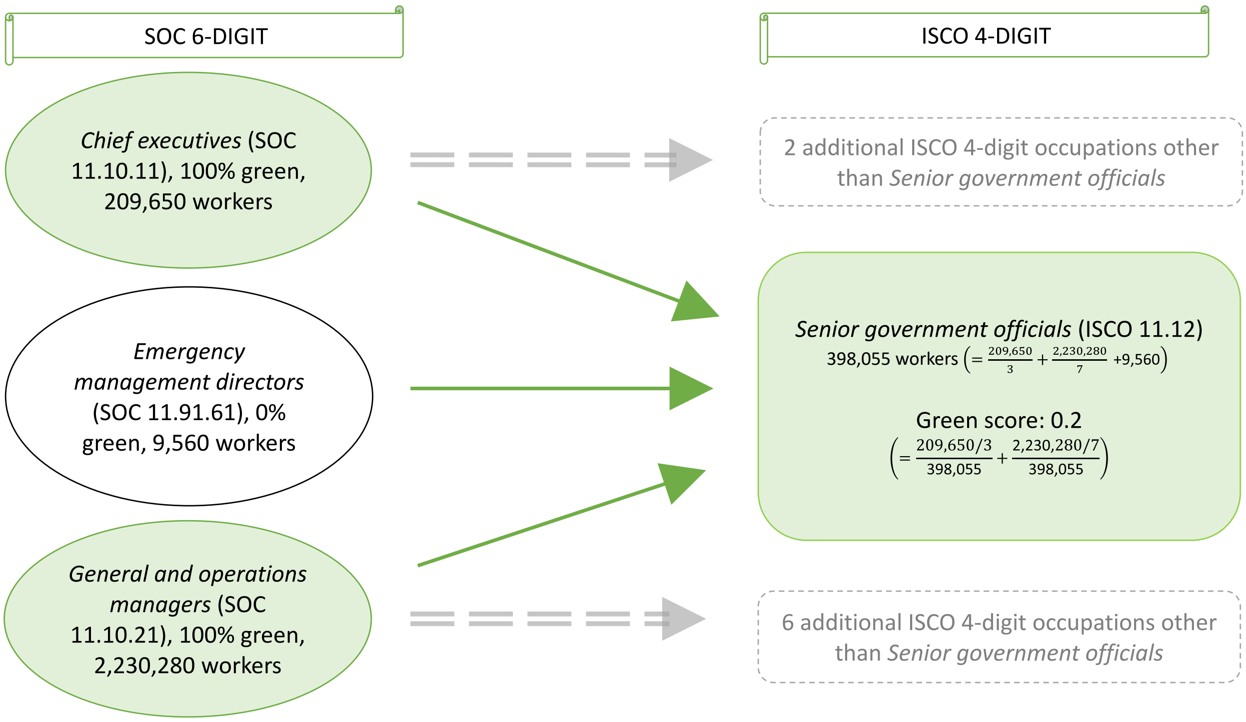
- In the narrowest sense, green jobs can be defined as jobs in (sub)sectors that directly relate to green technologies and processes. For instance, Eurostat defines a subset of industries producing environmental goods and services, based on national accounts data.[11] Employment in these industries concerns jobs that involve developing, producing or maintaining green technologies (e.g., renewables) and processes (e.g., recycling and reusing). Eurostat data on employment in environmental goods and services put its share in total employment at around 2% on average in the EU at present, with most of the jobs in water supply, manufacturing and construction (Vandeplas, Vanyolos, Vigany, & Vogel, 2022).
- The International Labour Organization (ILO) defines green jobs as those which “reduce the consumption of energy and raw materials, limit greenhouse gas emissions, minimize waste and pollution, protect and restore ecosystems and enable enterprises and communities to adapt to climate change”. In addition, it postulates that green jobs must be decent in terms of workers’ rights, access to social protection, adequate pay and working conditions.
- Some countries have developed their own approach to define green jobs. For example, the French *Observatoire national des emplois et métiers de l’économie verte* developed a nomenclature of green jobs which is regularly applied by the national statistical office INSEE to monitor the level and evolution of green jobs in French regions.[12] While not directly comparable and therefore not usable in a cross-country setting, the various country-specific approaches can be key inputs for countries to identify specific local issues and policy challenges.
- A real-time analysis of labour demand for green jobs can be done by monitoring the job vacancies posted on online platforms, released among others by the analytics software company Burning Class Technology. For the US and UK, Sato et al. (2023) have used an analogous approach to isolate low-polluting emission activities in online job vacancies, combining natural language processing and a survey of experts. Going forward, this methodology may be deployed on a wider range of countries: A promising project by the data solution company Lightcast for example has scrapped over 35,000 websites of job postings, resulting in a database of over a billion job postings over recent years, which can then be classified in green and non-green jobs using natural language processing techniques applied to the job description.[13]
- The International Energy Agency produces long-term scenarios for global employment in fossil fuels and clean energy as part of the World Energy Outlook publication, based on its Global Energy and Climate Model. Results from IEA (2022) suggest that the development of new energy-related projects, including the manufacture of their components, is the largest driver of energy employment, accounting for over 60% of energy-related jobs. This includes workers from several activities, including constructing new power generation facilities and transmission lines, carrying out efficiency retrofits, installing heat pumps, completing new oil and gas wells, as well as building other infrastructure. In all IEA model-based scenarios, the number of jobs created in clean energy outweighs the number of those lost in fossil fuel, although the newly created jobs may neither be in the same places nor require the same qualifications as those that are lost.

[11] ESTAT data on Employment in the environmental goods and services sector from national accounts data (online data code: ENV_AC_EGSS1).

[12] See for example the case of Occitanie on INSEE website 12 000 emplois verts en Occitanie - Insee Flash Occitanie - 113

[13] See https://lightcast.io/

Figure 2. Mapping and weighing exercise: an example



Note: The figure shows the steps involved in computing the green score of the ISCO 4-digit occupation *Senior government officials* (11.12), starting from the shares of green occupations in the corresponding SOC 6-digit.

2. High polluting jobs

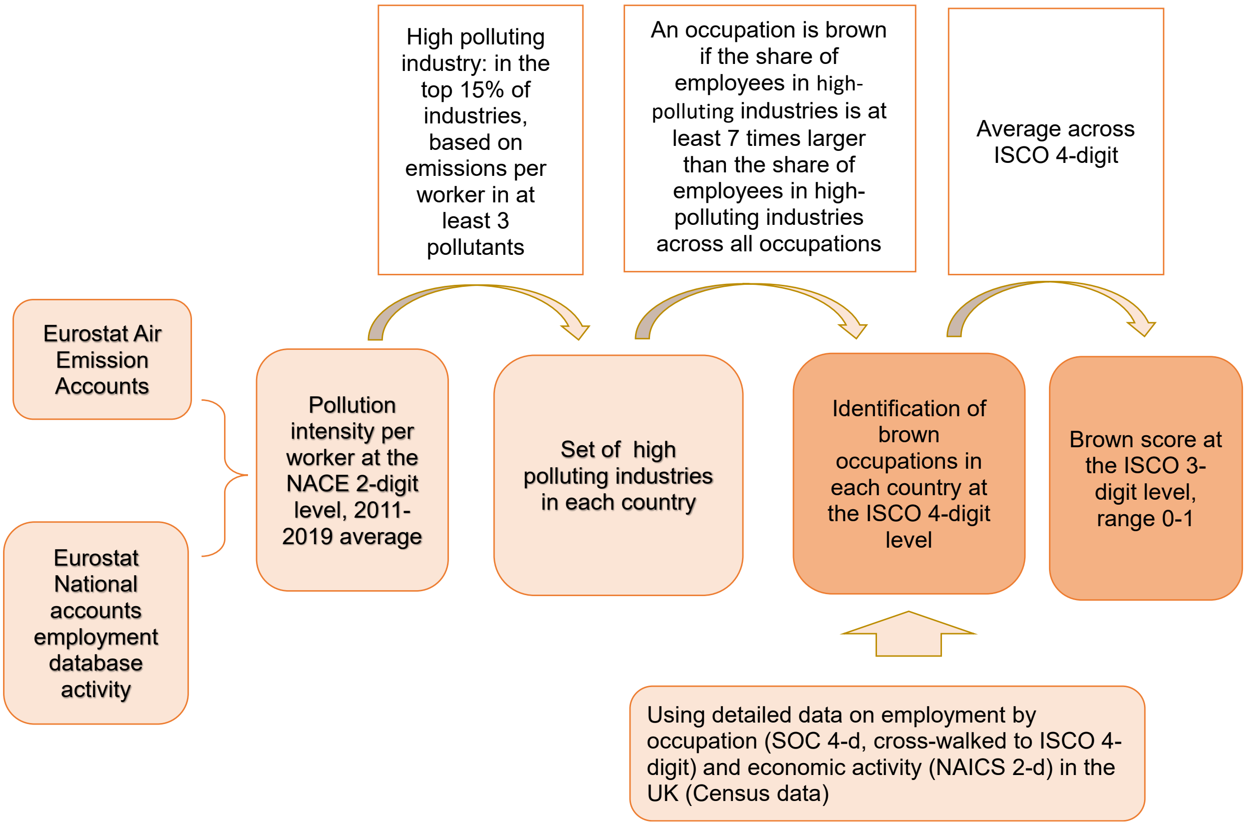
The standard approach for identifying high-polluting jobs is based on industry-level emissions data combined with data on the distribution of occupations per industry, ultimately delivering an occupation-based measure of polluting jobs. Vona et al. (2018) assess polluting jobs in the US based on two steps: 1) defining high-polluting ("brown") industries as those above the 95th percentile in emissions per worker for at least three polluting substances (including CO, VOC, NOx, SO2, PM10, PM2.5, lead, and CO2); 2) identifying high-polluting jobs as those occupations where the share of employees in high-polluting industries is at least 7 times larger than the share of employees in high-polluting industries across all occupations.[14] This results in 62 NAIC 4-digit high-polluting industries and 87 SOC 6-digit high-polluting occupations in the US. This approach can be applied to European countries by cross walking from US SOC occupations to European ISCO occupations, as done for green jobs (Scholl, Turban, & Gal, 2023), (Tyros, Andrews, & De Serres, 2023). One clear limitation of this approach is the implicit assumption that high-polluting industries are the same on both sides of the Atlantic.

The present study adopts Causa et al. (2024 forthcoming) novel classification of high polluting industries and countries, which is a careful adaptation of the standard one in Vona et al. (2018) to country-specific

[14] This second step is needed for labour market analysis because relevant available data sources are based on workers' responses to surveys' questions and these sources systematically report more granular information about occupation than industry. The reason is that workers tend to be more accurate in reporting their occupation than their industry of employment.

data on polluting emissions. The polluting emissions data, by country and industry, come from Eurostat's Air Emission Accounts. Emissions are normalized by the number of workers in the industry, from Eurostat National Accounts data: combining emissions and employment data by country and industry is complicated by the presence of significant data gaps.[15] Analogously to Vona et al. (2018), high polluting jobs are again defined in two steps: 1) industries are defined as high-polluting if above the 85th percentile in emissions per worker for at least three polluting substances, based on (country and industry specific) average emissions per worker between 2011 and 2019; 2) Occupations are defined as high-polluting if their share of employees in high-polluting industries is at least 7 times larger than the share of employees in those industries across all occupations.[16] In the first step, the use of a lower threshold than the one used by Vona et al. (2018) for the US (85th percentile instead of 95th) is due to the fact that EU emission data are defined at a more aggregate level than US data. The steps involved are detailed in Figure 3.

Figure 3. From Eurostat air emission accounts to high-polluting jobs scores across European countries: overview of a new approach



Source: (Causa, Soldani, & Nguyen, 2024 forthcoming).

Causa et al. (2024 forthcoming) novel approach ultimately delivers: i) a separate list of high-polluting industries for each European country and ii) analogous country-specific lists of high-polluting occupations

[15] The same data on emissions by industry has been recently used by the OECD for an analysis of the geography of polluting activities in the manufacturing sector across European regions (OECD , 2023).

[16] This is based on 2011 UK census data, due to the lack of harmonized European data on the joint distribution of workers across occupations and industries at a suitable level of granularity.

at the ISCO 4-digit level. In order to apply this occupational classification to the available labour force data, a further aggregation from ISCO 4-digit to ISCO 3-digit is necessary: each ISCO 3-digit occupation is assigned a fractional score based on the share of high-polluting 4-digit ISCO occupations it contains. The score takes value 1 if all underlying 4-digit occupation are high-polluting and zero if none is.

With respect to the standard US-based classification, this novel method has the major advantage that its validity does not rely on the assumption that the ranking of industries in terms of polluting emissions be the same in all European countries (see Causa et al. (2024 forthcoming) for evidence against this assumption). The use of European air pollutant emissions data might seem to come at the cost of granularity, as these data are available at a much more aggregated level for EU countries than for the US. In the context of the present study this cost is however negligible, as the labour market data to which the classification is ultimately applied is equally aggregated: even if the standard methodology were to be used, it would still need to be aggregated (Scholl, Turban, & Gal, 2023), (Tyros, Andrews, & De Serres, 2023).[17]

High-polluting is not the complement of green: some jobs are both green and high-polluting

The lists of green and high-polluting occupations resulting from the approach detailed in Sections 2 and 3 are not mutually exclusively, nor do they span the entire universe of occupations. An occupation could belong to only one of the two lists, to both, or neither.

Occupations that are neither green nor high-polluting are unlikely to be severely affected by the green transition, other than through indirect effects. Labour demand in occupations that are solely green is expected to increase through the transition, as they are concerned with the reduction or mitigation of the environmental impact on human activities, and they are not over-represented in high-polluting industries. The opposite can be expected for the occupations that are solely high polluting: their labour demand will likely shrink along with the economy’s shift towards greener production. A small share of occupations are classified as both green and high-polluting: their tasks content make them likely to be pivotal in the green transition, and they are over-represented in high-polluting industries. One implication of this is that some workers in high-polluting industries may have the competencies to perform green tasks: this is the case, for example, of Physical and engineering science technicians, Life science professionals, Machinery mechanics and repairers, Chemical and machine operators. This is important for the labour market transition and reallocation towards “green” activities because: i) workers able to perform green tasks can contribute to greening high-polluting industries, and ii) workers able to perform green tasks can reallocate to greener industries. While part of the literature decides to not consider these occupations as green, they are arguably relevant for the transition and therefore they are included in the subsequent analysis.

3. Data

The analysis presented exploits micro-data for the period 2011-2019 from the EU-Labour Force Survey, a large household sample survey providing information on labour participation and employment characteristics of individuals aged 15 and above.[18] The EU-LFS data ensures full cross-country comparability and is the primary source of information for official EU-level labour market statistics. One

[17] Indeed, The US-based classification refers to NAICS 4-digit industries and SOC 6-digit occupations (corresponding to 311 industries and 867 “detailed occupations”), while the EU-based classification can only be constructed at the NACE 2-digit level for industries, and ISCO 4-digit for occupations (corresponding to a total of 64 industries and 436 occupations).

[18] Countries covered are Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Italy, the Netherlands, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, the United Kingdom. Given the purpose of this exercise, the analysis excludes transitions during the COVID-19 period (2020 data).

drawback of the data is that, because information on past occupation is limited to non-employed respondents, it does not allow the analysis of job-to-job transitions. For example, it is not possible to assess how frequently workers move from a non-green to a green job. In addition, when zooming in on specific categories of workers, the sample size for some countries in the EU-LFS is too small for statistical inference purposes. In the context of this paper, when this is deemed to be the case, the countries concerned are not included in the descriptive charts (see the Appendix for more details).

In addition to the EU-LFS data, the analysis also relies on other data sources for the definitions of green and high-polluting jobs, detailed in Section 2. The definition of green jobs relies on O*NET data on the task contents of occupations in the U.S. and on SOC-ISCO crosswalks prepared by the U.S. Bureau of Labour Statistics (BLS). The definition of high-polluting jobs relies on Air Emissions Accounts and National Accounts on Employment by industry, both prepared by Eurostat, and, for the crosswalk from high polluting industries to occupations, on the U.K. Census data on the distribution of occupations by industry (see Causa et al. (2024 forthcoming) for details on the reasons for the choice of these data sources and on the derivation of the list of high-polluting occupations).

For the analysis of transitions from work to unemployment and from non-employment to work, the focus is on transitions into green jobs and out of high-polluting jobs, as these are the ones predicted by the progressive green transition. Following the existing literature, such transitions are defined by comparing respondents' working status at the time of the survey and, retrospectively, one year earlier ((Causa, Abendschein, Luu, & Cavalleri, 2022) and (Causa, Luu, & Abendschein, 2021)) analysis covers the working-age population and goes granular by looking at different socioeconomic groups identified by age, area of residence, and educational attainment. This allows to shed light on relevant distributional implications of greening labour markets; for example, territorial implications due to the spatial concentration of economic activities.[19]

4. Green and high-polluting jobs: stylised facts and distributional aspects

Having laid out the methodology and limitations for assessing green and high-polluting jobs, this section first offers some more details about what occupations are identified as green, and what industries and occupations as high-polluting, and then presents illustrative stylised facts on their prevalence over time, across countries, and among different socio-economic categories of workers.

Based on their occupational mix across the European countries covered, the top ranked green occupations include refuse workers, electrotechnology engineers, manufacturing and construction managers, and architects (Table 1). The list of green occupations does not vary across European countries because it is obtained by cross walking US occupations. Associated jobs are present in various industries such as manufacturing, construction, and energy; some of these industries may be highly polluting, implying that green occupations can also be classified as high-polluting, depending on countries' emissions by industry and employment structures. Such is the case of refuse workers for Czechia, Denmark, Germany, Greece and Hungary.

[19] On the issue of decarbonisation, spatial concentration of economic activities and implications for local labour markets, ongoing OECD work is focusing on the manufacturing sector in European regions (OECD , 2023). See (Hanson, 2023) for a recent in-depth analysis in the case of the United States.

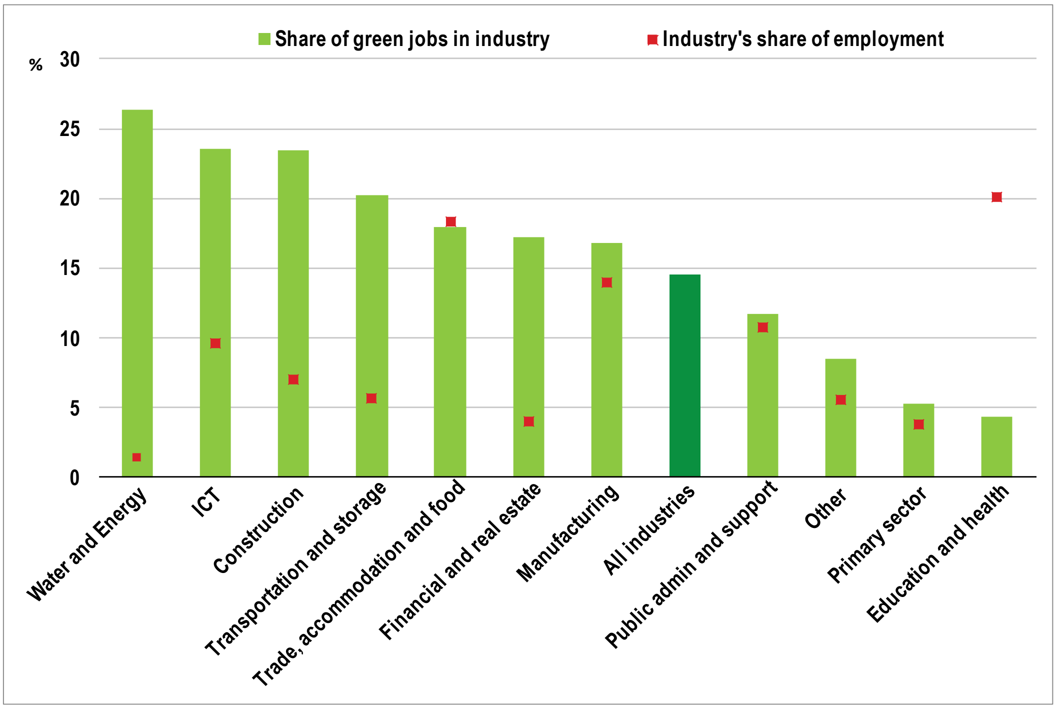
Table 1. Greenest occupations across European countries, 2019

Occupation ISCO 3-digit code and label	Share of green tasks	Industries employing these occupations	Distribution of occupation employment across industries (%)
961- Refuse workers	0.47	Water and energy	51.7%
		Public administration and administrative support	32.8%
		Trade, accommodation, and food	5.8%
		Financial and real estate	2.3%
		Education and health	2.1%
132 -Manufacturing, mining, construction, and distribution managers	0.26	Manufacturing	35.3%
		Construction	24.5%
		Transportation and storage	10.2%
		Information, communication, and professionals	9.2%
		Trade, accommodation, and food	9.0%
214-Engineering professionals (excluding electrotechnology)	0.22	Manufacturing	38.0%
		Information, communication, and professionals	28.7%
		Construction	11.6%
		Public administration and administrative support	5.9%
		Trade, accommodation, and food	4.4%

Note: Greenest occupations across the European countries covered. How to read: the 3-digit ISCO occupation with the highest greenness score is ISCO 3-digit 961 - Refuse workers. Across the countries covered, 50.3% of refuse workers are employed in the water and energy industry, 34.9% in Public administration and administrative support and 5.1% in Trade, accommodation and food and 2.0% in Education and health as well as in Financial and real estate.
Source: Own elaboration on EU-LFS data.

Figure 4 reports the shares of green jobs by broad industry along with the industry's share of total employment, on average across the European countries covered in the data. The industries with the highest share of green jobs are water and energy (26%), information and construction (23% each). This shows that green occupations tend to be more prevalent in low-employment industries (e.g., water and energy, not even 2% of total employment) than in high-employment industries (e.g., education and health, almost 20% of total employment). This also reveals that high-emitting industries (e.g., energy and transport) account for a sizeable proportion of green jobs, consistent with the previous point about green-high-polluting overlap.

Figure 4. Green employment by industry, average across European countries, preliminary estimates, 2019



Note: Industries sorted by share of workers in green jobs. Average across the 26 countries covered by the data (Austria, Belgium, Switzerland, Czech Republic, Germany, Denmark, Spain, Estonia, Finland, France, UK, Greece, Hungary, Ireland, Iceland, Italy, Lithuania, Luxemburg, Latvia, Netherlands, Norway, Poland, Portugal, Slovak-Republic, Slovenia and Sweden). 20 NACE industry categories grouped into 11 categories as labelled. The primary sector includes Agriculture and Mining and quarrying. Sample includes employed workers aged 16-65. EU-LFS individual weights applied.

The high-polluting occupations identified in this paper vary across European countries because they are obtained from country-specific emissions by industry. Table 1 lists all high-polluting occupations ranked by their occurrence across countries.[20] According to this metric, the most common high-polluting occupations include manufacturing, mining, and construction managers, ship and aircraft controllers as well as mining and mineral processing plant operators.[21] Yet there is relevant cross-country heterogeneity, with a number of occupations being classified as high-polluting in few countries. This mostly reflects cross-country heterogeneity in industrial structures. For example, agricultural labourers and managers and animal producers in countries with a relatively large agricultural sector, e.g., France and Italy; heavy truck and bus drivers in countries with a relatively large land transport sector, e.g., Czechia and the Slovak Republic.

[20] Some occupations classified as high-polluting may be less intuitive than others, for example travel attendants and guides and handicraft workers. This reflects the fact that available Eurostat emission accounts are defined based on a relatively high level of industry aggregation, a limitation discussed in the text and in the Annex.

[21] High-polluting occupations are likely to differ in terms of retraining and reskilling needs in the green transition. For example, ship and aircraft controllers and ships' deck crew and related workers may require less re-training to drive or fly a hydrogen-powered boat/plane compared to workers in the manufacturing industry who will have to start designing completely different products. Analysing this aspect is beyond the scope of the current project due to clear data limitations, yet model-based analysis such as Borgonovi et al (2023) can make progress in this research area.

Table 2. High-polluting occupations across European countries

ISCO	Label	Occurrences
132	Manufacturing, mining, construction, and distribution managers	21
315	Ship and aircraft controllers and technicians	21
811	Mining and mineral processing plant operators	21
818	Other stationary plant and machine operators	21
313	Process control technicians	20
835	Ships' deck crews and related workers	20
511	Travel attendants, conductors and guides	20
721	Sheet and structural metal workers, moulders and welders, and related workers	19
812	Metal processing and finishing plant operators	19
834	Mobile plant operators	19
731	Handicraft workers	18
813	Chemical and photographic products plant and machine operators	17
921	Agricultural, forestry and fishery labourers	14
215	Electrotechnology engineers	13
211	Physical and earth science professionals	13
131	Production managers in agriculture, forestry and fisheries	12
612	Animal producers	12
722	Blacksmiths, toolmakers and related trades workers	12
752	Wood treaters, cabinet-makers and related trades workers	10
831	Locomotive engine drivers and related workers	5
832	Car, van and motorcycle drivers	5
833	Heavy truck and bus drivers	5
621	Forestry and related workers	5
961	Refuse workers	5

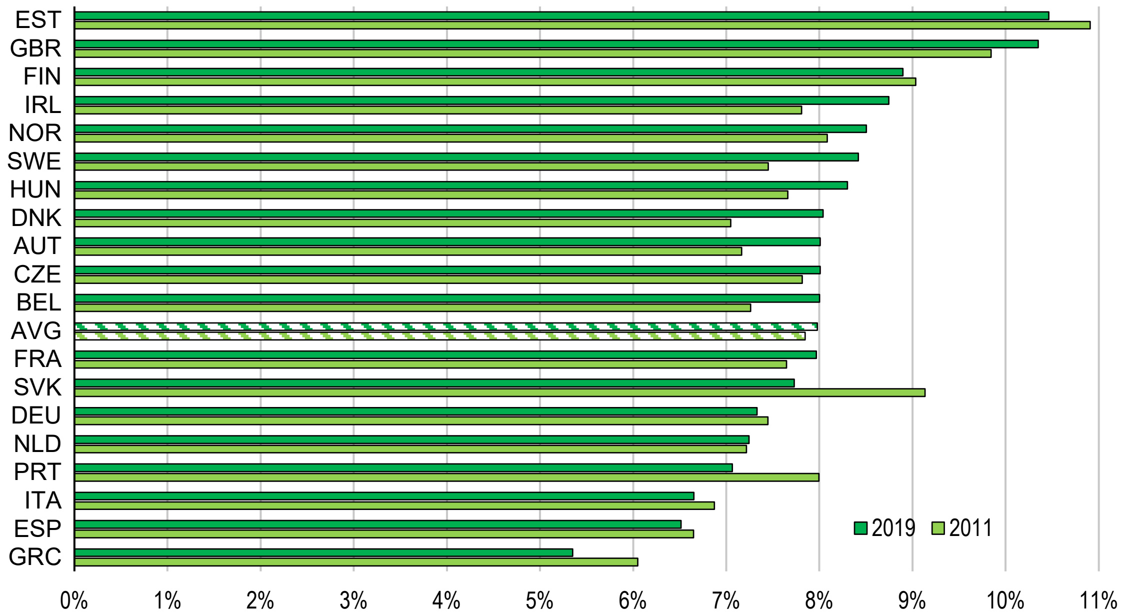
Note: See text for the assessment of high-polluting occupations across European countries. The table reports the number of countries in which each of the listed ISCO occupation is classified as high-polluting. The 21 countries covered are AUT, BEL, CZE, DEU, DNK, ESP, EST, FIN, FRA, GBR, GRC, HUN, IRL, ITA, NLD, NOR, POL, PRT, SVK, SVN, SWE.
Source: Eurostat Air Emission Accounts, Eurostat National Employment database, UK census data.

Keeping in mind that the numbers are contingent upon the methodology and data, Figure 5 reports the estimated shares of green and high-polluting occupations in the sample and period covered by the analysis, based on EU-LFS data (the Appendix contains further details on the data, sample and methodology to count workers in green and high-polluting occupations). The estimated share of green jobs is 8%, on average across the countries covered, varying between around 10% in the United Kingdom and Estonia and 5% in Greece. The estimated share of high-polluting jobs is around 4%, on average across the countries covered, varying from around 9% in Czechia and Slovak Republic to 2% in Austria and Portugal. This confirms the idea that high (low) shares of green (high-polluting) jobs do not necessarily imply low (high) shares of high-polluting (green) jobs, because green is not the complement of high-polluting. While some countries feature a low-incidence of high-polluting and high-incidence of green jobs, e.g., the United Kingdom, others feature low-incidence of both high-polluting and green jobs e.g., the Netherlands. Overall, the main message is that labour markets have not become significantly greener over the last decade, on average across the European countries covered. There has been no significant change in the share of green and high-polluting jobs and some countries, such as Greece, even exhibit a decline in green and an increase in high-polluting jobs shares.

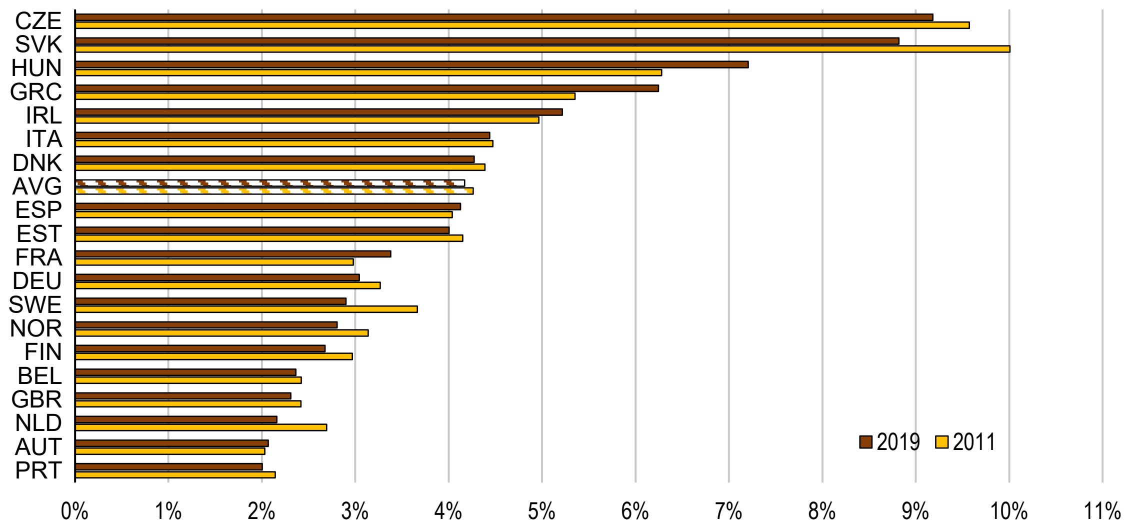
Figure 5 Figure 5. Green and high-polluting jobs across European countries, 2011-2019

Share of total employment (%)

Panel A. Green jobs



Panel B. High-polluting jobs



Note: How to read: The estimated employment share of green jobs in Belgium is 7.3% in 2011 and rises to 8% in 2019; while that of high-polluting jobs is stable at 2.4%. See text for definitions.
Source: EU-LFS data.

These results are consistent with previous literature. For green jobs, the estimates in Figure 5 lie around the middle of the wide range of estimates in the literature, which vary significantly depending on the classification approach and data used. The estimated "direct" green job shares for European countries lie between 3% to more than 20%, as reported in the literature review by Valero et al. (2021). For high-polluting jobs, the results in this paper are qualitatively in line with previous literature, which in most cases is based on a crosswalk of Vona et al. (2018) US emission-based metrics, yielding a roughly similar ranking across countries. At the same time, the estimates in Figure 5 tend to be more widespread across countries, possibly because they better capture the cross-country differences in emissions by industry. The fact that countries can have a high share of high-polluting and green jobs at the same time is in line with previous literature at the country (Tyros, Andrews, & De Serres, 2023) and regional level (OECD, 2023) l. Last but certainly not least, the finding that in many countries labour markets have not become much greener over the last decade is surprising in light of the attention that green policies receive, but it is in line with available evidence in Valero et al (2021), OECD (2023), and Scholl et al (2023).[22]

Figure 6 provides a comparative overview about the distribution of green jobs across different socioeconomic groups.[23] In all countries, women are less likely to hold green jobs (Figure 6, Panel A).[24] For example, in the United Kingdom, 15% of male workers are employed in green jobs, more than double the rate (6%) for female workers. At the same time, Causa et al. (2024 forthcoming) note that women are also less likely than men to work in high-polluting occupations. This apparent conundrum largely reflects the over-representation of women in service industries like hospitality, health and education, which are mostly neutral from an environmental perspective. By contrast men are overrepresented in manufacturing, construction, and utilities (the industries with the highest share of both green and high-polluting jobs). This stark gender divide is in line with recent cross-country findings (OECD , 2023), as well as with official country-specific estimates, such as for France.[25]

Turning to educational attainment, workers with higher levels of education are more likely to hold green jobs relative to workers with middle and lower levels of education (Figure 6, Panel B). For example, in Germany 11% of workers with high levels of education are employed in green jobs, which is almost double the rate (6%) for workers with low or middle levels of education. This pattern is in line with evidence from the US showing that green occupations are, on average, higher-skill and less routine-intensive than non-green occupations and that they require high-level analytical and technical skills linked to technology (Vona F. , Marin, Consoli, & Popp, 2018). In contrast, Causa et al. (2024 forthcoming) document the opposite pattern for high-polluting jobs: these are most prevalent among workers who attained a lower or medium level of education. Therefore, individuals with lower and medium educational attainment might face higher risks of displacement due to the green transition, being over-represented in high-polluting jobs. Data inspection does not highlight any significant and consistent differences across age groups, in line with Causa et al. (2024 forthcoming) and OECD (2023).

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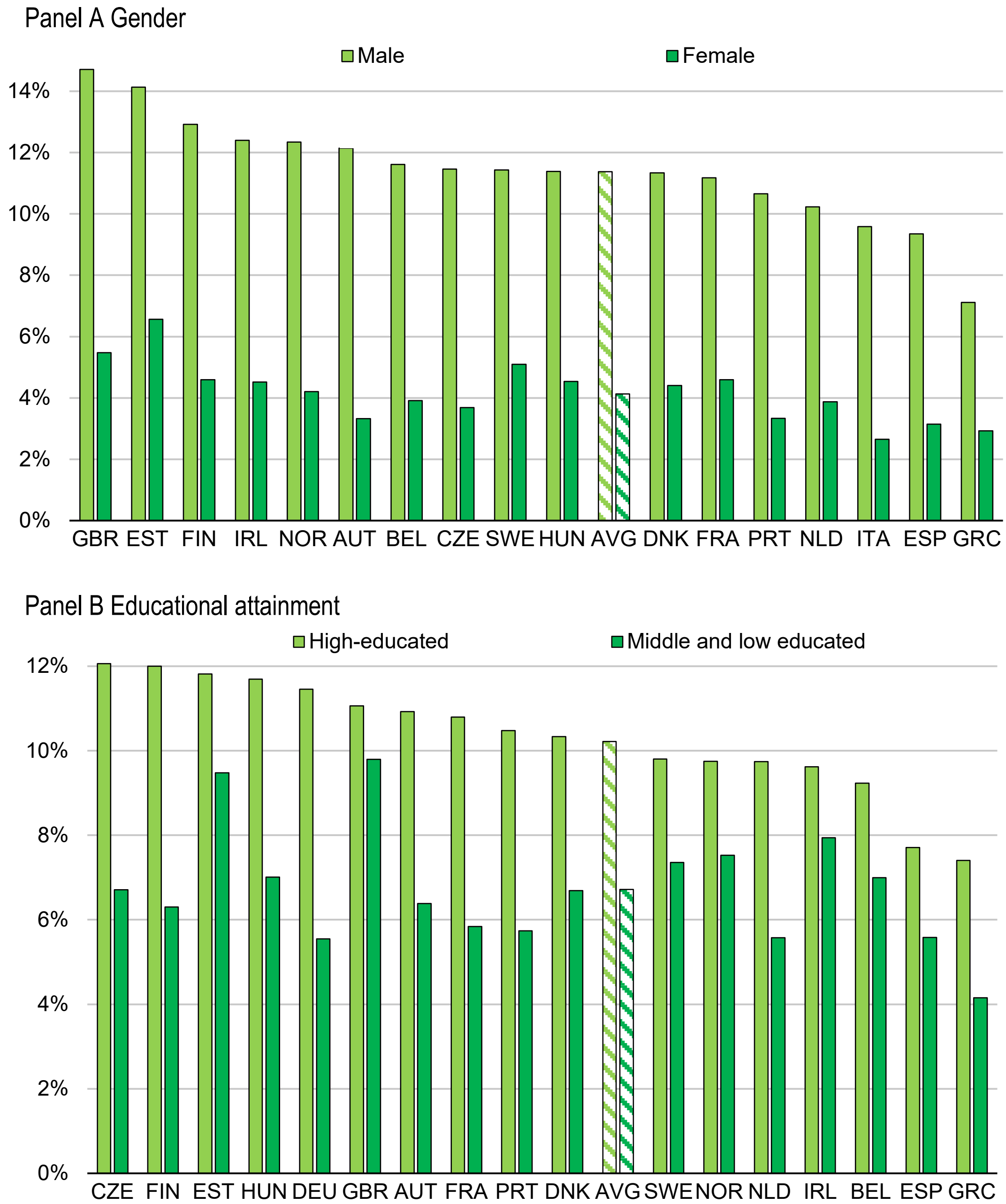
[22] These national developments can hide differences at the subnational level. OECD (2023) shows that most capital regions recorded further increases to already relatively higher shares of green jobs across the OECD.

[23] This picture is based on bivariate correlations, i.e., it does not isolate the effect of one individual factor (e.g., gender) while keeping other factors (e.g., education) constant. The numbers should thus not be interpreted causally as e.g., the effect of gender on the probability to hold a green job, all else equal.

[24] The Slovak Republic cannot be covered in the rest of this paper due to data and sample size-related issues.

[25] https://www.statistiques.developpement-durable.gouv.fr/metiers-verts-et-verdissants-pres-de-4-millions-de-professionnels-en-2018

Figure 6. Green jobs across socioeconomic groups, share of group employment in 2019



Note: How to read: in France, 11% of employed males hold green jobs, by contrast with 4.6% of employed females. In Germany, 11% of the workers with higher educational attainment hold green jobs, by contrast with 5.6% of low and middle educated workers.
Source: EU-LFS data.

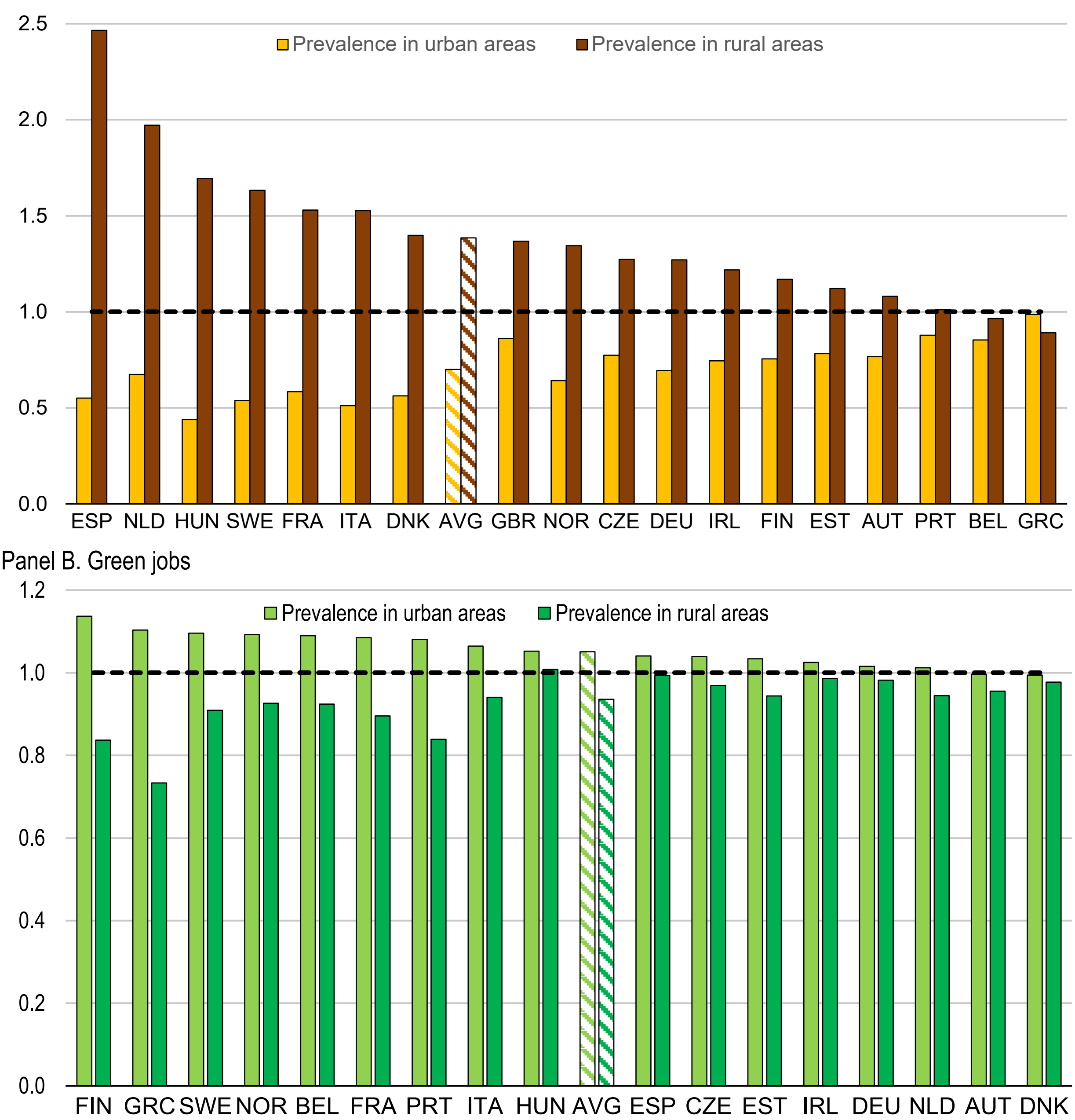
The distribution of green and high-polluting jobs also varies between different areas, especially between urban and rural areas; in particular, high-polluting jobs are systematically overrepresented in rural areas

(Figure 7). The spatial polarization of green and high-polluting jobs has been documented in recent OECD work on the green transition and local economic development (OECD, 2023).[26]

Figure 7. The prevalence of high-polluting and green jobs in rural and urban areas, 2019

Ratio between the share of high-polluting/green jobs located in rural /urban areas and the share of all jobs located in rural/urban areas

Panel A. High-polluting Jobs



[26] See OECD (OECD, 2023) for an analysis of greening labour markets at the local level. That report shows that capital regions stand out with more green-task and fewer polluting jobs. Chapter 2 presents regional divides within countries, with country-specific fiches available online, e.g., https://www.oecd.org/cfe/leed/GBR.pdf

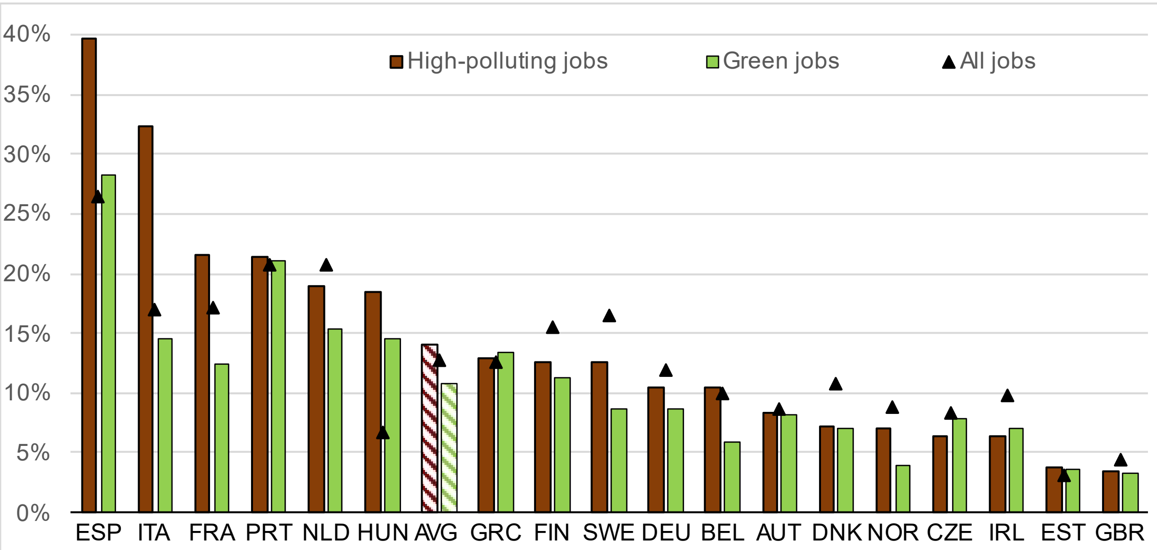
Note: How to read: in Spain, high-polluting jobs are more than twice as prevalent in rural areas than they are in the whole country, while they are half less prevalent in urban areas.
Source: EU-LFS data.

As previously emphasized, job quality is not formally included in the measurement of green (high-polluting) jobs: This reflects the fact that the literature has not yet reached any consensus on measuring quality alongside the quantity of green (high-polluting) jobs. Yet the labour force survey data used in this paper shed some light on this important issue, keeping in mind that results should be interpreted with caution due to the simple bivariate nature of the exercise. The assessment is based on three relevant dimensions of job quality: 1) the temporary nature of work contracts for dependent employees, 2) the degree to which workers participate in training, and 3) the incidence of green and high-polluting jobs across the wage distribution. The first dimension is a relevant aspect of job quality insofar as holding a permanent contract is generally associated with job stability and access to essential forms of social protection like unemployment benefits. The second dimension, whether a worker participates to training,[27] is an especially relevant aspect of job quality insofar as moving towards greener activities may require requalification. The third dimension considers job quality through the prism of the earnings distribution.

The incidence of temporary employment tends to be higher for high-polluting relative to green job holders in a number of countries, in particular those where temporary contracts are relatively frequent. Such is the case of Italy, where the incidence of temporary contracts is more than twice as high among workers in high-polluting jobs relative to workers in green jobs (Figure 8).

Figure 8. Incidence of temporary contracts among workers employed in green and high-polluting jobs, 2019

Percentage of dependent employees with temporary contracts



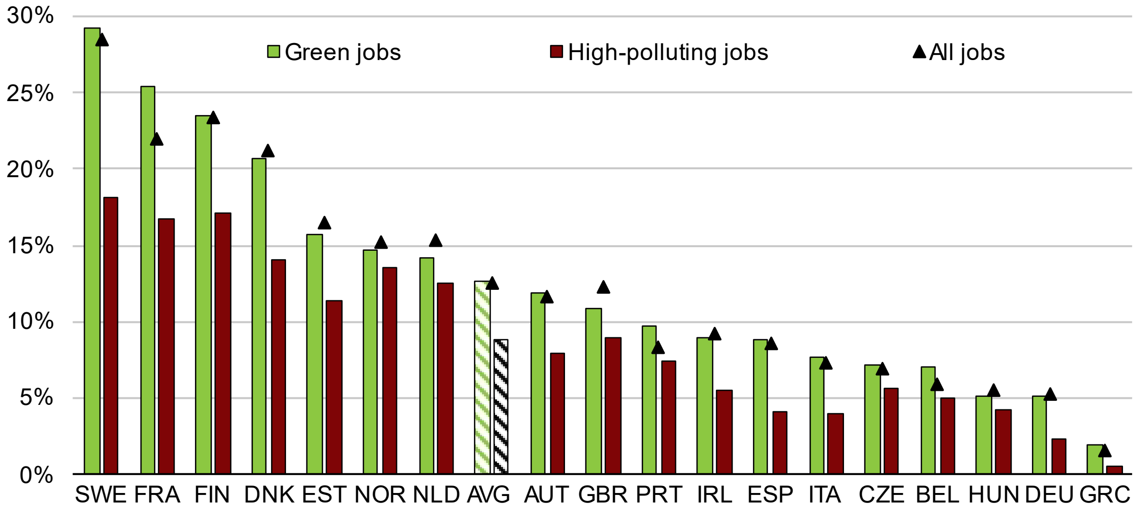
Note: The permanency of the job is defined for (dependent) employees. How to read: in Italy, 32% of dependent employees in high-polluting jobs have a temporary contract, by contrast with 15% of dependent employees in green jobs.
Source: EU-LFS data.

[27] One limitation is that the relevance of the training will depend on its content, quality, targeting, etc; all of which is not measured in the data.

In all countries covered, workers employed in high-polluting jobs are less likely to participate in training relative to workers employed in green and other jobs (Figure 9).[28] This raises policy concerns in the context of the green transition to the extent that workers in high-polluting jobs may be more likely to be displaced and to require requalification training to facilitate labour market mobility.

Figure 9. Participation to training among workers employed in green and high-polluting jobs, 2019

Percentage of workers who have attended non-formal education learning during the last 4 weeks



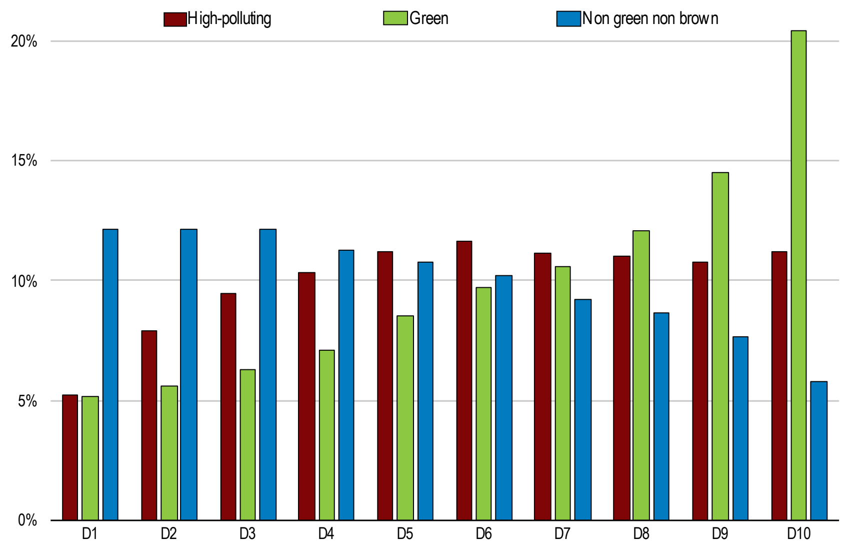
Note: How to read: in France, 25% of workers in green jobs have participated to non-formal training during the last four weeks, by contrast with 17% of workers in high-polluting jobs.
Source: Own elaboration on EU-LFS data.

On average across the countries covered, both green and high-polluting jobs tend to be under-represented at the lower end of the wage distribution, with employment shares significantly lower than 10% in both the first and the second decile (Figure 10). For example, 5% of both green and high-polluting jobs workers have earnings falling in the first decile of the wage distribution. Green jobs tend to be underrepresented in the lower end and overrepresented at the higher end of the wage distribution, with over 20% of green jobs in the top wage decile. The occupations that are neither green nor high-polluting exhibit an opposite pattern, being overrepresented in the lower deciles and underrepresented in the higher ones. For example, 12% of workers in these jobs belong to the first decile of the earnings distribution, and only 6% to the top decile. High-polluting jobs are concentrated in the middle of the wage distribution, in particular relative to green jobs. For example, 10% of high-polluting jobs have wages in the fourth decile, compared to only 7% of green jobs. As stressed above, this comparison is only descriptive and does not factor out relevant individual characteristics such as education and area of residence.

[28] This result is in line with OECD (2023).

Figure 10. Share of high-polluting and green jobs across the deciles of the wage distribution, 2015-2019

Share of workers by decile of the dependent employees' wage distribution, cross-country average



Note: Simple cross-country average of the following countries: AUT, BEL, CZE, DEU, DNK, ESP, EST, FIN, FRA, GBR, GRC, ITA, NLD, PRT. The analysis excludes Ireland, Hungary and the Slovak Republic due to data-related issues. How to read: on average across the European countries covered, 5% of high-polluting jobs, 5% of green jobs, and 12% of neither green nor high-polluting jobs earn wages in the lowest decile of the dependent employee's wage distribution.
Source: Own elaboration on EU-LFS data.

5. Labour market transitions and displacement risks in the greening economy

Greening the economy is expected to entail some expansion of green jobs relative to high-polluting jobs. Yet, the available data do not show any evidence of such transition so far. One possible reason for this is the difficulty in identifying and implementing policies to spur an effective and inclusive process of worker reallocation. This requires encouraging transitions into green jobs and out of high-polluting jobs while minimising displacement costs, especially among disadvantaged socioeconomic groups because, as shown above, green and high-polluting jobs are unequally distributed. Against this background, this section presents stylized facts about labour market transitions and displacement risks in the greening economy. [29] The focus is on transitions in and out of jobs. The EU-LFS data are not suited to accurately document job-to-job transitions between e.g., high-polluting to green, reflecting two major constraints: 1) only industry information, not occupation, is available for individuals that remain in employment from one period to the other and change job; 2) this information is of little relevance for statistical inference due to the too aggregated nature of the industry classification in the data.[30]

[29] This part of the analysis does not cover all countries due to limited sample sizes that may affect the representativeness of the data and evidence. As a result, the illustrative charts do not report the cross-country average.

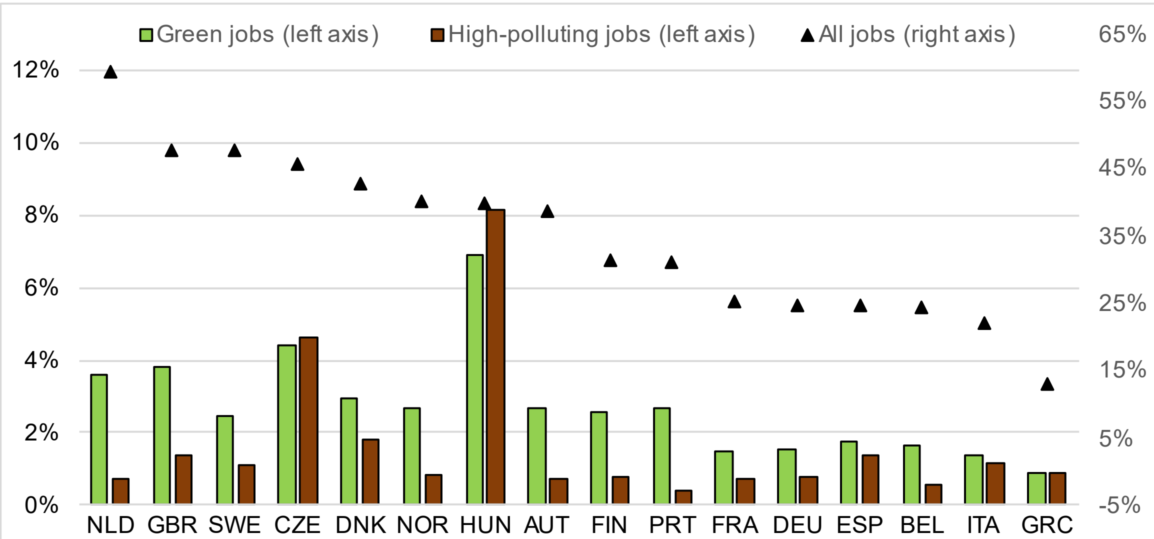
[30] As discussed, the data do not allow identifying direct job-to-job transitions from e.g., high-polluting to green jobs; but taking those into account is unlikely to dramatically change the general finding of a moderate shift out of high-polluting and into green jobs. See Causa et al. (2022) for an analysis of job-to-job transitions and a discussion about limitations associated with using EU-LFS data to assess transitions between industries. The 2024 edition of the OECD

Individual transitions from unemployment into a job are fundamental for labour market and economic dynamism, for social mobility, inclusiveness, and resilience. The literature has delivered a large body of evidence about the cyclical, structural and policy drivers of these transitions, (see e.g., Causa et al. (2022), and Monastiriotis et al.). Less is known about their green dimension. Several features emerge from the European cross-country overview of labour market transitions from unemployment to green/high-polluting jobs (Figure 9). The main findings are:

- Unemployed workers are more likely to transition to green than to high-polluting jobs in most countries covered, especially in those with high general job-finding rate, such as the Netherlands, the United Kingdom and Sweden. But even in such countries, moving from unemployment to a green job is still a rare event and most unemployed individuals find employment in jobs which are neither green nor brown. In the Netherlands, while almost 60% of the unemployed transition to jobs from one year to the next, only 4% transition to green jobs.
- Unemployed workers are equally likely to transition to green as to high-polluting jobs in some countries featuring a low job-finding rate overall, especially Greece and, to a lesser extent, Italy.
- Unemployed workers are less likely to transition to green than to high-polluting jobs in Hungary and Czechia, two countries characterized by very high stocks of high-polluting jobs and high job-finding rates relative to other countries in the sample. For example, in Hungary around 40% of unemployed workers find a job from one year to the next, 8% get a high-polluting and 7% a green job.

Figure 11. Unemployment to job transitions

Percentage of individuals transitioning from unemployment to job over a one-year period



Note: Transitions are defined over a one-year period. Yearly transitions are averaged across the years 2015-2019. How to read: in Sweden, 47% of unemployed individuals transition to jobs from one year to the next; 2% of unemployed individuals transition to green jobs from one year to the next, and 1% of unemployed individuals transition to high-polluting jobs from one year to the next.
Source: own elaboration on EU-LFS data.

Helping young people in the transition from study to green jobs, given the definition in this paper as jobs requiring the capacity to perform green tasks, is an indispensable building block to achieve environmental

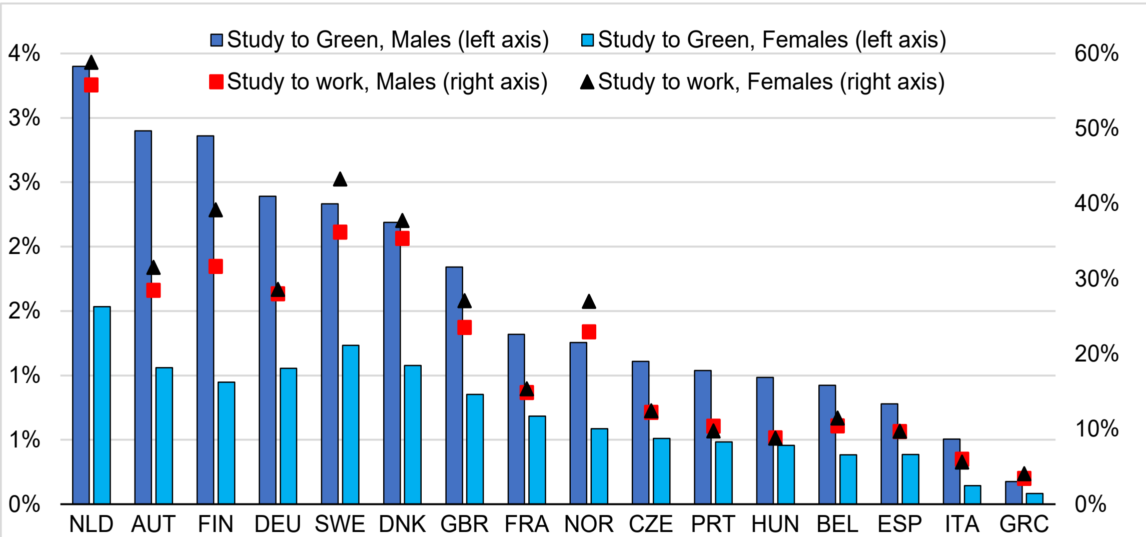
Employment Outlook should deliver descriptive evidence about these job-to-job transitions for a set of countries featuring linked employee employer data.

goals. Figure 10 provides a picture of labour market transitions from study-related inactivity to green jobs, reporting data separately by gender in order to zoom in on gender gaps in the flow into green jobs, given the above-documented gender gaps in the stock of green jobs.[31] Figure 10 shows that transitions from study to green jobs vary from around 3% to less than 0.3%, partly reflecting the wide variation in transitions from study to any job (for instance, almost 60% of students move to jobs from one year to the next in the Netherlands, but less than 4% in Greece). Across all countries, female students are much less likely than males to transition to green jobs even though they tend to be more likely to transition to any job. For example, in Finland around 40% of female and 32% of male students transition to a job from one year to the next; but male students are three times more likely to transition to green jobs (3% versus less than 1% for females). At the same time, female students are also much less likely to transition from study to high-polluting jobs (Figure A1 in the Appendix).

The finding that young women are less likely than men to move from studying into green jobs, or even high-polluting ones, may reflect the fact that they are more likely to take up jobs in the service sector (where most jobs are neither green nor high-polluting) and less likely to engage in the type of studies and curricula that tend to be conducive to green jobs, such as science, technology, engineering and mathematics (STEM).[32] This is in spite of widely reported evidence that females tend to achieve higher graduation rates and, as reported here, higher rates of study to job transitions than males. This may indicate that gender differences in the stock of green jobs carry over in the flows into green jobs, raising concerns about the effectiveness and gender inclusivity of the transition towards cleaner economic activities.

Figure 12 Study-related inactivity to green jobs transitions, by gender

Percentage of young individuals transitioning from study-related inactivity to green jobs over a one-year period



Note: Transitions are defined over a one-year period. Yearly transitions are averaged across the years 2015-2019. The sample is people aged 20-29. How to read: in Finland, around 40% of female and 32% of male students transition to job from one year to the next; 3% of male students transition to green jobs, less than 1% of female students transition to green jobs.
Source: Own elaboration on EU-LFS data.

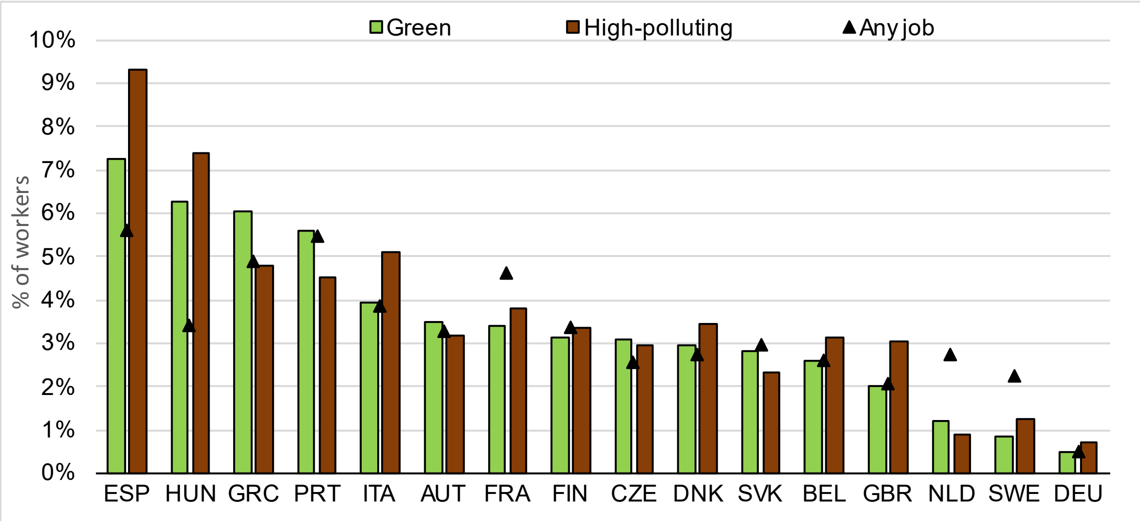
[31] The sample is people aged 20-29. This age group is chosen instead of the standard 15-24 one in order to analyse a more homogeneous group of young people exiting study (e.g., the 15-24 age group covers both youth dropping out from high school and youth graduating from university).

[32]See https://oecdedutoday.com/looking-for-green-engineers-insights-from-pisa-2018/ and more recently, the special chapter on gender of the June 2023 edition of the OECD Economic Outlook (André, Causa, Soldani, Sutherland, & Unsal, 2023).

Risks and consequences of displacement are key policy concerns associated with the labour market effects of the green transition, in particular to the extent that high-polluting activities are expected to downsize. To shed light on such risks, Figure 13 shows the share of workers who, over a one year period, move from employment to unemployment, depending on whether the latest job was in a green or high-polluting occupation. The data suggest that transitions from job to unemployment in European countries are not systematically different for workers previously employed in high-polluting jobs; yet job losses are significantly higher for high-polluting jobs workers in some countries, such as Spain, Hungary and Italy (the Appendix contains further details on the underlying calculations).

Figure 13. Job to unemployment transitions

Percentage of workers transitioning from job to unemployment over a one-year period

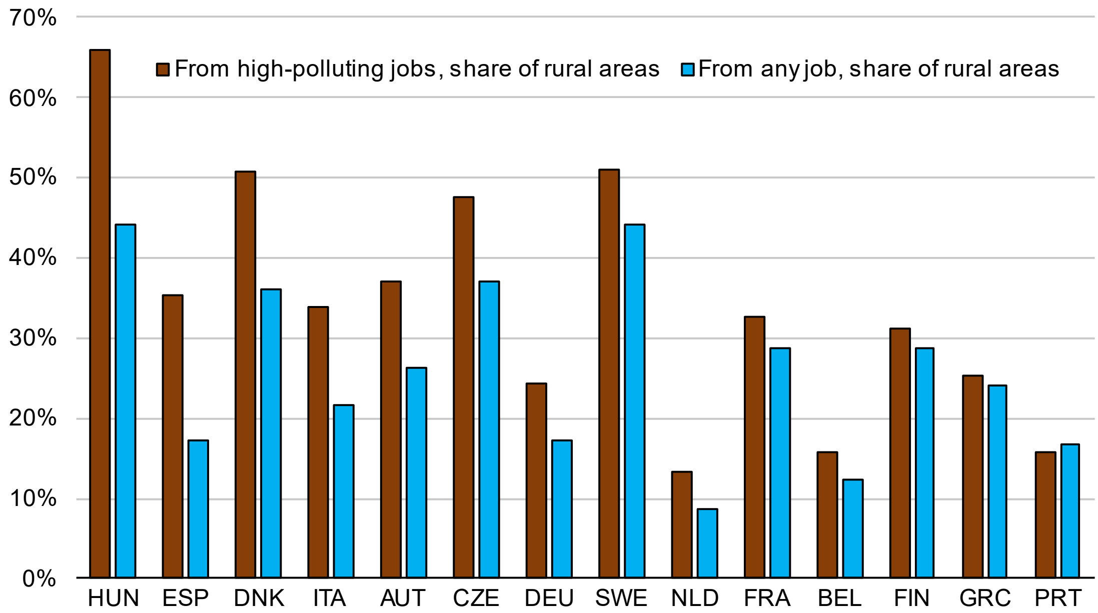


Note: Transitions are defined over a one-year period. Yearly transitions are averaged across the years 2015-2019. The denominator for green (high-polluting) jobs to unemployment transitions is defined as the number of individuals that had a green (high-polluting) job last year plus those that have the same green (high-polluting) job this year, while the numerator is defined as the number of individuals that are unemployed this year and had a green (high-polluting) job last year.
How to read: in Spain, nearly 6% of workers transition to unemployment from one year to the next; 7% of workers employed in green jobs transition to unemployment from one year to the next, and 9% of workers employed in high-polluting jobs transition to unemployment from one year to the next.
Source: Own elaboration on EU-LFS data.

The fact that, in most EU countries, workers employed in high-polluting jobs do not systematically face higher risks of displacement may reflect heterogeneities and compositional effects in terms of industry, type of employment, seniority and job stability. In addition, national aggregates hide sub-national differences, in particular those between rural and urban areas, due to the spatial concentration of jobs. Indeed, the evidence presented in Figure 14 suggests that displacement from high-polluting jobs tends to affect rural areas disproportionately. For example, in Hungary, rural areas account for around 44% of job to unemployment transitions but 66% of high-polluting job to unemployment transitions. This raises policy concerns about inclusiveness and local development perspectives. For example, the chances of finding a new job tend to be limited in rural areas, all the more so if this requires changing industry or activity. The possibilities of moving to and within urban areas for better job opportunities are often hampered by housing affordability and policy-related barriers (Causa, Abendschein, & Cavalleri, 2021).

Overall, even though workers at risk of displacement could be a relatively small share of a country's population, losses could be considerable for households and communities. In addition, dissatisfaction among small but vocal shares of the population that live in marginal districts could induce powerful political effects. The experience in adjusting to employment changes due to international trade provides a telling example. International trade was beneficial on aggregate - and was far less important as a source of structural change than technology and demand – yet its negative effects on some workers and communities have had important economic, social, and political consequences in both the United States and European countries.[33]

Figure 14. Job to unemployment transitions, share of rural areas (%)



Note: See previous chart. Transitions are defined over a one-year period. Yearly transitions are averaged across the years 2015-2019.
How to read: in Hungary, rural areas account for around 44% of job to unemployment transitions and 66% of high-polluting job to unemployment transitions.
Source: Own elaborations based on EU-LFS data.

Job displacement can leave lasting scars on workers' labour market prospects and well-being, especially when it is associated with long unemployment spells.[34] To investigate whether such risks are significantly higher for workers displaced from high-polluting jobs, Figure 15 reports the incidence of long-term unemployment (based on the standard threshold of more than one year unemployment) among workers with declared work experience, singling out those whose last job was high-polluting.[35] The figure does not convey evidence of a systematically higher incidence of long-term unemployment among workers displaced from high-polluting jobs. While this is the case in some countries such as Austria and the United Kingdom, the opposite holds in other countries, such as Italy and Spain, where workers displaced from high-polluting jobs have a lower incidence of long-term unemployment.[36] This finding could indicate that the transition out of polluting activities has hitherto not implied major scarring effects from job displacement; but it could also result from compositional effects behind country aggregates, reflecting significant but

[33] For a recent discussion on localised displacement effects from high-polluting jobs, see material from the June 2023 conference on "The macroeconomic implications of climate action" at the Peterson Institute for International Economics (PIIE) https://www.piie.com/events/macroeconomic-implications-climate-action

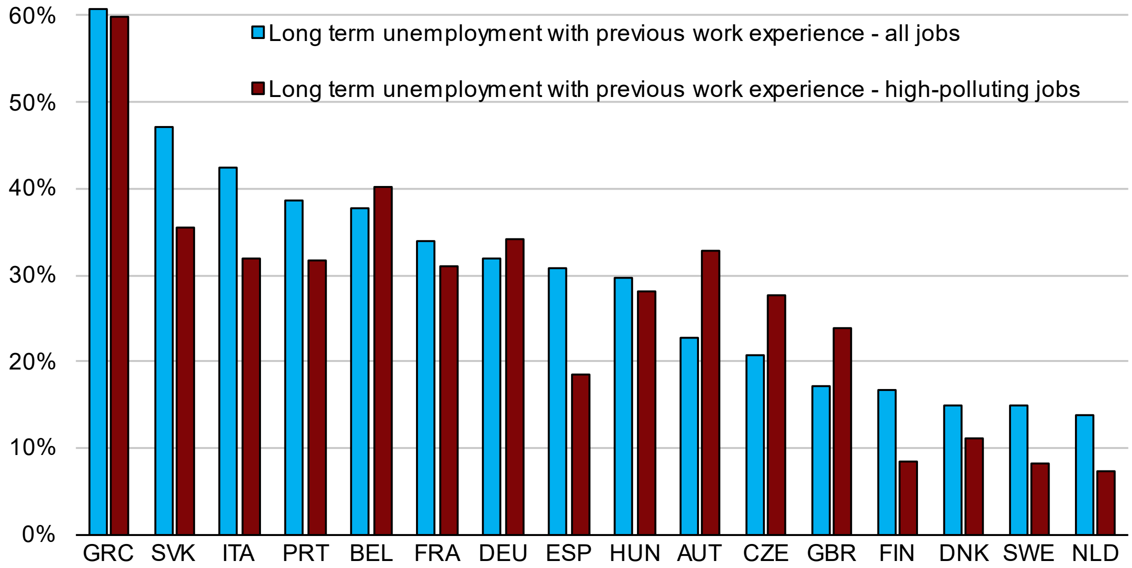
[34] Long periods of unemployment have been shown to have potentially 'scarring' effects which have a harmful impact in later life. It can lower future income levels, skills validity, future employability, job satisfaction, happiness, and health levels. See e.g., Abraham et al. (2016).

[35] Information on previous job is available for jobless individuals with declared work experience in the last 8 years.

[36] The evidence is not qualitatively different if 2019 as opposed to 2015-2019 average is used.

spatially concentrated displacement costs, as discussed before. Multivariate regression analysis is needed to try shedding light on the underlying structural and, possibly, policy factors influencing labour market transitions in the greening economy.

Figure 15. Incidence of long-term unemployment among individuals with previous work experience



Note: 2015-2019 average. Long-term unemployment refers to unemployment spell longer than one year. Information on previous job is available for unemployed individuals with declared work experience in the last 8 years. How to read: in Austria, 23% of unemployed with work experience have been unemployed for more than one year, 33% of unemployed whose last job was high-polluting have been unemployed for more than one year.
Source: Own elaboration on EU-LFS data.

Conclusions and policy considerations

This paper contributes to a collective and ongoing effort, by economists and social scientists in academia and by national and international organisations, to understand the labour market implications of the green transition and mitigation policies. This technical, laborious and resource-intensive work highlights the urgent need to address important data limitations that create obstacle to and complicate the analysis of the labour market impact of greening the economy, especially on a comparable and harmonised basis across countries.

In particular, the analysis of green jobs is hampered by the lack of a comprehensive and homogeneous European based taxonomy of green jobs: [37] this dictates the need to adapt the US-based taxonomy, at the cost of strong assumptions (over the mutability of job content of occupations between the United States and European countries) and possibly introducing measurement errors (implicit in the use of crosswalks). Similarly, the highly aggregated nature of cross-country data on emissions by industry hinders a more granular assessment of highly polluting industries and high-polluting occupations.[38] An additional issue in the identification of high-polluting occupations based on high-polluting industries is the absence of cross-

[37] See reference above to ongoing work by the European Commission.

[38] As discussed briefly in the paper and more extensively in the Annex, emissions data exists at the 6-digit level of aggregation for the US, but only at the 2-digit level for European countries.

country data on the bivariate distribution of workers by occupation and industry, which forces the use of a single country's data, in this case the UK.[39]

Addressing these and other data-related limitations is a key priority to understand labour market developments and thereby help shape policy packages to address the labour market consequences of climate mitigation efforts. This applies to all countries and requires international cooperation and coordination to support providing the needed evidence-base for policy.

Notwithstanding these methodological issues and data limitations, the descriptive evidence in this paper points to key policy challenges associated with greening the economy from a labour market perspective, in particular: i) the low progress achieved in terms of green jobs expansion, ii) the inequalities in terms of the socioeconomic composition of green jobs, especially the pervasive under-representation of women and low-educated workers, iii) the spatial divides associated with the geography of high-polluting and green jobs, particularly the concentration of high-polluting jobs in rural areas. The stylized facts documented in the analysis suggest that European countries face common challenges, for instance creating more and more equally distributed green jobs; but also that European countries feature heterogenous patterns regarding the greening of labour markets, which could reflect structural differences in labour market dynamism but also underlying differences in framework conditions and policy settings.

Overall, the evidence points to a possible role for policy and institutions in shaping labour market transitions associated with the greening economy. Against this background, future empirical research will need to explore some of the key policy issues likely to shape the viability of greening the economy from the labour market perspective, uncovering distributional and spatial aspects beyond aggregate patterns.

[39] While employment data by occupation *or* by industry is generally available, Eurostat and most national statistical institutes in Europe do not report the joint distribution by occupation *and* by industry.

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Appendix

Data sources

Table A1 reports the sources for the different data used in the paper.

Table A1. Data sources

Data	Source
Labour force survey data from a selected sample of EU countries. The microdata is collected at the individual level and cover the demographic and socio-economic characteristics of the respondent, including data on current or latest employment. Representative sample for each member country.	Eurostat, EU-LFS microdata, repeated cross-section 2011-2019
List of occupations classified as green based on the O*NET detailed taxonomy of occupations for the United States. Occupations observed at the SOC 8-d level of aggregation.	Vona et al. (2018)
Weighted crosswalk from SOC 6–digit to ISCO 4-digit. This is used to match each of the green occupations from the Vona et al. (2018) list to the corresponding ISCO 4-digit occupations.	Scholl et al. (2023)
Number of workers in each SOC 6-digit occupation. Necessary to define employment-based weights to be used in the crosswalk, following the Dingle and Neimann (2020) approach	US Bureau of Labour Statistics, 2016-2018
Number of workers employed in each NACE 2-digit industry, in each country and year.	Eurostat National Accounts Employment Statistics[40]
Pollution emitted by the production activities, across 7 pollutants, 2011-2019	Eurostat Air Emissions Accounts[41], 2011-2019
Number of workers in each occupation-industry combination.	UK Office for National Statistics, 2011 Census[42]
Official Crosswalk from UK SOC 4-digit to ISCO 4-digit	UK Office for National Statistics[43]

Estimating the number of workers in green and brown jobs

EU-LFS data contains information on respondents' occupation at the 3-digit International Standard Classification of Occupation (ISCO) level. As detailed in the paper, each ISCO 3-digit occupation is assigned a green score and a brown one, each ranging from zero to one and reflecting the share of underlying green and brown occupations. The green score reflects the ONET list of occupations expected to be heavily affected by the green transition in terms of required changes in content and tasks and is obtained through a careful crosswalk of this US-based measure to the ISCO taxonomy of occupations used by EU countries and Eurostat. The brown score is obtained, through an innovative approach summarized in the paper and detailed in the Annex, based on country-specific industry-level emissions data.

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40 https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Employment_statistics_within_national_accounts

41 https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Greenhouse_gas_emission_statistics_-_air_emissions_accounts&oldid=551152#Analysis_by_economic_activity/

42 https://www.nomisweb.co.uk/census/2011/ct0144

43 https://www.ons.gov.uk/methodology/classificationsandstandards/standardoccupationalclassificationsoc/soc2020/classifyingthestandardoccupationalclassification2020soc2020totheinternationalstandardclassificationofoccupationsisco08

For each year *y* and geographical unit *c*, the total numbers of workers employed in green and brown occupations are therefore obtained as

$$\mathrm{N.of}\ Workers\ in\ Green\ jobs_{c,y} = \sum_{j\in J}\sum_{\mathrm{i}\,\in\, I_j} \mathrm{GreenScore}_j \cdot w_i$$

$$\mathrm{N.of}\ Workers\ in\ \mathrm{Brown}\ jobs_{c,y} = \sum_{j}\sum_{\mathrm{i}\,\in\, I_j} Brown\mathrm{Score}_j \cdot w_i$$

where *J* is the entire set of occupations, *j* is any specific occupation, I_j is the set of all workers in said occupation and w_i is her sampling weight. This approach allows to properly take into account not only the sampling weights (hence achieving statistical representativeness), but also the fact that the green (brown) scores of many occupations are well below one, indicating that a non-negligible share of the workers in the occupation are probably employed in non-green (brown) sub-occupations. In the formulas above, the scores are used as weighting factors in computing the total number of workers employed in green (brown) jobs in a given country and year. In practice, the score is assumed to reflect the share of workers within that occupation who carry out a green job. For example, production and operations department managers (ISCO 122) have a green score of approximately 0.5: about half of all workers in these occupations are therefore counted as green. Note that any occupation characterized by a green (brown) score of zero does not contribute to the total count of workers in green (brown) jobs.

This analytical approach is used to perform the granular, distributional analysis e.g., to estimate number and share of green or brown jobs by socioeconomic group and area of residence.

Analysing labour market transitions for green and brown jobs workers

The analysis of labour market transitions for green and brown jobs workers is based the European Labour Force Survey (EULFS), for 16 OECD countries selected based on the availability of relevant data.[44] The survey reports the labour market status of each respondent in the current and, retrospectively, the previous year. This covers information about the characteristics of the current job for employed individuals and of the latest job for non-employed individuals. EULFS data form the basis of official Eurostat labour market statistics[45] and are relied-upon for labour market studies by academics and international organizations, including the OECD: see for instance Causa et al (2022), Bassanini and Garnero (2013), IMF (2022).

Against this background and in the context of the current focus on labour market transitions for green and brown jobs work, the analytical framework builds on the following definitions:

Transitions from unemployment to employment: share of individuals who report being employed at the time of the survey and unemployed in the previous year relative to individuals being unemployed in the previous year. Weighting each individual observation by the green (brown) score of her current occupation yields the transitions from unemployment into green (brown) jobs between t-1 and t:

$$U\ to\ Green_{(t-1,t)} = \frac{N.of\ workers\ who\ are\ in\ a\ green\ job\ in\ year\ t\ and\ unemployed\ in\ t-1}{N.of\ workers\ unemployed\ in\ year\ t-1} = \frac{\sum_i w_i \cdot GreenScore_{ijt} \cdot U_{it-1}}{\sum_i w_i \cdot U_{it-1}},$$

Where, for each respondent *i* working in occupation *j* in at the time of the survey (t), w_i indicates the sampling weight and $GreenScore_{ijt}$the green score of the respondent's occupation. U_{it-1} is an indicator taking value 1 if respondent *i* was unemployed in the year before. Transitions from unemployment to brown jobs are defined analogously.

Transitions from study-related inactivity to employment: share of individuals who report being employed at the time of the survey and inactive due to study in the previous year relative to individuals being inactive due to study in the previous year. The sample is in this case restricted to the age group 20-

[44] The countries are Austria, Belgium, Czechia, Denmark, Finland, France, Germany, Greece, Hungary, Italy, the Netherlands, Portugal, Slovak Republic, Spain, Sweden, the UK.

[45] https://ec.europa.eu/eurostat/web/lfs/database

29. As in transitions from unemployment, the corresponding transitions into green (brown) jobs are obtained by considering individual sampling weights along with green (brown) scores.

Transitions from employment to unemployment: share of individuals who report being unemployed at the time of the survey and employed in the previous year relative to individuals being employed in the previous year. The green (brown) score of the respondent's past job can only be defined for those that are currently unemployed and those that are currently employed in the same job as in the previous year. This reflects data limitations that preclude identifying transitions between (green) brown and (brown) green jobs with EULFS because information on previous occupation is not available for those currently employed. In this context, transitions out of brown (green) jobs are defined as follows:

Brown to Unemployment: $\frac{\sum_i w_i BrownScore_{i,j,t-1} \cdot U_{it}}{\sum_i w_i \cdot BrownScore_{i,j,t-1} \cdot U_{i,t} + \sum_i w_i \cdot BrownScore_{i,j,t} \cdot 1\{Tenure_{ijt} \geq 12 months\}}$, (4)

where U_{it} is an indicator taking value 1 if respondent *i* is unemployed in time *t* (and 0 otherwise), and $BrownScore_{ijt}$ and $BrownScore_{ijt-1}$ respectively represent the brown score of the occupation *j* that she held in the year of the survey (*t*) and in the previous one. The numerator therefore corresponds to the number of workers who had a green occupation in time t-1 and are unemployed in *t*. The denominator equals the sum of the numerator plus the number of respondents *i* who at the time of the survey have been in a brown job since at least 12 months (i.e., the number of workers who were in a brown job in t-1 and are still in the same job).

Incidence of long-term unemployment among workers with previous work experience: long-term unemployment (LTU) refers to unemployment spell longer than one year. Information on previous job is available for unemployed individuals with declared work experience in the last 8 years. The Incidence of long-term unemployment among individuals with previous work experience in all/brown jobs is defined as follows:

$$Long\ term\ unemployment\ (LTU): \frac{\sum_i w_i \cdot U_{it} \cdot 1\{UnemploymentSpell \geq 12 months\}}{\sum_i w_i \cdot U_{it}}$$

$$LTU\ from\ brown\ jobs: \frac{\sum_i w_i \cdot U_{it} \cdot 1\{UnemploymentSpell \geq 12 months\} \cdot\ BrownScore_{i,lastjob}\}}{\sum_i w_i \cdot U_{it} \cdot\ BrownScore_{i,lastjob}}$$

where $B rown\mathrm{Score}_{j,last\ job}$ indicates the brown score of the most recent occupation held by the individual.

Throughout the paper, stylised facts on yearly transitions refer to the average over the 2015-2019 period in order to smooth out the influence of outliers and cyclical swings.

Sample size

The sample covers working age (15-69) respondents living in private households, excluding the self-reported invalid-to-work. Table 2 provides a summary overview of this sample.

For most countries, the sample size is large enough to ensure that enough individuals are observed in each of the transitions above, especially when pooling them over the period 2015-2019. In cases when the sample size in a given transition is too small to ensure statistical significance, the country is excluded from the figures in the paper.

Table A.2. Sample size and composition

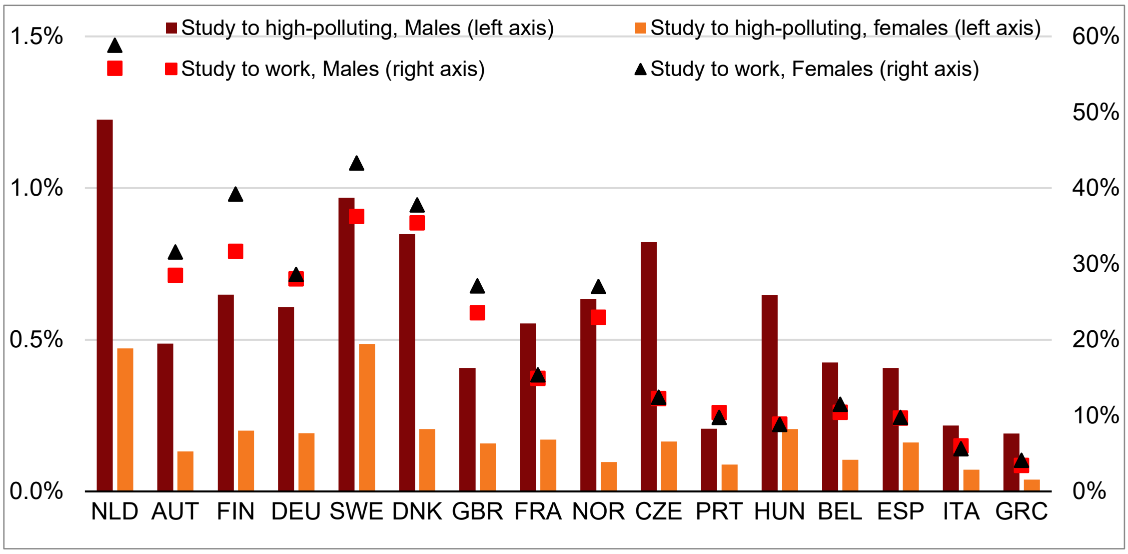
Country	Freq.	Percent
AUT	1,145,199	5.34
BEL	520,006	2.43
CZE	374,571	1.75
DEU	2,565,412	11.97
DNK	679,517	3.17
ESP	609,933	2.85
EST	159,807	0.75
FIN	157,309	0.73
FRA	619,962	2.89
GBR	486,060	2.27
GRC	1,476,597	6.89
HUN	1,473,219	6.87
IRL	1,157,211	5.4
ITA	3,480,594	16.24
NLD	542,580	2.53
NOR	159,429	0.74
POL	2,067,713	9.65
PRT	929,808	4.34
SVK	599,997	2.8
SVN	407,060	1.9
SWE	1,825,951	8.52
Total	21,437,935	100

Note: The table refers to the general sample, including all working age respondents who live in a private household (thus excluding military, religious and correction institutes). The sample excludes individuals who declare being invalid to work.
Source: EULFS.

Additional stylized facts

Figure A.1. Transitions from study-related inactivity to high polluting jobs, by gender

Percentage of young individuals transitioning from study-related inactivity to high-polluting jobs over a one-year period



Note: Transitions are defined over a one-year period. Yearly transitions are averaged across the years 2015-2019. The sample includes all respondents in the age range 20-29. How to read: in the Netherlands, out of all the female students who in a given are not in the labour force due to studying, 0.5% gets a high-polluting job and 40% get any job within a year. Among male students, 1.2% get a high-polluting job, and 32% any job.