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Stefanos Tyros,

Dan Andrews,

Alain de Serres

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ABSTRACT / RESUME

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The need to rapidly decarbonise economies raises questions about whether countries' workforces possess the requisite skills to achieve the net zero transition as well as the capacity to redeploy workers from "brown" to "green" jobs. This paper applies a task-based framework to granular data from the Occupational Information Network (O*NET) and country-specific employment sources to generate new indicators of the green skills structure of labour markets for a large number of OECD countries and non-OECD EU countries. Significant cross-country differences emerge in the underlying supply of green skill and the potential of economies to reallocate brown job workers to green jobs within their broad occupation categories. In a majority of detailed brown occupations, workers have in principle the necessary skills to transition to green jobs, with the exception of those in production occupations, who may require more extensive re-skilling. In contrast, workers from most highly automatable occupations are generally not found to have the sufficient skills to transition to green jobs, suggesting more limited scope for the net-zero transition to reinstate labour displaced by automation.

Keywords: green skills, reallocation, green transition

JEL codes: J24, J62, J68, J82

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La transition verte : implications pour la réallocation des compétences et des emplois

La nécessité de décarboner rapidement les économies soulève la question de savoir si la main-d'œuvre des pays possède les compétences requises pour réaliser la transition nette zéro, ainsi que la capacité de redéployer les travailleurs des emplois "bruns" vers les emplois "verts". Cet article utilise des données granulaires du réseau d'information sur les professions (O*NET) et d'autres sources d'emploi spécifiques à chaque pays afin de générer de nouveaux indicateurs de la structure des compétences vertes des marchés du travail pour un grand nombre de pays de l'OCDE et de pays de l'UE non-membres de l'OCDE. D'importantes différences entre les pays apparaissent dans l'offre sous-jacente de compétences vertes et dans le potentiel des économies à réaffecter les travailleurs occupant des emplois bruns à des emplois verts au sein de leurs grandes catégories professionnelles. Dans une majorité de professions brunes détaillées, les travailleurs possèdent en principe les compétences nécessaires pour passer à des emplois verts, à l'exception des travailleurs du secteur de la production, qui pourraient avoir besoin d'une requalification plus poussée. En revanche, les travailleurs de la plupart des professions hautement automatisables n'ont généralement pas les compétences suffisantes pour passer à des emplois verts, ce qui laisse supposer que les possibilités de réintégrer la main-d'œuvre déplacée par l'automatisation dans le cadre de la transition nette zéro sont plus limitées.

Mots-clés : compétences vertes, réaffectation, transition verte

Codes JEL: J24, J62, J68, J82

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Doing green things: skills, reallocation, and the green transition

By Stefanos Tyros, Dan Andrews and Alain de Serres[1]

1. Introduction

1. The urgent need for the decarbonisation of the world economy raises questions about whether the countries' workforce possess the green skills needed to support the widespread diffusion of climate-friendly technologies. OECD 2022 questions whether education systems are fit for purpose to advance the green transition. But since reforms to education systems can take a long time to reap benefits, the continued progress of climate goals will also depend on improving the allocation of the existing stock of human talent (Adalet McGowan and Andrews, 2017). This will hinge on the ease at which skilled workers can reallocate to perform new green tasks, as well as the ability to manage the political economy of job displacement in polluting sectors. Yet research on the skill requirements of the green transition is limited, in contrast to the burgeoning literature on the labour market impacts of the two other megatrends: globalisation and automation (Autor et al 2016; Acemoglu and Restrepo 2018).

2. The ease at which skilled workers can be redeployed to support the green transition hinges on the specificity of skills. If the skill profile of jobs in the expanding green sector has little overlap with the skill profile of contracting jobs, then the barriers to reallocation and adjustment costs will be higher. The skill similarity between occupations emerges as key determinant of worker reallocation costs, as opposed to the skill specificity of a particular firm (Poletaev & Robinson, 2008; Kambourov & Manovskii, 2009; Gathmann & Schönberg, 2010). Using US data, Vona et al. (2018) identify a set of transferable *green skills* that are required by workers in *green occupations*. They show that within most broad occupation groups, green skill levels of workers in brown jobs are similar to those required in green jobs. In turn, Popp et al. (2020) show that green fiscal stimulus programs are more likely to create green jobs in areas with a higher underlying level of green skills.

3. Building upon this US literature, our paper explores four key questions related to the workforce and skill requirements of the green transition in 31 OECD and EU countries:

- In which countries are the workforce's skills most conducive to the creation of green jobs?

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[1] Tyros: VU University Amsterdam and Tinbergen Institute (Stefanos.tyros@vu.nl); Andrews: e61 institute (dan.andrews@e61.in); de Serres: OECD, (alain.deserres@oecd.org). The authors would like to thank Manuel Bétin for statistical support, Alessandro Saia for facilitating access to data and Ines Gomez Palacio for editorial support. They would also like to thank Orsetta Causa, Lilas Demmou, Emilia Soldani, Douglas Sutherland, Filiz Unsal and Francesco Vona, as well as delegates from the OECD Working Party No. 1 of the Economic Policy Committee, for useful comments and suggestions.

- Which countries have the ability to reallocate workers – necessary to accommodate the green transition – more smoothly?
- In which broad occupations can workers from brown jobs potentially undertake green jobs? Towards which specific brown occupations should policy efforts be directed in order to prevent workers from being “left behind” from the green transition?
- Can the new employment opportunities induced by the green transition potentially reinstate workers displaced from highly automatable jobs?

4. To shed light on these questions, we follow Vona et al. (2018) in applying a task-based framework to granular data from the Occupational Information Network (O*NET) to identify green occupations and green skills. Brown occupations are identified from sectoral pollution data and their green skill profile is compared to that of green occupations. While O*NET is based on the United States, the underlying tasks undertaken by occupations are technologically determined, and thus unlikely to vary significantly across our sample countries. Accordingly, we overlay country-specific employment shares of 3-digit occupations on this task-based structure. In turn, this yields a range of structural indicators that are informative of the green skills structure of labour markets in OECD and EU countries.

5. We begin by documenting significant cross-country differences in the share of the employment in green, brown, and highly-automatable occupations across countries. We then construct the **Green Skills Index** (GSI), which reveals that the underlying green skill level of the workforce is much higher in northern European countries than in Southern and Eastern Europe. Cross-country differences in the GSI are largely driven by the top and bottom quartiles of occupational green skills. In Norway where the GSI is highest, the top (bottom) quartile of green skills accounts for 32% (16%) of employment. By contrast, top (bottom) quartile of green skills accounts for 18% (34%) of employment in Portugal, where the GSI is lowest.

6. The GSI reflects a range of structural factors, including whether education systems produce graduates that match the technological requirements of decarbonisation. But the stock of green skills is also shaped by the ease at which economies can reallocate labour to underpin the growth potential of productive firms, which differs across OECD countries (Andrews and Cingano, 2014). To this end, we construct the **Green Transition Index** (GTI), which captures the extent to which green jobs exist in occupation groups where brown jobs are present as well. We interpret the GTI as increasing in the potential of economies to reallocate brown job workers to green jobs *within* their broad occupation categories. Cross-country patterns in the GSI are broadly reflected in the GTI, reinforcing the importance of allocative considerations to policy debates on decarbonisation.

7. We then turn our attention to detailed occupations and two questions that go to the heart of the economic restructuring challenge implied by climate change and automation – the two great megatrends of our time.

8. First, we show that workers from *most* detailed brown occupations have the necessary skills to transition to green jobs. Thus, as the brown sector shrinks and the green one expands, workers can use these transferable skills to reallocate directly from brown jobs to green jobs. A notable exception, however, are workers in production occupations (e.g. tire builders, metal pourers & casters), where the transition of brown workers to green jobs appears less feasible. Policymakers may need to accommodate the particularly high transition costs that these workers face.

9. Second, we explore the potential for the expanding green sector to reinstate labour that automation displaces. At first glance, the share of the workforce susceptible to automation is lower (higher) in countries with higher (lower) green employment shares. Moreover, we find that workers from *most* highly automatable detailed occupations are generally not found to have the sufficient skills – green or other types – to undertake such transitions. One implication is that for emerging new green tasks to materially reinstate labour displaced by automation, policy needs to find ways to lower the cost of transition for workers from highly-automatable jobs with large skills gaps.

10. Our results imply that decarbonisation may – on average – entail smaller labour market transition costs than automation. Indeed, this is consistent with the estimated share of employment at risk of automation being materially higher than the share of the workforce in brown jobs. Nevertheless, this should not understate the reallocation challenge implied by decarbonisation. Indeed, pockets of the workforce remain vulnerable to displacement from decarbonisation – a politically salient group given their likely geographical concentration (Hanson, 2023).

11. Cross-country differences in the GSI and GTI raise key questions about whether policy can play a role to boost the supply of green skills and the potential to reallocate workers from brown to green jobs. In this regard:

- A robust correlation emerges across countries between environmental policy stringency and higher GSI and GTI, and lower share of brown workers that cannot transition to green jobs.
    - This suggests that tighter environment policy can create demand for green skills by inducing the necessary economic restructuring for the green transition and creating the business case for investment in low carbon technologies.
- Framework policies that shape labour mobility more generally also appear relevant.
    - More stringent employment protection legislation is associated with a higher share of brown workers that cannot transition to green jobs, potentially because it creates barriers to exit of low productivity polluting firms. In turn, this may congest markets and reduce the incentive for green firms to enter.
    - Active labour market policy expenditure as a share of GDP is lowest in those countries that have the largest share of brown workers that cannot transition to green jobs.

12. The next section places our study in the context of the existing literature. Section 3 describes the underlying data, while Section 4 outlines the empirical methodology. Section 5 presents new cross-country evidence on the distribution of employment across green, brown, and highly automatable activity, as well as the Green Skills and Transition indices. Section 6 explores the correlation of the new indices with structural policy indicators, while Section 7 offers some concluding thoughts.

2. Background and literature

13. Combating climate change requires the rapid decarbonization of economies. This constitutes a technological transformation wherein inherently brown sectors (e.g. oil extraction) shrink, green sectors (e.g. housing insultation) expand (OECD, 2021), while others transform in order to use emerging clean technologies (e.g. car mechanics dealing with car batteries instead of engines; Montt et al., 2018). The first hurdle in this process is generating the capital investments required to update the old technologies. Given that investments in old vintages of technology are sunk, policy makers have incentivised new capital investments with subsidies. The second, is matching these new technologies with workers that have the relevant skills. Den Nijs & Tyros (2023) show that beyond sunk investment costs in the transforming sectors, skill supply and sorting can shape the speed of adoption of emerging clean technologies, and thus the green transition.

14. In task-based frameworks of the labour market (Acemoglu & Autor, 2011) jobs comprise a collection of tasks that workers undertake using a certain production process. For example, school teaching comprises numerous tasks, including lesson preparation, public speaking in the class, and contact with parents. Workers' skills constitute the endowments they utilise in order to undertake these job tasks. Workers acquire on-the-job skills used to undertake specific job tasks (e.g. being able to undertake financial bookkeeping), but also have transferable skills that form the basis of the job specific skills (e.g. having the basic mathematics knowledge needed for the bookkeeping).

15. The supply and re-deployability of skills necessary to perform green tasks will play a crucial role in determining the speed of the decarbonisation of the economy, as well as the displacement costs for the affected workers. Vona et al. (2018) identify a set of transferable *green skills* that are required by workers in *green occupations*. They show that within most broad occupation groups, green skill levels of workers in brown jobs are similar to those required in green jobs. Crucially, this suggest that as the brown sector shrinks and the green one expands, workers can use these transferable skills to reallocate directly from brown jobs to green jobs.

16. In broad occupations where this re-deployment is less possible, brown job workers will need to find a non-green jobs and green vacancies will necessarily be filled by workers from other (i.e. neither green nor brown) jobs. This will raise the adjustment costs of the green transition, both on the economy-wide as well as on the individual worker level. Popp et al. (2020) provide evidence for this using data for the United States, showing that green fiscal stimulus programs are more likely to create green jobs in areas with a higher underlying level of green skills. We estimate the green skills level of the workforce across selected OECD and EU members, thus identifying countries better prepared to create green jobs.

17. IMF (2022) use the same skills data as Vona et al. (2018) to show that high greenness and pollution intensity of jobs is concentrated in a small number of detailed occupations. They find that more green-intensive occupations tend to have higher-skilled and more urban workers, while the opposite is true for more pollution-intensive jobs. They also study currently observed job-to-job transitions from pollution-intensive and neutral jobs to green jobs in the US and the EU and find them to be lower than those within the pollution intensive and neutral sectors.

18. In a parallel literature, Bechichi et al. (2019) identify the cross-occupation transitions that can occur with various levels of re-training. Using EU data on the skills required by occupations and the skills workers possess, they focus on the ability of workers in automatable occupations to transition away from them. They find that this usually requires significant cognitive and task-based skills-related training.

19. Hence, even though brown job workers have the green skills on average, workers in certain occupations might lack other skills relevant for transitioning to green jobs. We use a similar framework to Bechichi et al. (2019) in order to identify these brown occupations workers that cannot transition to green jobs.

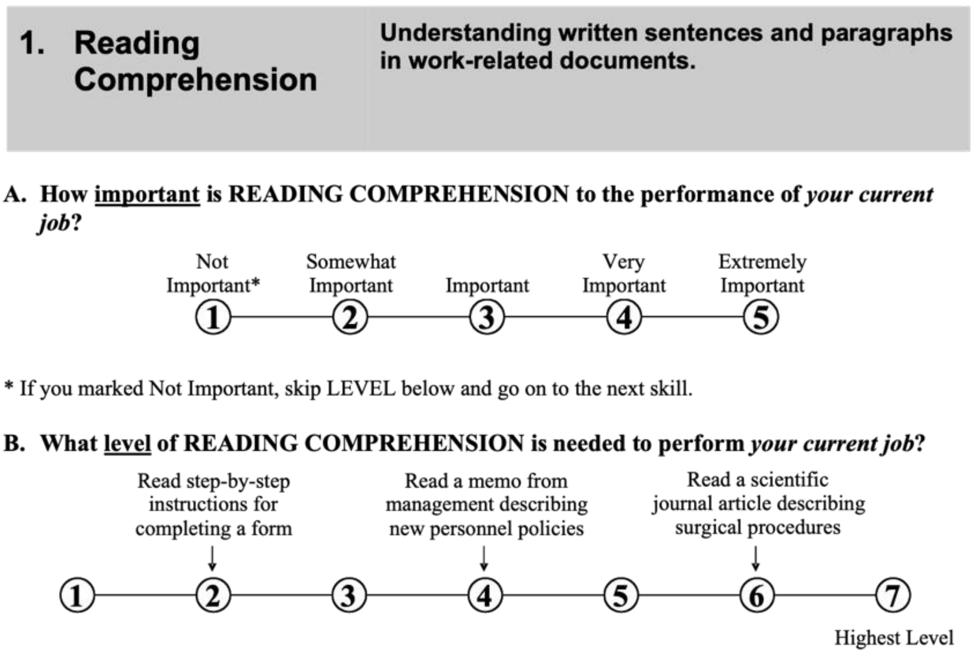
20. Finally, Acemoglu and Restrepo (2018) describe automation as the process of capital taking over job tasks from workers, putting downwards pressure on employment and wages. This is countered by the creation of new tasks on which labour is reinstated. They show that in recent years automation has taken over reinstatement in the US, and similar patterns are observed in some EU countries (Kerkemezos & Tyros, 2021). If emerging green jobs include many new tasks that reinstate labour, then the green transition could potentially counter displacement effect associated with automation. Thus, we also study whether workers in automatable occupations have the necessary green skills needed to transition to green occupations.

3. Data

21. We use the O*NET database to derive information on the tasks comprising different occupations and the skills needed to undertake them. The dataset describes US occupations, defined at the level of 8-digit SOC codes, using information from incumbent workers and occupation experts. It includes a description of the detailed tasks for each occupation (roughly 20, e.g. “Interview and hire applicants”) as well as a flag variable denoting whether these tasks are “green tasks”. These tasks are identified as those tasks whose purpose is focused on green activities (e.g. activities that lead to a reduction in greenhouse gas emissions) and technologies, and are thus relevant for the decarbonization of the economy.

22. The skills datasets include information on manual and cognitive skills. For each such skill, “an importance” score denotes how important (i.e. relevant) the skill is in the performance of the job. A “level” score denotes the minimum level at which this skill is required. Figure 1 shows how the questionnaire is structured for the 108 different skill questions of O*NET.

Figure 1. An example, for the skill “Reading Comprehension” of the O*NET questionnaire that incumbent workers and occupation experts answer



1. Reading Comprehension | **Understanding written sentences and paragraphs in work-related documents.**

A. How important is READING COMPREHENSION to the performance of *your current job*?

Not Important* (1) — Somewhat Important (2) — Important (3) — Very Important (4) — Extremely Important (5)

* If you marked Not Important, skip LEVEL below and go on to the next skill.

B. What level of READING COMPREHENSION is needed to perform *your current job*?

Read step-by-step instructions for completing a form → 2

Read a memo from management describing new personnel policies → 4

Read a scientific journal article describing surgical procedures → 6

1 — 2 — 3 — 4 — 5 — 6 — 7

Highest Level

*Source: O*NET*

23. The employment data of the Occupational Employment Statistics (OES) are defined on the 6-digit SOC level and are matched with the occupations in O*NET using a crosswalk provided by the Bureau of Labor Statistics. Therefore, our analysis is on the 6-digit SOC level and includes 748 different occupations, accounting for more than 97% of employment in the United States.

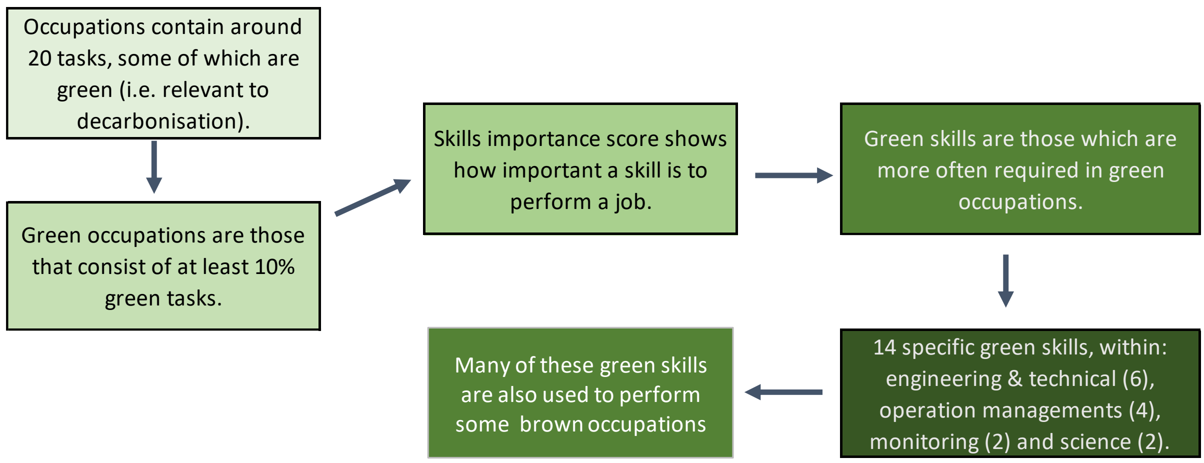
24. We assume that the underlying tasks undertaken by occupations do not vary significantly across countries – i.e. they are technologically determined – and thus the granular information in the O*NET database for the United States provides a suitable technological benchmark for all the countries in our sample.

25. With that in mind, we undertake a cross-country analysis for 31 OECD and EU countries, comprising: the United States, Australia, the European Union member states (except Finland and Malta), the United Kingdom, Switzerland, Iceland, and Norway. We use employment shares from the pre-pandemic years 2017-19. The employment shares for the US are taken from the Bureau of Labor Statistics, for the EU, Switzerland, Iceland, Norway, and UK from the European Labour Force Survey, and for Australia from the Australian Bureau of Statistics.

4. Methodology

26. In this section we introduce the building blocks of our analysis: green tasks, green skills, as well as green, brown and highly automatable occupations. We use these to define two cross-country indices – the green skills and the green transition indices -- that identify the countries where the supply-side is most conducive to the creation of green jobs and the reallocation of workers from brown to green jobs. These building blocks are summarised in a schematic Figure 2. It underscores how the identification of both green tasks and the skills required to perform those tasks is crucial to assess the potential ease of reallocation during the green transition.

Figure 2. The building blocks of green skills and green transition indices



4.1 Green tasks, skills, and occupations

27. Green tasks are those associated with the pursuit of environmental activities, not least tasks that are relevant for the decarbonisation of the economy. Green skills are the transferable skills that workers need to undertake green tasks. For example, construction skills are needed to undertake the insulation of buildings, and standards compliance skills are needed to identify which firms are polluting too much. Hence, green skills can be identified as the skills more relevant to undertake green compared to non-green tasks.

28. Using the O*NET task and skill dataset, Vona et al. (2018) calculate the greenness of each occupation, defined as the share of their tasks that are green (noting that occupations are a bundles of tasks).[2] Therefore, occupation greenness estimates the relevance of jobs to the green transition. Following their methodology, we identify green occupations as those that have 10% or more of their tasks being green (i.e., for an average of 20 tasks per occupation, those that have at least 2 green tasks). Box 1 illustrates this with a few examples.

29. For reasons mentioned in Vona et al. (2018) we have chosen not to estimate green employment as the employment share of these green occupations. In short, doing so would likely over-estimate the true measure, as an occupation having a high share of tasks being green does not mean that all their labour is directed towards green production. For that reason, we estimate green employment in country i, GE^i, as the employment share of all occupations, o, weighted by their greenness

$$GE^i = \sum_o G_o^{O*NET} e_o^i$$

where G_o^{O*NET} is the greenness of occupation *o* based on the US O*NET data and e_o^i is the employment share of that occupation in the country. The interpretation of this estimation is that the share of green tasks in a certain occupation gives an estimate of the labour share that is used in green production. Vona, et al. (2016) find that in the United States this figure is in line with the share of total production that is classified as green.

30. Furthermore, Vona et al. (2018) identify the skills that are more often required by occupation with a high greenness. They do this by regressing occupation greenness on the importance score of all the O*NET skills and singling out the skills that are required with a significantly higher importance in green jobs. The identified skills are interpreted as being the transferable skills that are needed to undertake green tasks, namely the green skills. They identify 14 specific green skills, which are classified in four groups of green skills: engineering and technical skills, operation management skills, monitoring skills, and scientific knowledge. Table 1 presents these four green skill groups and the 14 specific green skills included in them.

31. Using this analysis, we calculate the green skill level of workers across all O*NET occupations. The working assumption, borrowed from Vona et al. (2018), is that, on average, workers possess – or acquire on the job – the skills that their current occupation requires. Hence, for each occupation we use the skill importance scores from O*NET of these 14 specific green skills. Taking their average, we calculate the level of each of the four green skill groups. Finally, the green skill level of each occupation is calculated by taking the Pythagorean sum of these four numbers, as illustrated in Box 1.

[2] Following Vona (2021), when aggregating from 8-digit O*NET to 6-digit SOC codes we choose the greenness of certain occupations by hand, to avoid inflated greenness measures. We also set the greenness of occupation 53-7081" Refuse and Recyclable Material Collectors" to zero, as they are "green" in the sense of being environmental, but not in the terms of the goal of carbon neutrality.

Table 1. Identified green skills classified in four groups

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

Source: Vona et al. (2018).

4.2 Brown Occupations, Highly-Automatable Occupations, and Reallocation

32. Vona et al. (2018) identify brown occupations as those that have a large share of their employment in highly polluting industries. These industries are taken to be the top 5% of US industries in terms of emissions per worker. Estimating the green skill level of workers in brown jobs, they find that within most broad occupation categories, the green skills of workers in brown jobs are of similar level to those in green jobs. This means that, although green skills are defined as those more correlated with green jobs, they are not possessed only by green job workers, but, importantly, by brown job workers as well. One potential implication is that the transition costs arising from the labour reallocation required to supply the Green Transition may be lower than otherwise thought.

Box 1. Occupation greenness and green skills

We illustrate the difference between the greenness of occupations and green skills indicators by considering three occupations: Climate Change Analyst, General Maintenance and Repair Workers, and Auditors.

Their respective greenness levels (the share of tasks that are green) are 1, 0.18, and 0:

- Auditors undertake no green tasks. Two tasks that they do undertake are “Prepare detailed reports on audit findings.” and “Supervise auditing of establishments and determine scope of investigation required.”
- General Maintenance and Repair Workers undertake 30 tasks, 4 of which are green. An example of a task that is not specific to the green transition is “Dismantle machines, equipment, or devices to access and remove defective parts, using hoists, cranes, hand tools, or power tools.”. An example of a green task that they undertake is “Install equipment to improve the energy or operational efficiency of residential or commercial buildings.”
- All 14 tasks undertaken by Climate Change Analysts are green. Two examples are “Provide analytical support for policy briefs related to renewable energy, energy efficiency, or climate change.” and “Promote initiatives to mitigate climate change with government or environmental groups.”

The table below demonstrates the calculation of the green skill level of each occupation. Columns 2-5 indicate the average importance level of the specific green skills within each green skill group presented in Table 2. The Green Skill Level is the Pythagorean sum (divided by 4) these four numbers.

Table 2. Occupation greenness and green skills

Occupation	Engineering & Technical	Operation Management	Monitoring	Science	Green Skill Level
Climate Change Analyst	0.25	0.69	0.68	0.44	0.27
General Maintenance and Repair Workers	0.46	0.35	0.36	0.23	0.18
Auditors	0.13	0.67	0.75	0.01	0.25

What becomes clear is that, although related on the aggregate level, there is no one to one correspondence between greenness and green skills at the occupation level. Auditors do not perform any green tasks, but the tasks they do undertake require a high level of Operation Management and Monitoring Skills. But since these skills are needed to undertake green tasks in other occupations, there is high level of green skills of Auditors.

33. Using data from Frey and Osborne (2017), we also identify highly-automatable occupations as those with a larger than 95% probability of being automated in the future[3]. We set our threshold at 95%, compared to the usual 70%, as we are not interested in long-term automation, but within the next two decades during which the green transition will take place. When occupations that we identify as highly-automatable have also been identified as green or brown, we keep their original green/brown identification. We extend the analysis of Vona et al. (2018) by also comparing the green skill level of workers in highly automatable jobs to those in brown and green jobs.

34. For the case of brown and highly-automatable occupation we estimate their employment shares by taking the simple sum of the employment shares of the identified respective occupations.

4.3 The Green Skill Index

35. Popp et al. (2020) show that the presence of a high level of green skills in local economies in the United States boosted the creation of green jobs associated with the green stimulus of the 2009 *American Recovery and Reinvestment Act*. The green stimulus led to a long-term increase of employment in green occupations in areas with a high pre-existing green skill base.

36. We, thus, create the **Green Skill Index (GSI)** to calculate the underlying green skill level of the workforce for all countries in our dataset. The GSI is defined as the average green skill level of the countries', *I*, workforce:

$$GSI^i = \sum_o GS_o^{O*NET} e_o^i$$

where e_o^i is the employment share of occupation *o* in the country and GS_o^{O*NET} the green skill level of the occupation's workers in the US O*NET dataset. Annex A discusses our method for connecting the O*NET occupation data with occupation codes across the countries in our sample.

4.4 The Green Transition Index

37. The GSI is an index of the general level of green skills in the economy. What is also relevant, though, is whether the brown jobs that will be lost are in occupation groups where green jobs are being created. Bechichi et al. (2019) suggest that crossing broad occupation boundaries tends to be difficult for workers.

38. Thus, we also create the **Green Transition Index (GTI)** that indicates which countries have a high potential to reallocate brown job workers to green jobs *within* their broad occupations. In each country, *I*, we calculate the GTI for each broad occupation, *O*, as the ratio of the average greenness of its detailed occupations over their brown employment share

$$GTI_O^i = \sum_{o \in O} e_o^i G_o^{O*NET} \Big/ \sum_{o \in O} e_o^i B_o^{US}$$

[3] Frey and Osborne (2017) hand-label 70 occupations, based on experts' assessments, assigning 1 to fully automatable occupations, where all tasks were considered to be automatable, and 0 if not. Assessment was based on the O*NET tasks and job description of each occupation. The hand-labelling of the occupations was made by answering the question "Can the tasks of this job be sufficiently specified, conditional on the availability of big data, to be performed by state-of-the-art computer-controlled equipment".

where $e_o^i$is the employment share of the specific occupation *o* in the country, G_o^{O*NET}its greenness according to the O*NET data, and B_o^{US} an index indicating whether the job is brown or not[4], based on US occupation data. This indicates how many green jobs there are within the broad occupation per brown job. Given that in Section 5, we provide evidence that green jobs are more likely to be created in local economies with an already highly green employment share, the GTI is a measure of the potential reallocative capacity from declining brown to – newly created – green jobs. The aggregate GTI is then constructed as the employment share weighted average of the broad occupation GTIs

$$GTI^i = \sum_O GTI_O^i \, e_O^i$$

where $e_O^i$is the employment share of the broad occupation *O* in the country.

4.5 Workers in danger of being left behind

39. Finally, green skills are not the only relevant skills for transitioning across occupations. Even if brown job workers have – on average – the relevant green skills, other skill deficits may inhibit the transition of workers from specific brown occupations to green jobs.

40. Bechichi et al. (2019) analyse the International Standard Classification of Occupations (ISCO-08) 3-digit occupations to find which occupation-to-occupation transitions are possible. They use data from the Survey of Adult of Skills (PIAAC) to estimate the skills gap between workers and occupations, as well as whether workers are able to take up the tasks of the job and whether they have the relevant knowledge. Using these, they estimate the possible transitions that can occur with a short, medium and long retraining period. Finally, they explore which of these transitions would be acceptable, by requiring a wage drop of at most 10% and that the workers are not too overqualified.

41. We follow a similar method to calculate the possible and acceptable transitions across O*NET occupations, which includes five times more occupation codes. O*NET skills encompass a wider variety of transferable skills and knowledge, but not task-specific skills. The OES data allows us to estimate the wage drop of a possible transition. As above, we estimate worker's skills by assuming that they possess (on average) the skills required by their current occupation.

42. Following Brügemann et al. (2023), we estimate the skill gap of a worker transitioning from one occupation to another based on the methodology outlined in Box 2.

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[4] Brown jobs are identified for the US SOC occupation classification, hence B_o is either 0 or 1 for the US GTI. For the rest of the countries where crosswalks are used B_o can also take fractional values, indicating that only a share of the occupation is brown.

Box 2. Estimating the skills gap between occupations

Brügemann, et al. (2023) estimate the skills gap between occupations. To do this, they use a model of worker-firm productivity to estimate the productivity loss of a firm hiring a worker from different occupation than the one of the optimal worker. This productivity loss can be utilized as a proxy for the skills gap between occupations.

They define x to be the one-dimensional skills gap between the skills of a worker and the skills that a job requires, and γ the importance of the skills gap in production (i.e., the specialization of the job). Using a second order expansion in x of the production function, the productivity, Y, of a job-worker match reads as

$$\boldsymbol{Y = \alpha\left(1 - \frac{1}{2}\gamma x^2\right)}$$

where α is the productivity if the optimal worker is hired, and the first term of the expansion is 0, as productivity is optimal at a zero skills gap.

This is generalized for the multi-dimensional O*NET skills data. They define N as the total number of O*NET skills, γn,J the importance of the skill n is the job's production process, sn,J the level of skill n required by the job, and sn,W the level of skill n the transitioning worker possesses. They associate γn,J and sn,J with the importance and level of each skill from the O*NET questionnaire required by the occupation of the job. Sn,W is associated with the level of each skill from the transitioning worker's occupation. Hence, the productivity of a transitioning worker, W, to a job, J, in a different occupation is given by

$$Y = \alpha \prod_{n \in N} \left(1 - \frac{1}{2}\gamma_{n,J}\left(s_{n,J} - s_{n,W}\right)^2\right)^{I\left(s_{n,J} > s_{n,W}\right)}$$

where the I function indicates that a skills gap exists only if the skill level required by the job is larger than the skill the worker possesses. Dividing by the optimal match productivity, α, they acquire the relative productivity of the transitioning worker in the new occupation.

43. Intuitively, we estimate the implied (percentage) productivity loss of a job when hiring a worker from certain occupation. To calculate this, Brügemann, et al. (2023) use the skills gap between the worker (defined as the skill requirements of their occupation) and the job for all O*NET skills, as well as how important this skill is in the production process of this job, to estimate the productivity of the worker-job pair.

44. Following Bechichi et al. (2019), we define as possible the transitions at the lowest productivity-loss quantile of all possible transitions. In their analysis, this corresponds to transitions that require minimal (re)training (up to 6 months) for the worker to be able to undertake the job. Larger skill gaps require moderate (up to 1 year) or important (up to 3 years) retraining, which we interpret as infeasible for the market to provide without policy intervention. Hence, the lack of possible transitions in our analysis indicates the need for policy to assist the reallocation process of the green transition.

45. Acceptable transitions are defined as the possible transitions that lead to at most a 10% wage drop[5]. Using this, we identify which brown and highly-automatable occupation workers are not able to transition to a green job, as those that have less than two acceptable transitions to green occupations. We, therefore, identify which occupations' workers will be in danger of being left behind during the green transition. We also estimate the employment share of such brown workers across our sample countries.

4.6 Aggregation

46. The available employment shares in the United States are in the 6-digit SOC level, in Australia in the 4-digit ANZSCO level and in Europe in the 3-digit ISCO level. The latter is the most aggregate level.

47. Vona (2021) discusses the complications of using the O*NET data in combination with European data. On the one hand, the assumption that occupations in Europe include the same tasks and skill as in the United States is reasonable. On the other hand, aggregating this data from the roughly 1000 US occupations to the roughly 100 European ones can give rise to large errors. More specifically, the lack of granular level employment data in Europe means that one has to take unweighted means of the greenness, brown, automatable, and green skill occupations. If, within broad occupations, the values of these indicators differ significantly across specific occupations, then the aggregate estimates will be less precise.

48. As a first step, to ensure that errors are minimised, we estimate all our country variables on the same level of aggregation. More specifically, we first crosswalk the indicators from the US data to Europe and Australia, as described in Appendix 1, and then we estimate everything at the 3-digit ISCO level, and its equivalent 3-digit ANZSCO and 4-digit SOC levels.

49. Vona (2021) indicates that greenness and brown indicators vary significantly within broad occupations, whereas the skills requirements do not. We observe that the latter holds true also for the automatable index. Thus, the main focus of this paper is the analysis of skills, and while the analysis of green and brown employment ought to be treated as a less precise guiding principle.

5. Results

50. In this section, we present cross-country evidence on the employment shares of green, brown, and highly-automatable occupation groups, as well as the cross-country distribution of the GSI and the GTI. We then conduct a deep dive into specific brown and highly-automatable occupations, to shed light on the potential for workers to transition to green jobs.

5.1 Employment across relevant occupational groupings

51. Out of the 748 6-digit SOC occupations in the United States for which we have data, we identify 63 green, 75 brown, and 72 highly-automatable occupations (see Annex 2 for more details). Table 3 presents a few relevant examples of such occupations.

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5 This figure corresponds to approximately the average annual earnings loss of workers one year after displacement in 5 OECD countries (OECD, 2013).

Table 3. The number of green, brown, and highly-automatable occupations

(6-digit SOC, along with their US employment share and relevant occupation title examples)

Occupation groupings	Number of occupations	Examples of occupations
Green	63	Architectural and Engineering Managers;
		Environmental Engineers;
		Solar Photovoltaic Installers;
Brown	75	Petroleum Engineers;
		Industrial Machinery Mechanics;
		Tire Builders
Highly-Automatable	72	Credit Analysts;
		Postal Service Clerks;
		Shoe Machine Operators and Tenders
		Tax Preparers;

Source: Authors' calculations based on O*NET and Bureau of Labor Statistics

52. Figures 3, 4, and 5 present the green, brown, and highly-automatable employment shares, respectively, for our sample countries. In all three significant cross-country variation is observed. For green employment this ranged from around 3.5% in Norway and Estonia to roughly 2% in the United States, Italy, and Greece. Similarly, brown employment ranges from around 10% in Hungary and Bulgaria to 3% in the United Kingdom and the Netherlands. Finally, the employment share of highly-automatable occupations goes from roughly 17% in Cyprus and Italy to 11% in Norway and Latvia.[6] As mentioned in section 4.6, though, these estimates ought to be taken as a guiding principle only and not as a precise estimate.

[6] This is largely in line with OECD (2018), which estimates 14% of jobs in OECD countries to be "highly automatable".

Figure 3. The green employment share of 31 OECD and EU countries[7]

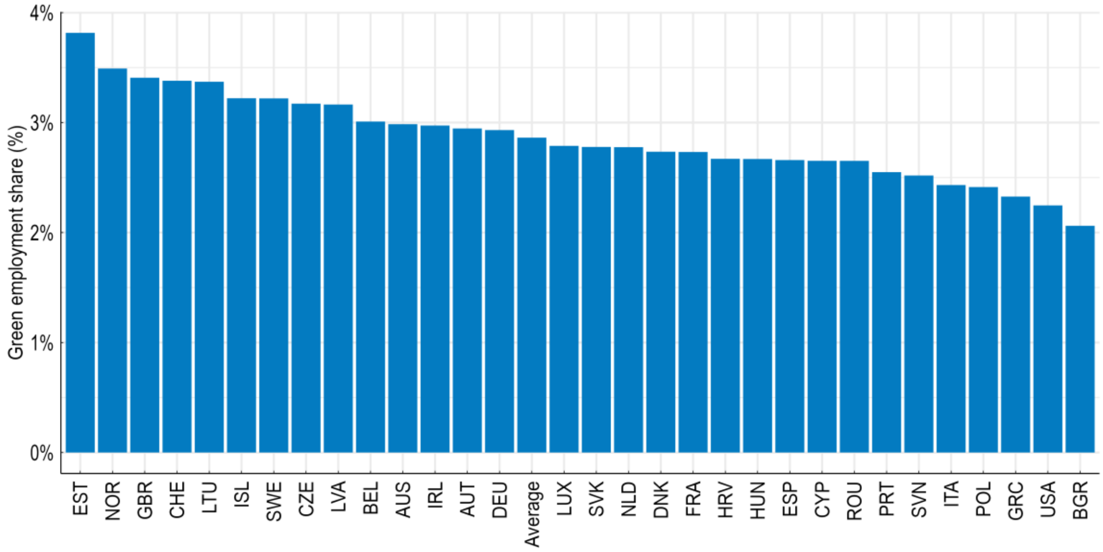
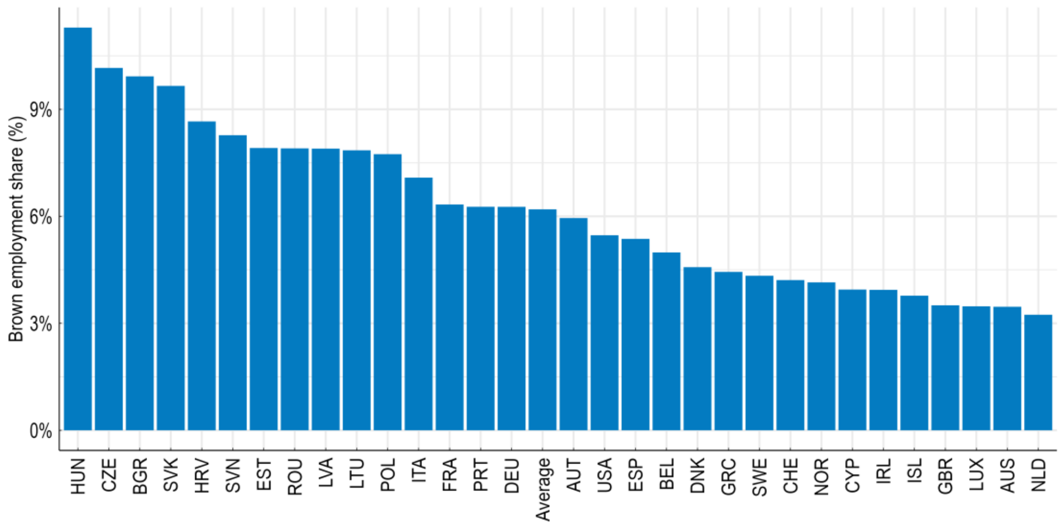


Figure 4. The brown employment share of 31 OECD and EU countries

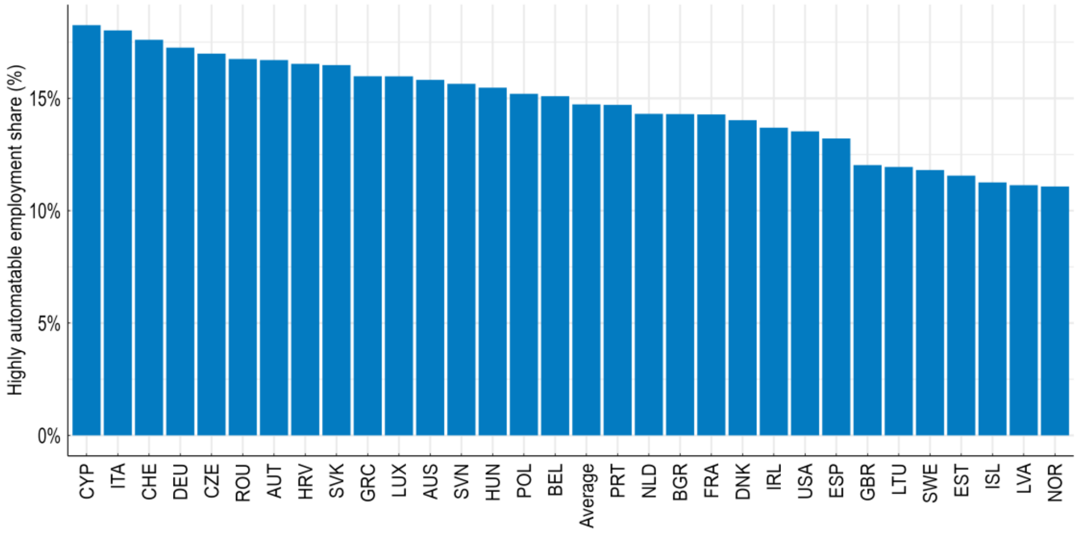


[7] Note by the Republic of Türkiye

The information in this document with reference to "Cyprus" relates to the southern part of the Island. There is no single authority representing both Turkish and Greek Cypriot people on the Island. Türkiye recognises the Turkish Republic of Northern Cyprus (TRNC). Until a lasting and equitable solution is found within the context of the United Nations, Türkiye shall preserve its position concerning the "Cyprus issue".

Note by all the European Union Member States of the OECD and the European Union:
The Republic of Cyprus is recognised by all members of the United Nations with the exception of Türkiye. The information in this document relates to the area under the effective control of the Government of the Republic of Cyprus.

Figure 5. The highly-automatable employment share of 31 OECD and EU countries



Sources for Figures 3 to 5: Authors' calculations based on O*NET, Vona et al. (2018), Frey and Osborn (2017), European Labour Force Survey, Australian Bureau of Statistics and US bureau of Labor Statistics.

53. A cross-country correlation emerges between highly-automatable and green employment shares (Table 4), implying that the share of the workforce susceptible to automation is lower (higher) in countries with higher (lower) green employment shares. By contrast, there is no correlation between brown and highly-automatable employment and green and brown employment.

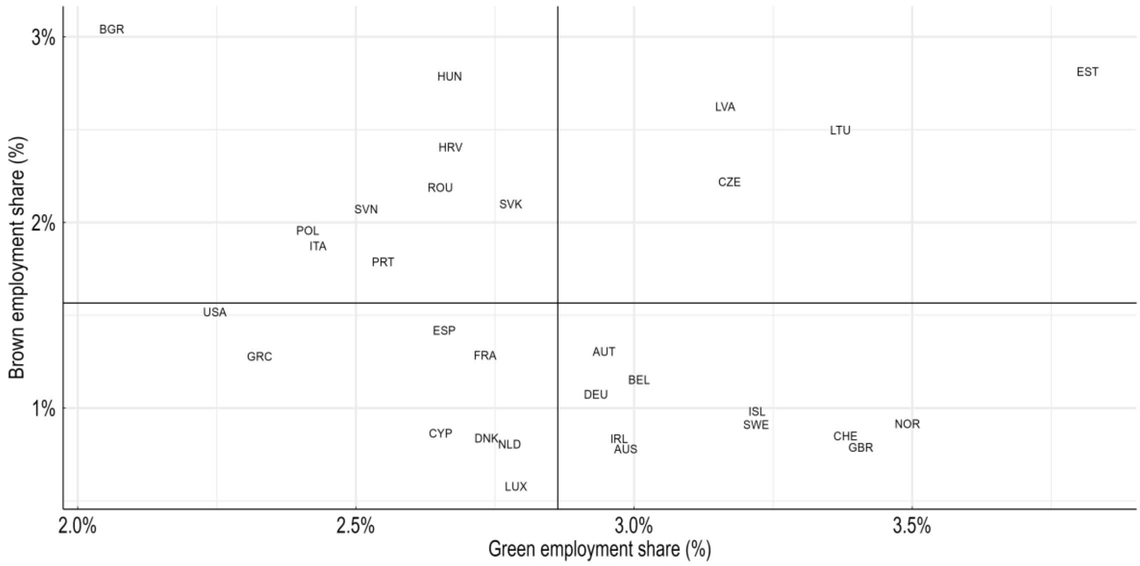
Table 4. The cross-country correlations between the green, brown, and highly-automatable employment shares

	Green-Brown	Green-Automatable	Automatable-Brown
Correlation	-0.22	-0.46*	0.18

Note: A star indicates that the corresponding regression coefficient is significant to the 5% level

54. Figure 6 presents the green and brown employment shares, expressed as deviations from the cross-country average. In the upper left quadrant, Bulgaria and Poland combine relatively low green employment shares with relatively high brown employment shares. An immediate conjecture is that these countries may encounter more significant restructuring challenges from decarbonisation than countries in the lower right quadrant – such as the United Kingdom and Norway – which have higher green and lower brown employment shares.

Figure 6. The green and brown employment shares of 31 OECD and EU countries compared to their mean values

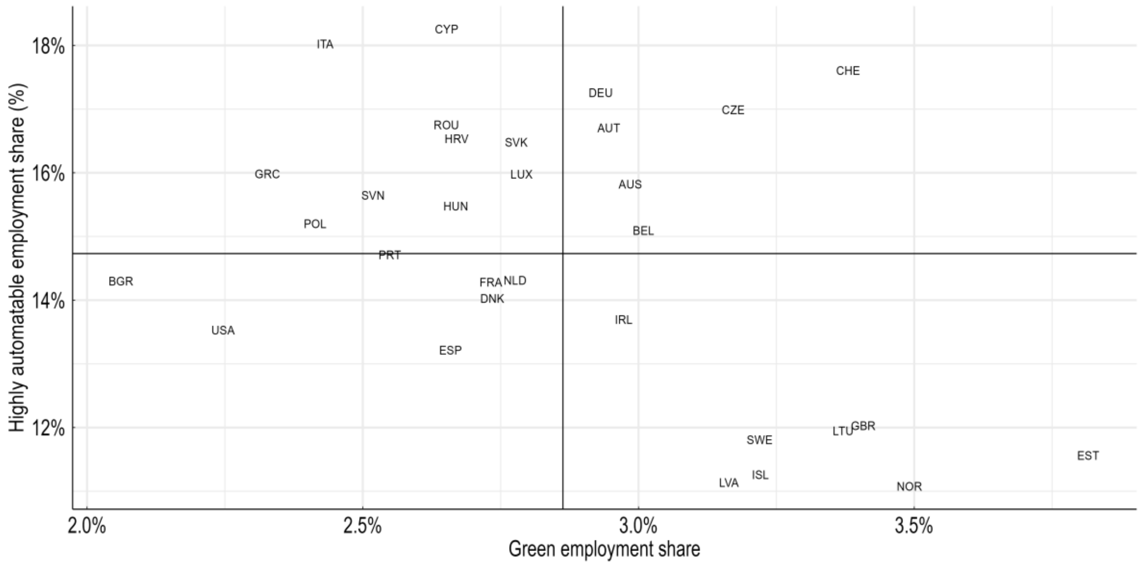


Source: Authors' calculations based on O*NET, Vona et al. (2018), European Labour Force Survey, Australian Bureau of Statistics and US Bureau of Labor Statistics.

55. Figure 7 plots countries in the green-automatable space. Most countries reside in either the upper left quadrant (high automation, low green) or the lower right quadrant (low automation, high green). By contrast, there are fewer countries in the upper right quadrant, where it may be more readily possible for the Green Transition to reinstate labour displaced by automation. This significant negative cross-country correlation is consistent with US evidence, which shows that greenness is particularly high in less routine occupations such as engineering (Vona et al., 2018).

Figure 7. The green and highly-automatable employment shares

(31 OECD and EU countries, compared to their mean values



Source: Authors' calculations based on O*NET, Frey and Osborne (2017), European Labour Force Survey, Australian Bureau of Statistics and US Bureau of Labor Statistics.

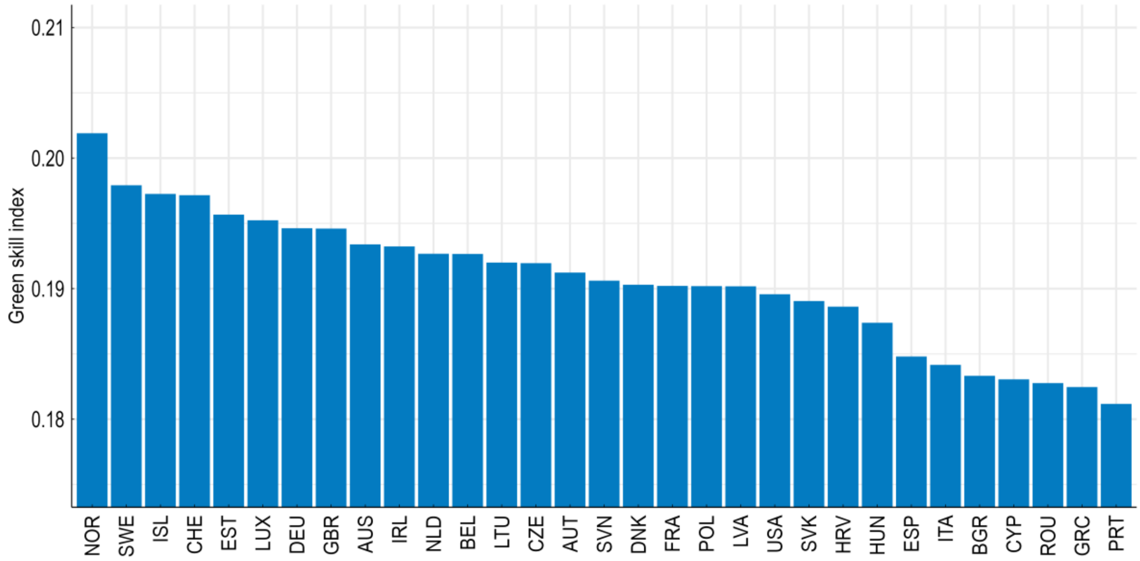
5.2 The Green Skills Index

56. Figure 8 presents the Green Skills Index (GSI), which reveals that the underlying green skill level of the workforce is much higher in northern European countries than in Southern and Eastern Europe.

57. Annex E presents the GSI of US Metropolitan Statistical Areas (MSAs). The size of the variation observed across MSAs is similar to the one in Figure 8 across our sample countries. Popp et al. (2020) find that the variation in the green skill supply observed across MSAs plays an important role in the creation of green jobs as a result of green stimulus. We estimate the measure of the green skill supply used by Popp et al. (2020) and find it highly correlated with the MSA GSI (correlation 0.84). Therefore, the observed differences of the GSI across countries in Figure 8 are similar in size to the differences across MSAs calculated by Popp et al. (2020). One implication is that the GSI variation across our sample countries is potentially predictive of the ease of creating green jobs – in response to a green fiscal stimulus – as well as an indicator of the existing stock of green skills.

58. Next, we segment occupations into quartiles according to their green skill level. Figure 9 presents the employment share distribution of these quartiles for Portugal (a low GSI country) and Norway (a high GSI country), as well as for the sample mean. In Portugal the low aggregate GSI reflects a disproportionately high share employment in the lowest GSI quartile, while the employment share in the top GSI quartile is low. This suggests that differences in the aggregate GSI across countries are mostly driven by differences in the top and bottom quartiles of occupational green skills. This pattern is confirmed by Table 5, which shows that that GSI is mostly correlated with employment in the top green skill quartile. Finally, Annex F, Box A.F1 exploits time-series data on employment shares for Australia to explore how the GSI and the employment shares of the green skill quartiles change over time.

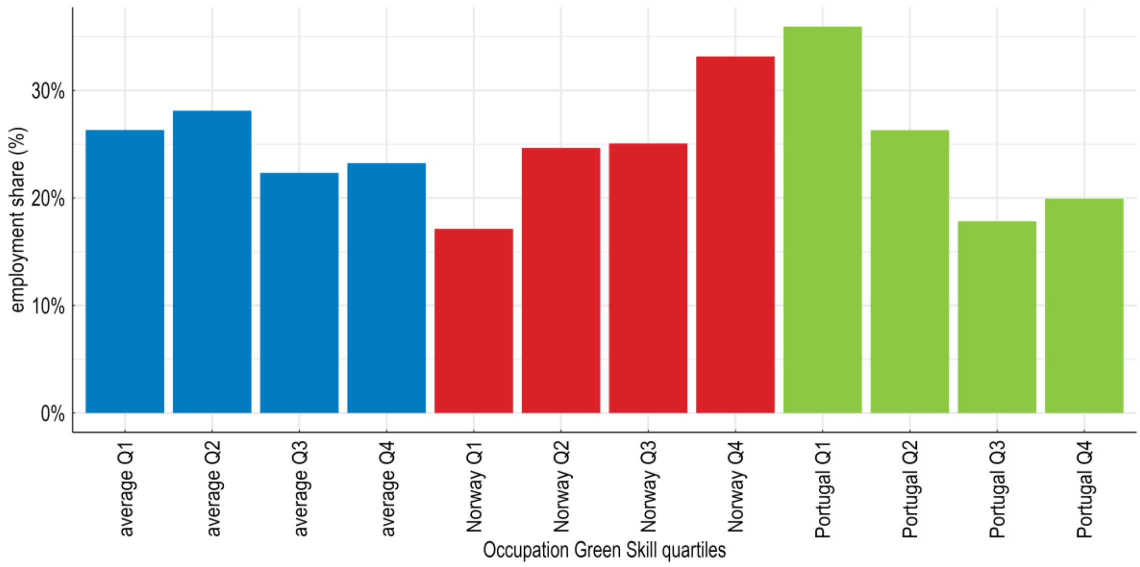
Figure 8. The Green Skill Index across 31 OECD and EU countries



Source: Authors' calculations based on O*NET, Vona et al. (2018), European Labour Force Survey, Australian Bureau of Statistics and Bureau of Labor Statistics.

59. Furthermore, we find that the GSI is highly correlated with the green employment share (correlation 0.75). This indicates that economies that have already a large green sector (green skills are those that correlate the most with green jobs) are in the best position to strengthen it further.

Figure 9. The distribution of employment share of the occupation green skills quantiles for Norway, Portugal, and the average of the sample



Source: Authors' calculations based on O*NET, Vona et al. (2018), European Labour Force Survey, Australian Bureau of Statistics and US Bureau of Labor Statistics.

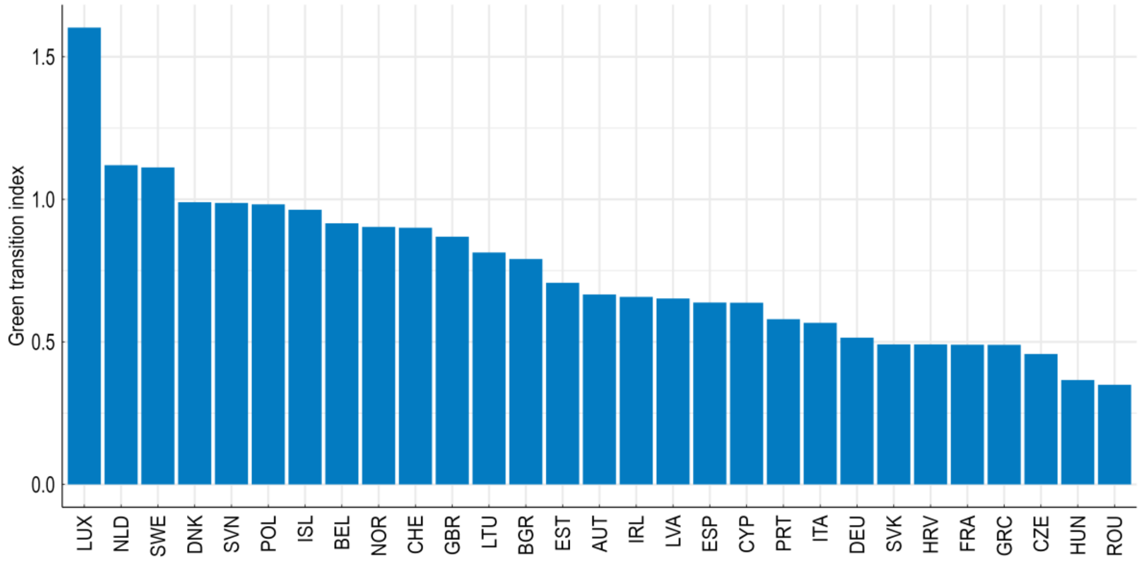
Table 5. The cross-country correlation of the GSI with the employment share of the four occupation green skill quartiles

Quartile:	Lowest	2nd	3rd	Highest
Correlation with GSI	-0.64	-0.42	0.176	0.80

5.3 The Green Transition Index: which countries can reallocate brown job workers more easily

60. As discussed below, brown job workers have a similar green skill level to the one required by green jobs, within their broad occupation group. Hence, the existence of green vacancies in broad occupations with brown jobs indicate low transition costs during the decarbonization of the economy. The GTI across our sample countries, excluding Australia and the United States, is presented in Figure 10[8], quantifies this by estimating whether green jobs exist in occupation groups where brown jobs are present as well. Our results so far indicate that these groups will also be the ones creating the most green vacancies. Thus, it indicates which countries have a higher potential to reallocate brown workers to green jobs within broad occupation categories and, thus, have lower transition costs.

Figure 10. The Green Transition Index across 29 OECD and EU countries



Source: Authors' calculations based on O*NET, European Labour Force Survey and US Bureau of Labor Statistics.

8 The GTI takes the average of the number of green jobs over brown jobs in each broad occupation group. Hence, a few groups with a very small number of brown jobs can create positive outliers, most noticeably Australia. Thus, the GTI ought to be mostly interpreted in an ordinal way. Annex G presents the GTI for all sample countries, including Australia and the United States.

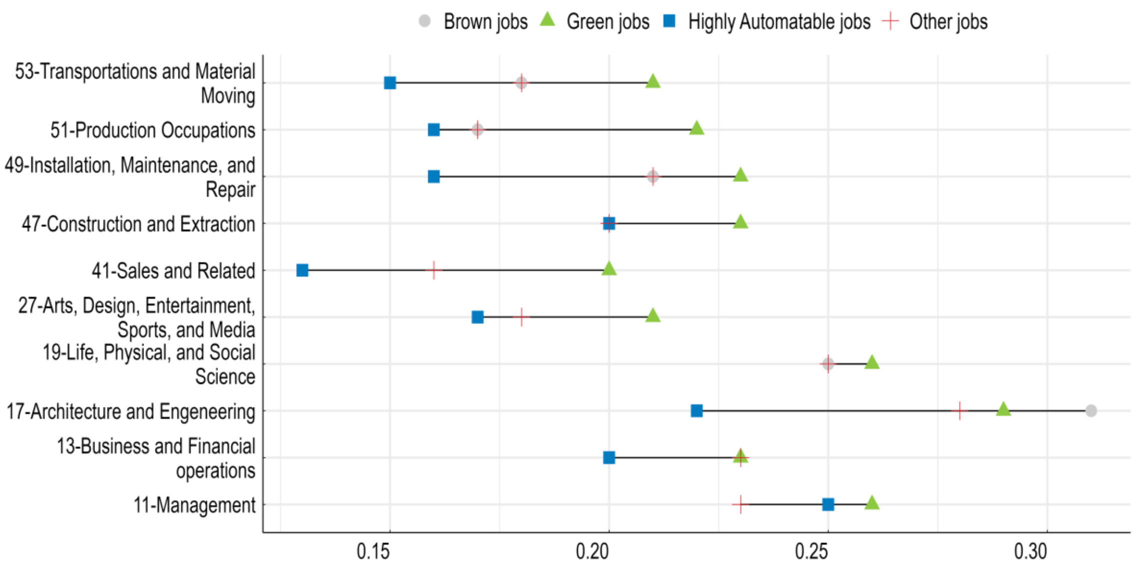
5.4 Can the Green Transition help reinstate workers from brown and highly-automated jobs?

61. Figure 11 shows the average green skill level of green, brown, highly-automatable, and other jobs across 2-digit US occupation groups. It confirms the finding of Vona et al. (2018), namely that brown job workers have a green skill supply close to the one required by green jobs. Hence, in countries with a high GTI, the high potential for worker reallocation from brown to green jobs can be utilized.

62. On the contrary, workers in highly-automatable jobs have, mostly, lower green skills than workers in other jobs (red), with the exception of two broad occupations – *Management* and Construction *& Extraction* (green). Hence, the needs of the green sector as it expands could be potentially accommodated by hiring workers from brown and other jobs' (jobs that are not green, brown, not highly-automatable) but less so through the re-deployment of displaced workers from automated jobs. Therefore, even in countries with a high potential for worker reallocation from automated to green jobs, re-deployment will be hindered by the green skills gap.

Figure 11. The green skill level of green, brown, highly-automatable, and other jobs

(2-digit occupation groups)



Source: Calculations based on O*NET, Vona et al. (2018) and Frey and Osborne (2017).

63. Next, we conduct our analysis on the level of specific occupations – that is, we consider more granular occupations, at the 6-digit level. While Figure 11 indicates in which broad occupations brown and highly-automatable job workers have the green skills to be reallocated to green jobs, it does not guarantee that all specific occupations within them can be reallocated. Indeed, aggregates may conceal the fact that some specific occupations have green skill levels that are well below average, or that workers may lack other types of skills needed to reallocate, even if workers possess adequate green skills.

64. Our analysis on the specific occupation level – based on Tyros et al. (2023) – confirms that that most detailed highly-automatable occupations do not have the skills necessary to transition to green jobs. More specifically, we find that only 11 out of the 72 highly-automatable occupations in our sample have at least two acceptable transitions to green occupations. Table 6 presents some examples of highly-automatable occupations whose workers can and cannot transition to green jobs. Annex C presents the full list.

65. On the contrary, 58 out of the 75 detailed brown occupations have at least two acceptable transitions to green occupations. This indicates that brown job workers do not only have the green skills needed to transition to green jobs, but also all other necessary skills as well. Table 6 presents some examples of brown occupations whose workers can and cannot transition to green jobs. Annex D presents the full list.

66. Most of the brown occupations that do not have the necessary skills to transition are concentrated in the production occupations. Since this is an area of the economy where policy efforts may need to focus to effectively manage transition costs,[9] we calculate the employment share of brown workers that cannot transition to green jobs, based on the employment shares of the 17 specific occupations found in Annex D.

Table 6. Examples of highly-automatable occupations whose workers can and cannot transition to green jobs

	Number of specific occupations	Occupation examples
Can transition to green jobs	11	Pesticide Handlers, Sprayers, and Applicators, Vegetation;
		Real Estate Brokers
Cannot transition to green jobs	61	Library Technicians;
		Cashiers

Table 7. Examples of brown occupations whose workers can and cannot transition to green jobs

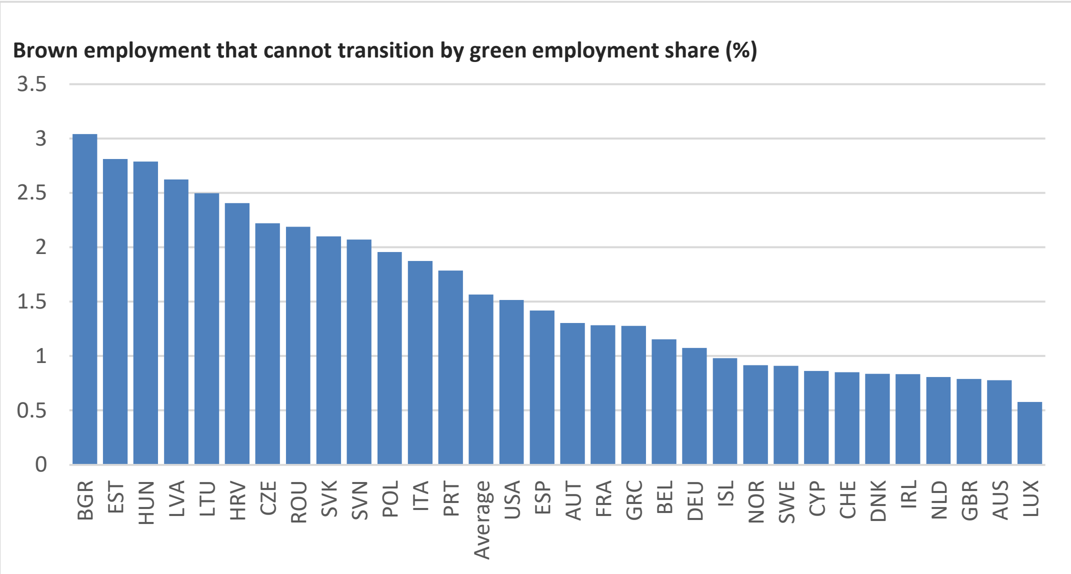
	Number of specific occupations	Occupation examples
Can transition to green jobs	58	Chemical Engineers;
		Gas Plant Operators
Cannot transition to green jobs	17	Tire Builders;

[9] This is in line with Chen, et al. (2020) that find that “Green stimulus investments are less likely to help brown workers in low-demand jobs, which are primarily manufacturing positions”.

67. Figure 12 presents the absolute employment share of these brown workers that cannot reallocate, which provides an indication of the segment of the workforce that is most vulnerable to the green transition. This group accounts for about 1.5 per cent of the employment on average, but there is significantly cross-country variation, with higher shares – closer to 3 per cent – recorded in selected eastern and southern European countries. Unsurprisingly, this metric is highly correlated with the employment share of brown jobs (correlation 0.89) and thus the cross-country ranking corresponds closely to that in Figure 4.

Figure 12. The employment share of brown job workers that cannot transition to green jobs

(31 OECD and EU countries)



Source: Authors' calculations based on European Labour Force Survey, Australian Bureau of Statistics and Bureau of Labor Statistics.

6. Links with policy

68. To draw some preliminary insights for public policy, we first plot countries in GSI-GTI space (Figure 13). From this, it is notable that most countries fall in either the lower left (below average GSI and GTI) or upper right quadrants (above average GSI and GTI), even though there is only a modest positive statistical correlation between GSI and GTI (correlation coefficient 0.51).

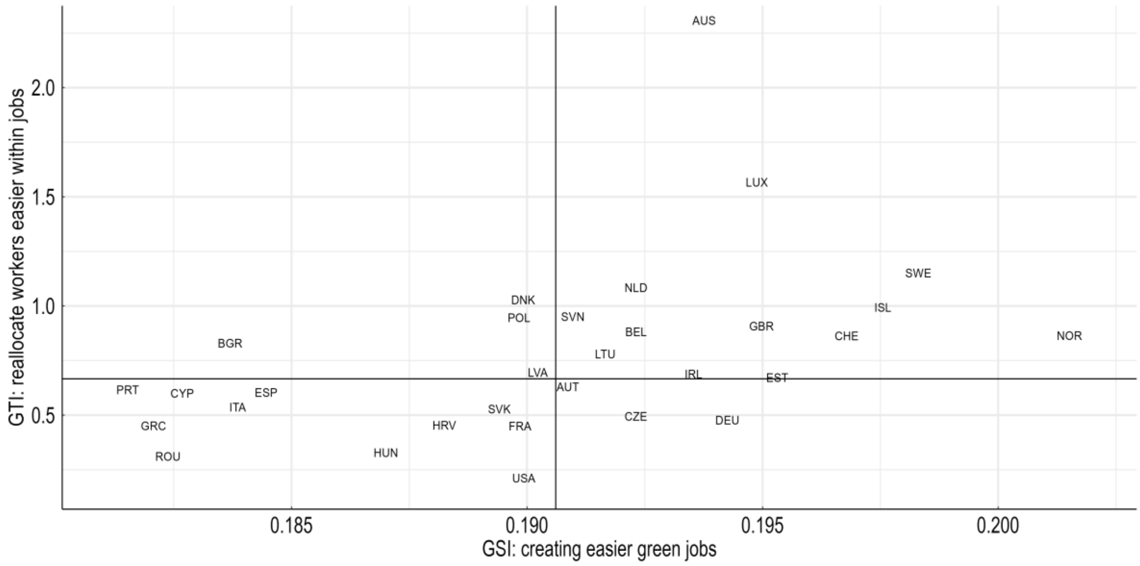
69. The labour market challenges associated with green transition for those southern and eastern European countries in the lower left quadrant appear particularly acute. A key question is whether policy frameworks in these countries are fit for purpose to foster the accumulation of green skills over time (e.g. education policy) and effectively reallocate the existing stock of skilled workers to supply the green transition. This brings into closer focus the need for: *i*) green up-skilling for the workforce as a whole; *ii*) retraining to equip workers in the "high potential" occupation groups with the skills to transition to green jobs (these skills can be different than green skills); and *iii*) reduce policy barriers to efficient resource reallocation. Beyond this, there is also a clear reallocation challenge for countries in the lower right quadrant.

70. While those countries in the upper right quadrant are potentially better positioned to accommodate the labour market demands of the green transition, policy challenges are likely to remain and the effectiveness of green stimulus could be increased by selected policy measures. For example:

- Vona (2019) indicates that brown and green industries are often concentrated in different regions of the country. Therefore, within-sector reallocation might be hindered by the costs of spatial reallocation, which policy needs to reduce.
- The advantage of high GSI areas is realised when retraining funds are also available (Chen, et al. 2020). Namely, for general green skills to realize their potential, training on specific green tasks is also needed.

71. Second, we explore the relation between our green skills indices and a range of structural policy variables that are relevant to the green transition and the reallocative capacity of labour markets more generally. The variables are presented in detail in Annex H. Table AH.1 indicates that our two indices, the GSI and the GTI, and the employment share of brown job workers that cannot transition to green jobs, are correlated, but there is no one-to-one correspondence. GDP per capita is positively correlated with the GSI and negatively correlated with the brown not-to-green share. This reflects the fact that many green jobs are high added-value jobs and that higher income countries have more resources to implement policies to green the economy and potentially compensate the losers of economic restructuring.

Figure 13. The 31 OECD and EU countries in the GSI-GTI plane



Source: Authors' calculations based on O*NET, Vona et al. (2018), European Labour Force Survey, Australian Bureau of Statistics and Bureau of Labor Statistics.

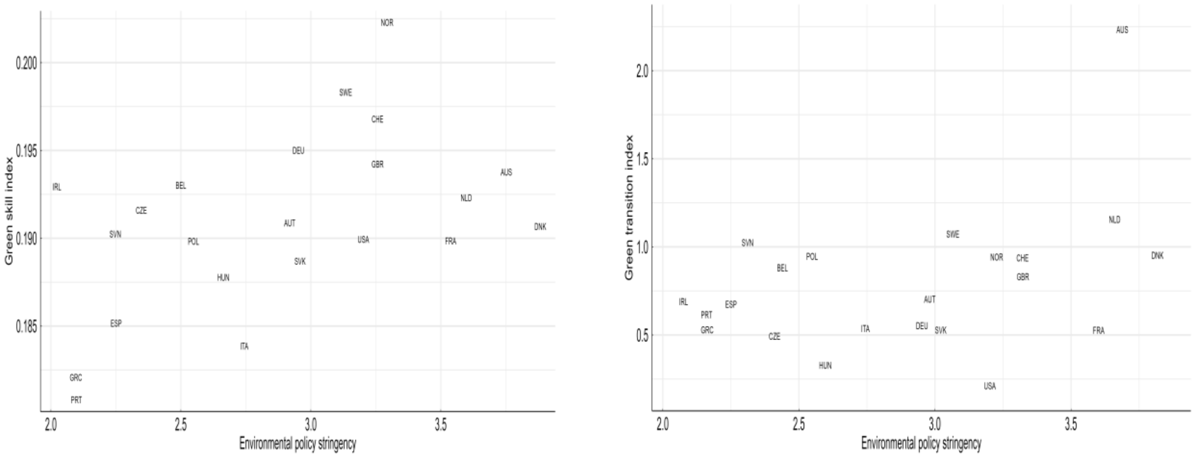
72. Importantly, we find the stringency of environmental policy to be significantly correlated with all our variables (Figure 14 and Figure 15, panel A), even after controlling for GDP per capita. This suggests that tighter environment policy can create demand for green skills by inducing the necessary economic restructuring for the green transition and creating the business case for investment in low carbon technologies. In the absence of exogenous variation, causal statements should be made with caution.

Nevertheless, these results are consistent with evidence from the United States, which shows a positive link between increases in environmental regulations and green skills (Vona, et al., 2016).

Figure 14. Environmental policy stringency versus GSI (Panel A) and GTI (Panel B)

(22 OECD and EU countries)

Panel A **Panel B**



Source: Authors' calculations based on O*NET and Kruse et al. (2022)

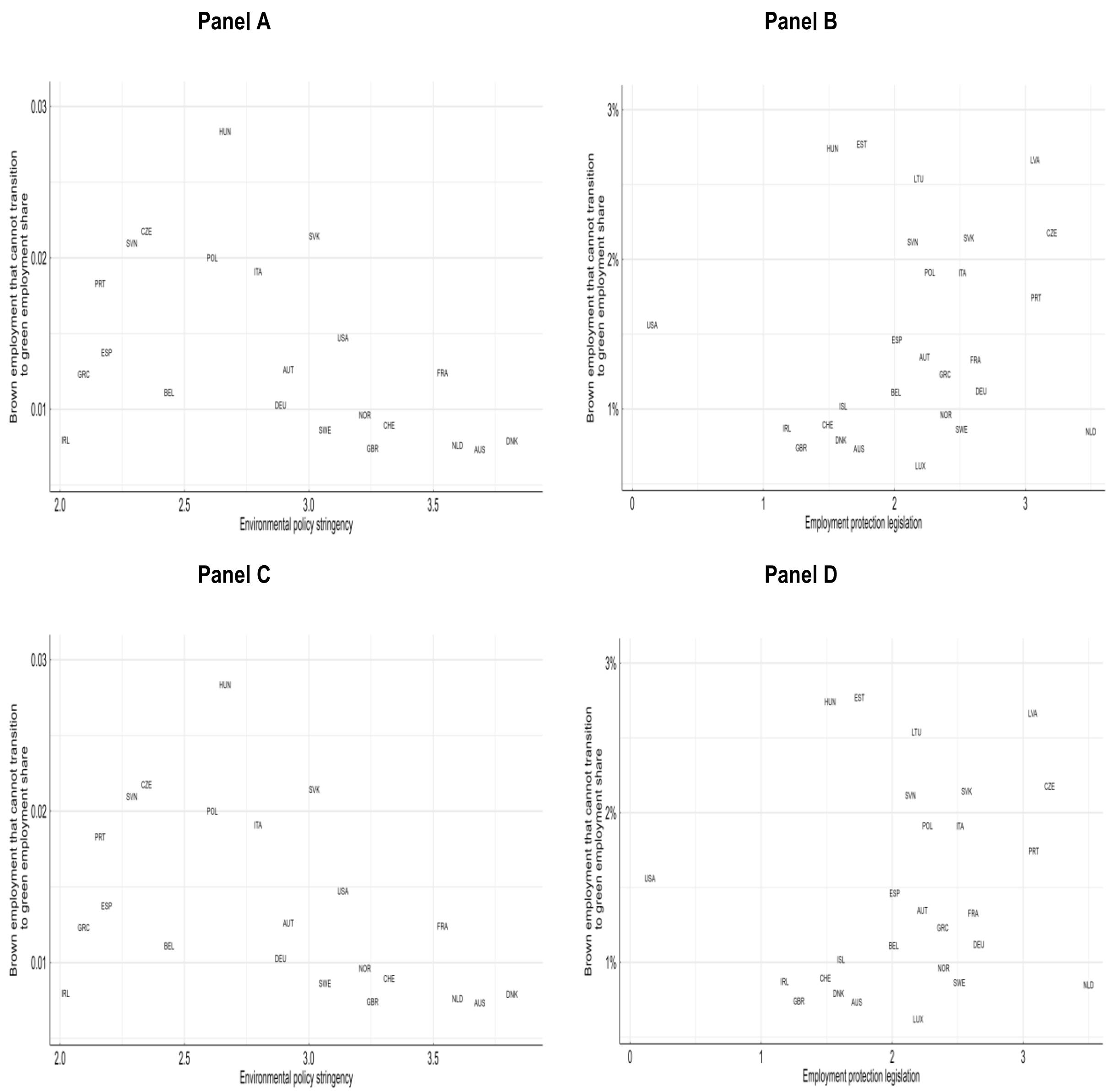
73. We also explore the correlation between our new green skills indices and structural policy variables that shape the reallocation of resources more generally. While the direction of the relationship is often intuitive – i.e. more rigid market regulations are associated with lower (higher) GSI and GTI (brown workers that cannot transition to green) – it is rarely statistically significant.

74. One exception is employment protection legislation, which is positively associated with the share of brown workers that cannot transition to green jobs (correlation coefficient 0.33; Figure 15, Panel B). This is consistent with the idea that by creating barriers to firm exit (Andrews and Cingano, 2014), more stringent EPL can lead low productivity brown firms to linger, thereby reducing the pace of shrinking of the brown sector and the incentive of new, green, firms to enter.

75. Finally, those countries with the largest share of brown workers who cannot transition to green jobs have relatively low spending on ALMPs (Figure 15, Panel C) and shares of low skilled workers participating in training (Figure 15, Panel D). This finding is particularly notable to the extent that group of workers are potentially most vulnerable to the green transition.

76. A range of other structural policies – that are more difficult to quantify – will also be relevant to the green transition, particularly finance. A long literature demonstrates the importance of well-functioning financial markets (including risk capital) for investment, resource reallocation and innovation (Andrews and Criscuolo, 2013). While this suggests that reforms that improve framework conditions affecting financing will aid the Green Transition, a range of financial market imperfections still place the financing of green projects at a disadvantage. This brings into closer focus efforts to improve climate disclosure as well as other climate finance initiatives, as discussed in Box 1.2 of OECD (2021).

Figure 15. Structural policy indicators versus the employment share of brown job workers who cannot transition to green jobs



Source: Authors' calculations based on O*NET, Kruse et al. (2022) and OECD Structural Policy Indicator Database for Economic Research.

7. Concluding Remarks

77. In this paper, we analyse the green skill level of the workforce of a number of OECD and EU countries, by constructing a Green Skill Index (GSI), which combines the number of green tasks by occupation with the type of skills that are most prevalent in occupations with a high share of green tasks (defined as "green" skills). Cross-country variations in the GSI are sizeable, similar to differences obtained by Popp et al (2020), where a high-level of GSI has been shown to play an important role in green job creation following fiscal stimulus.

78. Using in addition information on how important green tasks are in all specific occupations (i.e. including brown and highly-automatable occupations) and the share of brown employment within each broad occupation, we define a cross-country Green Transition Index (GTI), which captures the potential for the reallocation of brown job workers to green jobs within their broad occupation. Significant cross-country differences emerge in the underlying supply of green skills (Green Skills Index) and the potential of economies to reallocate brown job workers to green jobs within their broad occupation categories (Green Transition Index);

- The green skills level of the workforce is found to be highest in Nordic countries as well as Germany, United Kingdom and Australia, while it is lowest in Southern and Eastern European countries.
- Countries with the highest potential to reallocate workers from brown to green jobs within broad occupations include the Benelux, Denmark and Sweden, as well as Poland and Slovenia.

79. We also explore the potential for expanding green sectors to reinstate labour that routinisation displaces from highly automatable occupations. In general, workers from highly automatable jobs do not have the sufficient skills – green or other types – to undertake such transitions. One implication is that for emerging new green tasks to materially reinstate labour displaced by automation, policy needs to find ways to lower the cost of transition for workers from highly-automatable jobs with large skills gaps.

80. To the extent that workers from most brown occupations have the necessary skills to transition to green jobs, decarbonisation may – on average – entail smaller labour market transition costs than automation. Nevertheless, there remains pockets of the workforce who are vulnerable to displacement from decarbonisation. Workers in production occupations (e.g. tire builders, pourers & casters and metal) are a notable example – and policy will need to accommodate the particularly high transition costs that these groups may face. Indeed, it is notable that active labour market policy expenditure as a share of GDP is lowest in those countries having the largest share of brown workers who cannot easily transition to green jobs.

81. A robust correlation emerges across countries between tighter environmental policy stringency and higher GSI and GTI, and lower share of brown workers that cannot transition to green jobs. This suggests that tighter environment policy can create demand for green skills by inducing the necessary economic restructuring for the green transition and creating the business case for investment in low carbon technologies. More stringent employment protection legislation is associated with a higher share of brown workers that cannot transition to green jobs, potentially because it creates barriers to exit of low productivity polluting firms. These results are an important reminder of how environmental policies and broader structural reforms can interact to direct human talent in a direction that is conducive to the Green Transition.

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Annex A. Crosswalks

82. The O*NET database includes skill requirements for 966 8-digit SOC code occupations. Using a crosswalk from the Bureau of Labor Statistics (BLS) of the US these can be mapped into the 6-digit SOC occupation code for which the BLS has employment share statistics. The resulting database includes 747 occupations, covering 98.7% of US employment (O*NET does not have skill data for some occupations, e.g. legislators and army occupations). Out of those, 63 occupations are identified as green, 75 as brown, and 72 as highly automatable.

83. Employment share data on European countries are available from the European Labour Force Survey on the 3-digit ISCO-08 level, which is less granular than the 6-digit SOC level. For each ISCO 4-digit occupations we take the average of the greenness, brown, and highly automatable indicators. For the 3, 2, and 1-digit ISCO occupations we take the average of the specific occupations within them.

84. Australian employment share data are available on the 4-digit ANZSCO level, which is similar to the ISCO classification. We use a crosswalk from the Australian Bureau of Statistics between the 6-digit ANZSCO and 4-digit ISCO codes to calculate the green skills, greenness, brown, and highly-automatable indicators. As for the ISCO codes, we take average of specific occupations to estimate the variables for the more aggregate levels.

85. For the cross-country comparisons, the 4-digit US variables are used to avoid any bias due to different aggregation levels. For Australia, the 3-digit variables are used.

Annex B. Green, Brown, and Highly-Automatable 6-digit OES Occupations

Green Occupations	Brown Occupations	Highly-Automatable Occupations
Plant and System Operators, All Other	Chemical Engineers	Compensation and Benefits Managers
General and Operations Managers	Mining and Geological Engineers, Including Mining Safety Engineers	Claims Adjusters, Examiners, and Investigators
Marketing Managers	Petroleum Engineers	Insurance Appraisers, Auto Damage
Transportation Inspectors	Food Scientists and Technologists	Farm Labor Contractors
Transportation, Storage, and Distribution Managers	Chemists	Credit Analysts
Construction Managers	Chemical Technicians	Insurance Underwriters
Architectural and Engineering Managers	Meter Readers, Utilities	Loan Officers
Natural Sciences Managers	Log Graders and Scalers	Tax Preparers
Personal Service Managers, All Other; Entertainment and Recreation Managers, Except Gambling; and Managers, All Other	Septic Tank Servicers and Sewer Pipe Cleaners	Surveying and Mapping Technicians
Buyers and Purchasing Agents	Derrick Operators, Oil and Gas	Title Examiners, Abstractors, and Searchers
Logisticians	Rotary Drill Operators, Oil and Gas	Library Technicians
Training and Development Specialists	Service Unit Operators, Oil and Gas	Umpires, Referees, and Other Sports Officials
Project Management Specialists and Business Operations Specialists, All Other	Rock Splitters, Quarry	Gambling Surveillance Officers and Gambling Investigators
Personal Financial Advisors	Roustabouts, Oil and Gas	Cooks, Restaurant
Financial and Investment Analysts, Financial Risk Specialists, and Financial Specialists, All Other	Helpers--Extraction Workers	Hosts and Hostesses, Restaurant, Lounge, and Coffee Shop
Architects, Except Landscape and Naval	Electrical and Electronics Repairers, Powerhouse, Substation, and Relay	Landscaping and Groundskeeping Workers
Landscape Architects	Control and Valve Installers and Repairers, Except Mechanical Door	Pesticide Handlers, Sprayers, and Applicators, Vegetation
Aerospace Engineers	Industrial Machinery Mechanics	Gambling Dealers
Civil Engineers	Maintenance Workers, Machinery	Motion Picture Projectionists
Electrical Engineers	Refractory Materials Repairers, Except Brickmasons	Ushers, Lobby Attendants, and Ticket Takers
Electronics Engineers, Except Computer	Electrical Power-Line Installers and Repairers	Manicurists and Pedicurists
Environmental Engineers	First-Line Supervisors of Production and Operating Workers	Cashiers
Mechanical Engineers	Food and Tobacco Roasting, Baking, and Drying Machine Operators and Tenders	Counter and Rental Clerks
Nuclear Engineers	Food Batchmakers	Parts Salespersons
Engineers, All Other	Food Cooking Machine Operators and Tenders	Models
Electrical and Electronic Engineering Technologists and Technicians	Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic	Real Estate Brokers
Environmental Engineering Technologists and Technicians	Forging Machine Setters, Operators, and Tenders, Metal and Plastic	Telemarketers

Industrial Engineering Technologists and Technicians	Rolling Machine Setters, Operators, and Tenders, Metal and Plastic	Switchboard Operators, Including Answering Service
Mechanical Engineering Technologists and Technicians	Grinding, Lapping, Polishing, and Buffing Machine Tool Setters, Operators, and Tenders, Metal and Plastic	Telephone Operators
Calibration Technologists and Technicians and Engineering Technologists and Technicians, Except Drafters, All Other	Metal-Refining Furnace Operators and Tenders	Bill and Account Collectors
Soil and Plant Scientists	Pourers and Casters, Metal	Billing and Posting Clerks
Conservation Scientists	Patternmakers, Metal and Plastic	Bookkeeping, Accounting, and Auditing Clerks
Atmospheric and Space Scientists	Foundry Mold and Coremakers	Payroll and Timekeeping Clerks
Environmental Scientists and Specialists, Including Health	Heat Treating Equipment Setters, Operators, and Tenders, Metal and Plastic	Procurement Clerks
Geoscientists, Except Hydrologists and Geographers	Layout Workers, Metal and Plastic	Tellers
Production Workers, All Other	Plating Machine Setters, Operators, and Tenders, Metal and Plastic	Brokerage Clerks
Urban and Regional Planners	Tool Grinders, Filers, and Sharpeners	Credit Authorizers, Checkers, and Clerks
Social Scientists and Related Workers, All Other	Textile Bleaching and Dyeing Machine Operators and Tenders	File Clerks
Environmental Science and Protection Technicians, Including Health	Textile Knitting and Weaving Machine Setters, Operators, and Tenders	Library Assistants, Clerical
Geological and Hydrologic Technicians	Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders	New Accounts Clerks
First-Line Supervisors of Transportation and Material Moving Workers, Except Aircraft Cargo Handling Supervisors	Extruding and Forming Machine Setters, Operators, and Tenders, Synthetic and Glass Fibers	Order Clerks
Life, Physical, and Social Science Technicians, All Other	Upholsterers	Receptionists and Information Clerks
Occupational Health and Safety Technicians	Cabinetmakers and Bench Carpenters	Cargo and Freight Agents
Public Relations Specialists	Furniture Finishers	Dispatchers, Except Police, Fire, and Ambulance
Sales Representatives of Services, Except Advertising, Insurance, Financial Services, and Travel	Model Makers, Wood	Postal Service Clerks
Sales Representatives, Wholesale and Manufacturing, Technical and Scientific Products	Patternmakers, Wood	Shipping, Receiving, and Inventory Clerks
First-Line Supervisors of Construction Trades and Extraction Workers	Sawing Machine Setters, Operators, and Tenders, Wood	Weighers, Measurers, Checkers, and Samplers, Recordkeeping
Construction Laborers	Woodworking Machine Setters, Operators, and Tenders, Except Sawing	Legal Secretaries and Administrative Assistants
Plumbers, Pipefitters, and Steamfitters	Power Distributors and Dispatchers	Secretaries and Administrative Assistants, Except Legal, Medical, and Executive
Roofers	Chemical Plant and System Operators	Data Entry Keyers
Sheet Metal Workers	Gas Plant Operators	Insurance Claims and Policy Processing Clerks
Solar Photovoltaic Installers	Petroleum Pump System Operators, Refinery Operators, and Gaugers	Office Clerks, General
Construction and Building Inspectors	Chemical Equipment Operators and Tenders	Animal Breeders
Hazardous Materials Removal Workers	Separating, Filtering, Clarifying, Precipitating, and Still Machine Setters, Operators, and Tenders	Operating Engineers and Other Construction Equipment Operators
Miscellaneous Construction and Related Workers	Crushing, Grinding, and Polishing Machine Setters, Operators, and Tenders	Camera and Photographic Equipment Repairers
Continuous Mining Machine Operators	Grinding and Polishing Workers, Hand	Watch and Clock Repairers

Automotive Service Technicians and Mechanics	Mixing and Blending Machine Setters, Operators, and Tenders	Milling and Planing Machine Setters, Operators, and Tenders, Metal and Plastic
Bus and Truck Mechanics and Diesel Engine Specialists	Cutters and Trimmers, Hand	Molding, Coremaking, and Casting Machine Setters, Operators, and Tenders, Metal and Plastic
Heating, Air Conditioning, and Refrigeration Mechanics and Installers	Cutting and Slicing Machine Setters, Operators, and Tenders	Prepress Technicians and Workers
Maintenance and Repair Workers, General	Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders	Print Binding and Finishing Workers
Wind Turbine Service Technicians	Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders	Shoe Machine Operators and Tenders
Aircraft Structure, Surfaces, Rigging, and Systems Assemblers	Packaging and Filling Machine Operators and Tenders	Sewers, Hand
Nuclear Power Reactor Operators	Adhesive Bonding Machine Operators and Tenders	Textile Cutting Machine Setters, Operators, and Tenders
Power Plant Operators	Cleaning, Washing, and Metal Pickling Equipment Operators and Tenders	Inspectors, Testers, Sorters, Samplers, and Weighers
	Cooling and Freezing Equipment Operators and Tenders	Jewelers and Precious Stone and Metal Workers
	Molders, Shapers, and Casters, Except Metal and Plastic	Dental Laboratory Technicians
	Paper Goods Machine Setters, Operators, and Tenders	Ophthalmic Laboratory Technicians
	Tire Builders	Photographic Process Workers and Processing Machine Operators
	Rail Yard Engineers, Dinkey Operators, and Hostlers	Etchers and Engravers
	Dredge Operators	Driver/Sales Workers
	Hoist and Winch Operators	Locomotive Engineers
	Machine Feeders and Offbearers	Bridge and Lock Tenders
	Gas Compressor and Gas Pumping Station Operators	
	Pump Operators, Except Wellhead Pumpers	
	Wellhead Pumpers	

Annex C. Highly-Automatable job workers transitioning to green jobs

Can Transition to Green Jobs	Pesticide Handlers, Sprayers, and Applicators, Vegetation
	Operating Engineers and Other Construction Equipment Operators
	Dispatchers, Except Police, Fire, and Ambulance
	Textile Cutting Machine Setters, Operators, and Tenders
	Real Estate Brokers
	Order Clerks
	Cargo and Freight Agents
	Print Binding and Finishing Workers
	Surveying and Mapping Technicians
	Parts Salespersons
	Locomotive Engineers
Cannot Transition to Green Jobs	Loan Officers
	Tax Preparers
	New Accounts Clerks
	Etchers and Engravers
	Compensation and Benefits Managers
	Claims Adjusters, Examiners, and Investigators
	Insurance Appraisers, Auto Damage
	Farm Labor Contractors
	Credit Analysts
	Insurance Underwriters
	Title Examiners, Abstractors, and Searchers
	Library Technicians
	Umpires, Referees, and Other Sports Officials
	Gambling Surveillance Officers and Gambling Investigators
	Cooks, Restaurant
	Hosts and Hostesses, Restaurant, Lounge, and Coffee Shop
	Landscaping and Groundskeeping Workers
	Gambling Dealers
	Motion Picture Projectionists
	Ushers, Lobby Attendants, and Ticket Takers
	Manicurists and Pedicurists
	Cashiers
	Counter and Rental Clerks
	Models
	Telemarketers
	Switchboard Operators, Including Answering Service
	Telephone Operators
	Bill and Account Collectors
	Billing and Posting Clerks
	Bookkeeping, Accounting, and Auditing Clerks

	Payroll and Timekeeping Clerks
	Procurement Clerks
	Tellers
	Brokerage Clerks
	Credit Authorizers, Checkers, and Clerks
	File Clerks
	Library Assistants, Clerical
	Receptionists and Information Clerks
	Postal Service Clerks
	Shipping, Receiving, and Inventory Clerks
	Weighers, Measurers, Checkers, and Samplers, Recordkeeping
	Legal Secretaries and Administrative Assistants
	Secretaries and Administrative Assistants, Except Legal, Medical, and Executive
	Data Entry Keyers
	Insurance Claims and Policy Processing Clerks
	Office Clerks, General
	Animal Breeders
	Camera and Photographic Equipment Repairers
	Watch and Clock Repairers
	Milling and Planing Machine Setters, Operators, and Tenders, Metal and Plastic
	Molding, Coremaking, and Casting Machine Setters, Operators, and Tenders, Metal and Plastic
	Prepress Technicians and Workers
	Shoe Machine Operators and Tenders
	Sewers, Hand
	Inspectors, Testers, Sorters, Samplers, and Weighers
	Jewelers and Precious Stone and Metal Workers
	Dental Laboratory Technicians
	Ophthalmic Laboratory Technicians
	Photographic Process Workers and Processing Machine Operators
	Driver/Sales Workers
	Bridge and Lock Tenders

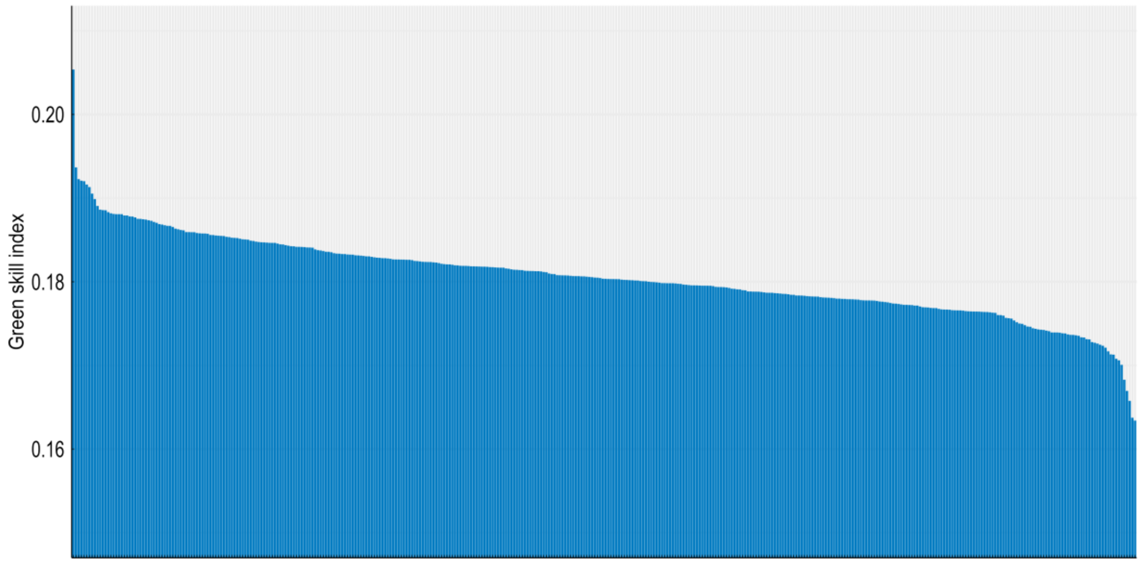
Annex D. Brown job workers transitioning to green jobs

Can Transition to Green Jobs	Chemical Engineers
	Mining and Geological Engineers, Including Mining Safety Engineers
	Petroleum Engineers
	Food Scientists and Technologists
	Chemists
	Chemical Technicians
	Log Graders and Scalers
	Septic Tank Servicers and Sewer Pipe Cleaners
	Derrick Operators, Oil and Gas
	Rotary Drill Operators, Oil and Gas
	Service Unit Operators, Oil and Gas
	Rock Splitters, Quarry
	Roustabouts, Oil and Gas
	Helpers--Extraction Workers
	Electrical and Electronics Repairers, Powerhouse, Substation, and Relay
	Control and Valve Installers and Repairers, Except Mechanical Door
	Industrial Machinery Mechanics
	Maintenance Workers, Machinery
	Refractory Materials Repairers, Except Brickmasons
	Electrical Power-Line Installers and Repairers
	First-Line Supervisors of Production and Operating Workers
	Food and Tobacco Roasting, Baking, and Drying Machine Operators and Tenders
	Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic
	Forging Machine Setters, Operators, and Tenders, Metal and Plastic
	Rolling Machine Setters, Operators, and Tenders, Metal and Plastic
	Grinding, Lapping, Polishing, and Buffing Machine Tool Setters, Operators, and Tenders, Metal and Plastic
	Patternmakers, Metal and Plastic
	Heat Treating Equipment Setters, Operators, and Tenders, Metal and Plastic
	Layout Workers, Metal and Plastic
	Plating Machine Setters, Operators, and Tenders, Metal and Plastic
	Tool Grinders, Filers, and Sharpeners
	Textile Bleaching and Dyeing Machine Operators and Tenders
	Extruding and Forming Machine Setters, Operators, and Tenders, Synthetic and Glass Fibers

	Upholsterers
	Cabinetmakers and Bench Carpenters
	Furniture Finishers
	Power Distributors and Dispatchers
	Chemical Plant and System Operators
	Gas Plant Operators
	Petroleum Pump System Operators, Refinery Operators, and Gaugers
	Chemical Equipment Operators and Tenders
	Separating, Filtering, Clarifying, Precipitating, and Still Machine Setters, Operators, and Tenders
	Crushing, Grinding, and Polishing Machine Setters, Operators, and Tenders
	Grinding and Polishing Workers, Hand
	Mixing and Blending Machine Setters, Operators, and Tenders
	Cutting and Slicing Machine Setters, Operators, and Tenders
	Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders
	Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders
	Packaging and Filling Machine Operators and Tenders
	Adhesive Bonding Machine Operators and Tenders
	Cooling and Freezing Equipment Operators and Tenders
	Molders, Shapers, and Casters, Except Metal and Plastic
	Paper Goods Machine Setters, Operators, and Tenders
	Rail Yard Engineers, Dinkey Operators, and Hostlers
	Hoist and Winch Operators
	Gas Compressor and Gas Pumping Station Operators
	Pump Operators, Except Wellhead Pumpers
	Wellhead Pumpers
Cannot Transition to Green Jobs	Meter Readers, Utilities
	Food Batchmakers
	Food Cooking Machine Operators and Tenders
	Metal-Refining Furnace Operators and Tenders
	Pourers and Casters, Metal
	Foundry Mold and Coremakers
	Textile Knitting and Weaving Machine Setters, Operators, and Tenders
	Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders

Annex E. US Metropolitan Statistical Areas (MSAs)

Figure A E.1. The Green Skill Index distribution across US MSAs



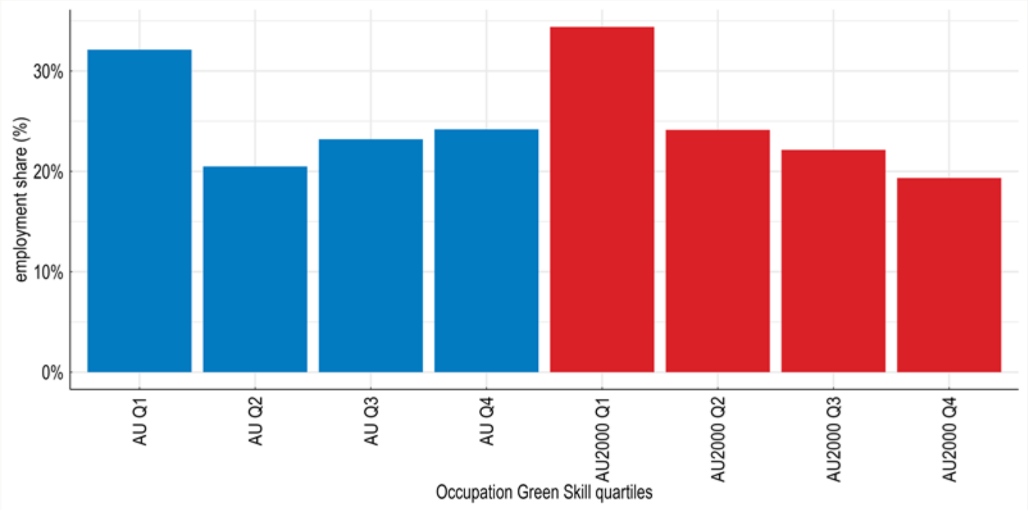
Source: Authors' calculations based on O*NET and US Bureau of Labor Statistics.

Annex F. Australian time series

Box A F.1. Case study: Australia 2000 – 2018

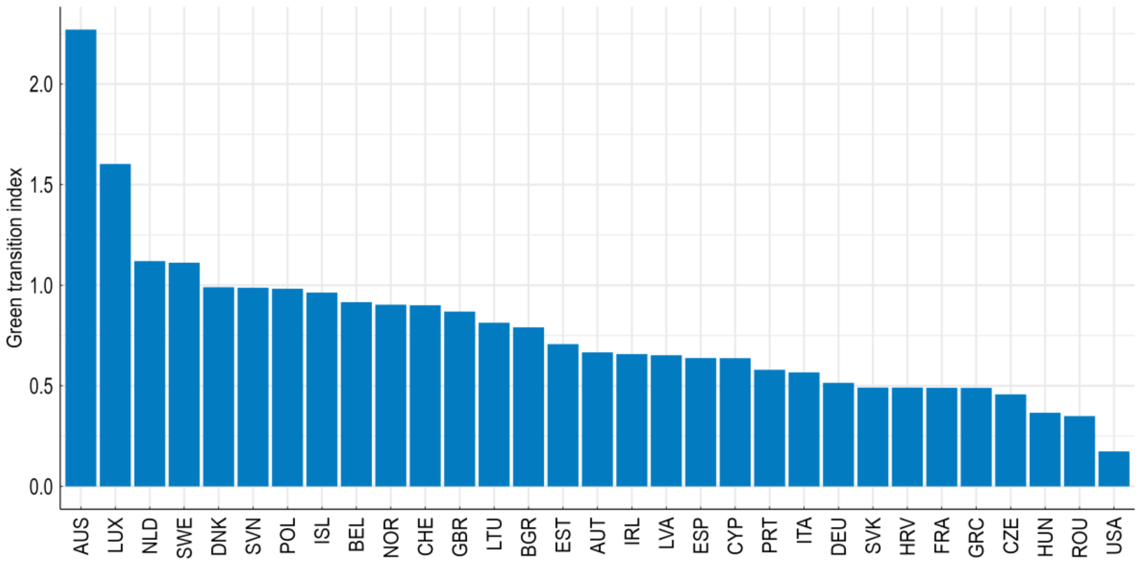
From 2000 to 2018 the Australian GSI increased from 0.1886 to 0.1933. This represents a material change and roughly corresponds to the difference between Hungary and Australia observed recently (Figure 5.6). While this increase in the GSI in Australia over time is underpinned by a redirection of employment from the lower to higher GSI quartiles (Figure 5.8), the share of employment in the lowest green skills quartile remains higher than the OECD average.

Figure A F.1. The distribution of employment share of the occupation green skill quantiles for Australia in 2000 and 2017-19



Annex G. The GTI including Australia and the US

Figure A G.1. The Green Transition Index across 31 OECD and EU countries



Source: Authors' calculations based on O*NET, European Labour Force Survey, Australian Bureau of Statistics and Bureau of Labor Statistics.

Annex H. Green indices and structural variables

86. From the OECD statistics (for the year 2018, unless otherwise noted) we use the public expenditure as a percentage of GDP for active labour market policies, the coverage percentage of carbon pricing at 60€/tonne, the environmental policy stringency index of 2012, the Gini coefficient, GFP per capita, the strictness of: product market regulation, employment protection legislation. Finally, we use the share of total production per country that is in green products, namely products with a high potential to minimize the harmful impacts of production on the environment (Bontadini & Vona, 2020) and the share of low and high literacy individuals in training. Table AH.1 presents the correlations between our green indices and these variables. Not all variables are available for all the 31 OECD and EU countries of our sample.

Table A H.1. The correlations between our green indices and various structural cross-country variables

	Green Skill Index	GTI	Brown not-to-Green share
Green Skill Index	1.00	0.51**	-0.40**
GTI	0.51**	1.00	-0.44**
Brown not-to-Green_share	-0.40**	-0.44**	1.00
Active Labour Market Policies	0.15	-0.37	-0.50**
Carbon Pricing	0.27	0.49	-0.54**
Environment Policy Stringency	0.48***^	0.28***^	-0.45***^
Market EPS	0.05	0.05	-0.09
non-Market EPS	0.56***	0.23	-0.49**
GINI	-0.34*	-0.18	0.24
GDP per capita	0.51***	0.53**	-0.70***
Administration Burdens on Start-Ups	-0.07	0.03	-0.03
Employment Protection	-0.18	0.12	0.17
Low Literacy Training	0.66***^	0.40	-0.52*
High Literacy Training	0.45*	0.35	-0.49*

Note: * indicates that the corresponding regression coefficient is significant to the level of 10%, ** to 5%, and *** to 1%. ^ indicates the variable being significant to at least 10% when controlling for GDP/capita.