Measuring and characterising green jobs: a literature review*

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Abstract:

This study presents a comprehensive literature review on green job measurement and characterisation across various countries and world regions. The study adopts a conceptual framework distinguishing between output-based and process-based greenness, and entity-level and occupation-specific measurement techniques. The wide-ranging green job estimates result from diverse concepts, measurement techniques, and employment scopes considered. This study discusses practical challenges in both entity-level and occupation-specific measurement approaches. Entity-level measurement approaches use aggregate statistics or survey data to examine green jobs through green entities, though identifying these entities remains challenging. In the US, studies often rely on the Green Goods and Services (GGS) or Green Technologies and Practices (GTP) surveys, while the EU employs the Environmental Goods and Services Sector (EGSS) approach, with individual countries using different estimation strategies. For occupation-specific green job research, the primary dataset is the ONET green job classification, linking occupations with tasks and skills. Various methods are used to measure green jobs, including discrete categories, constructing continuous green task indices for occupations, and constructing continuous green skill indices. The study highlights the need for future research to (1) identify, motivate, and assess conceptual choices, measurement techniques, and employment scopes, and (2) update green and brown job classification systems.

Key words: green transition, green jobs, green skills, labour market, literature review

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1. Introduction

Humanity’s impact on the earth system is leading to irreversible global change. Climate change, biodiversity loss, land-system change (e.g. loss of forests), large-scale dispersion of novel chemical entities (e.g. plastics) and biochemical flows (e.g. nitrogen flows to the oceans) all threaten to substantially alter earth system functioning [1,2]. For example, in the case of climate change, the IPCC's [3] middle of the road mitigation scenario predicts end of century global warming of around 2.7°C. Even end of century global warming of around 1.5°C is set to cause unavoidable negative impacts on both natural and human systems [3]. Substantial mitigation action is needed to remain within a safe operating space for humanity.

Public support for climate change mitigation efforts is high. Climate change and environmental problems are perceived as the main challenge for the EU’s future and a range of specific mitigation measures such as increasing renewable energy shares and promoting energy efficiency are seen as either “very important” or “fairly important” by at least 80% of respondents in a recent Eurobarometer study (European Commission, 2021). Nonetheless, the Yellow Vest movement in France and, perhaps more recently, the energy price crisis have highlighted that public support for environmental measures is not unconditional. Hence, mitigation action should not only be approached from a technological standpoint but also from a socio-economic perspective [4,5].

Due to the scale of the required green transition, substantial changes in economic structures seem likely. Moreover, the impact of mitigation efforts will likely differ considerably across economic sectors. These differential changes in economic activity will impact the labour market [6–9]. On the one hand, certain occupations or skills might become obsolete in the labour market. On the other hand, new occupations and skills are likely to emerge, and the demand for several existing occupations and skills will increase. Given the importance of distributional consequences for the acceptance of mitigation action [e.g. 10], understanding the impact of the green transition on the labour market has high policy relevancy and might lessen adverse social and inequality effects if the impacts are considered during all stages of the policy process [11].

This article provides a succinct review of the literature on the measurement and characterisation of green employment. In the following section, two main conceptualisations of “greenness” and two prevailing measurement approaches are discussed. Here we also lay out the conceptual framework guiding the literature review and used to compare the results from various studies and discuss their implications. Then a comprehensive overview of studies ordered by measurement approach and country/region follows. Finally, some suggestions for future research are provided.

Our literature review indicates that estimates of green jobs as a share of total employment differ considerably depending on the methodology used. Rather than reflecting inherent uncertainty, these different estimates appear partially driven by different conceptual, measurement, and green job scope choices. Therefore, the relevance of each different measurement depends on the impact one is aiming to assess. Nonetheless, some uncertainty seems to be due to the shortcomings of the two main measurement techniques (discussed at length throughout Section 3 and in Section 4). Regarding green job characteristics, studies tend to find that green jobs require technical skills, are higher-skilled, demand more educational attainment, are male-dominated, and are relatively high-quality (e.g. higher-paid, full-time, permanent contract).

This article focuses on recent studies measuring and characterising current green employment in the economy as a whole. Searches for this systematic literature review were primarily conducted with Google Scholar, using keyword combinations such as 'green'/'climate change'/'transition' and 'employment'/'job'/'occupation'. In addition, articles were identified based on citations in articles selected using Google Scholar. The following exclusion criteria were used: (1) published before 2010, (2) not being concerned with green employment in the economy as a whole, (3) not being concerned with *current* (in contrast to ex-ante) green employment.

These exclusion criteria are motivated as follows. While acknowledging the foundational value of older academic work, we focus on presenting a concise, up-to-date review of the empirical literature on green employment for current researchers and policymakers. Incorporating and discussing much older work, estimates for specific subsectors of the green economy [e.g. 12–14] or the extensive literature on the employment effects of environmental regulation (see Dechezleprêtre and Sato [15], for a recent overview) and the labour market impact of eco-innovation at the firm-level [e.g. 16–18] is incompatible with our aim. The methodology underlying projections of future green employment [e.g. 10,19,20] differs substantially from how current green employment is measured and characterised, and incorporating this branch of the literature would thus also be incompatible with the focused review we strive to provide.

Our study gives an up-to-date overview of the literature on measuring and characterising green employment. Therefore, it complements and expands earlier studies in scope and time. In particular, we go beyond reviewing the task-based approach excellently discussed by Vona [21] and include studies based on the entity-level measurement technique of green jobs. We complement the concise overview of Valero et al. [22] by adding several additional and newer studies and discuss green job studies in greater depth, as well as the earlier literature reviews by Bowen and Kuralbayeva [23] and Horbach et al. [24].

2. Two different conceptualisations of "green"

In the existing literature, "green" and "green jobs" have been defined in various ways, with Bowen [25] providing an insightful overview. Notably, two key conceptualisations of "green" – output-based and process-based – encompass most definitions found in previous studies [26–30].

The output-based conceptualisation defines "green" according to the output or product of an activity or job. Here, the degree of greenness is determined by the extent to which the output contributes to environmental quality. For instance, a job focused on manufacturing electric vehicles would likely rank high on an output-based greenness scale, as electric vehicles are essential for a low-carbon society.

Within the output approach, one can define "green output" in different ways. The US Bureau of Labor Statistics [31] classifies green output as output relating to (1) energy from renewable sources; (2) energy efficiency; (3) pollution reduction and removal, GHG reduction, recycling, and reuse; (4) natural resources conservation; and (5) environmental compliance, education and training, and public awareness. In contrast, Eurostat [32] defines green output as products and services contributing to either (1) preventing, reducing, or eliminating pollution or (2) preserving, maintaining or enhancing the stock of natural resources.

Apart from how one defines "green output", another important issue is the scope of jobs one aims to include [33]. More precisely, some studies classify as "green" only jobs that are explicitly involved in green activities (*direct* green employment) [31,34,35]. In contrast, others argue that jobs in supplying sectors should also be counted among green jobs (*indirect* green employment) [36–38].

On the other hand, “green” can be approached from a *process-based* vantage point. The process-based greenness concept takes two forms. In its most straightforward interpretation, process-based greenness is determined by the environmental impact of a particular activity or job itself [21]. For example, someone working in hospitality will likely score high on a process-based measure of greenness since the environmental impact of the activities found in the hospitality sector is relatively low.

As will become apparent from Section 3, the simple process-based greenness interpretation is often used to identify brown sectors as sectors with a high environmental impact. Except for identifying brown sectors, the simple process-based approach is rare in empirical research on green employment since it is challenging to identify the pollution/material use content of economic activities [21,39]. The reason for this is that ideally, the pollution and material use content of an economic activity would include the entire production chain and therefore also cross-border pollution and material use would have to be included. Hence, while high (economic) sectoral emissions are a clear indicator for the “brownness” of that particular sector, low sectoral emissions do not necessarily imply “greenness” since the supply chain might be unsustainable overall due to high sectoral emissions in downstream sectors.

Others define process-based greenness as jobs or activities that lower the environmental impact of production processes within firms [40–42]. For example, a worker maintaining the pollution abatement technology in a cookie factory would be classified as green under this definition since he or she reduces the environmental impact of the cookie production process. The US Bureau of Labor Statistics [27] notes that this process-based green job concept is needed since the output-based approach alone would not capture workers whose job consists of reducing the environmental impact of the production of non-green goods and services.

Green jobs

Irrespective of how "greenness" is defined, there are two primary approaches to empirically identifying "green jobs" [21,43,44]. The first approach, referred to as the entity-level approach, classifies industries or companies as green[1], considering all workers within these entities as holding green occupations.

The second approach, known as the occupation-specific approach, categorises individual occupations as green or non-green. This method can be further refined by assessing tasks within occupations, replacing the binary classification of "green" or "non-green" jobs with a continuous indicator that measures the extent to which activities within a specific occupation are green.

As mentioned above, the process-based reducing-impact greenness approach is required since output-based measures alone would not capture all workers engaged in green activities. This caveat only applies to the entity-level measurement technique. Occupation-specific measurement methods would directly measure green employment. For example, a worker maintaining the pollution abatement technology in a cookie factory would not be classified as green using an approach that (only) counts employment in green

[1] And in some cases, intracompany entities such as specific production facilities.

sectors as green (an entity-level measurement approach). In contrast, all workers maintaining pollution abatement technologies would be classified as green using occupation-specific measurement.

It is crucial to note that the two different conceptualisations of greenness and the two primary approaches to empirically identifying green jobs are not mutually exclusive. Vona [21] argues that both the process-based and output-based concepts capture essential aspects of the green transition. Additionally, Dierdorff et al. [45] highlight the utility of having various measurement approaches for green jobs, given the diverse purposes for which green job data is needed.[2]

Table 1 provides a high-level overview of the conceptual framework used in the literature review. A critical discussion of these job concepts and measurement techniques is provided in Section 4.

Table 1 – High-level overview of the conceptual framework used to analyse green job literature, with examples

		Green job concept			
		Output-based		**Process-based**	
		Direct *… whose output directly contributes to environmental quality*	**Indirect** *… whose output serves as input of directly green output*	**Low impact** *… whose activity has a low environmental impact*	**Reduction of impact** *… whose activity is performed environmentally friendly*
Measurement technique	**Entity** *Green if job is located in entity…*	solar industry	mining sector	hospitality sector	cookie factory with low emissions relative to peers
	Occupation *Green if job belongs to occupation…*	solar engineer	industrial production manager	server	/

Source: Authors

3. Measurement and characterisation of green employment

This section summarises the literature aimed at estimating and characterising current green jobs. Studies are structured based on whether they employ entity-level or occupation-specific measurement approaches and are further subdivided according to country/region.

3.1 The entity-level measurement approach

Several studies have examined the employment effects of the green transition through an entity-level lens [e.g. 46,47]. Once a list of green entities is defined, aggregate statistics or survey data can be used to

[2] Some research and policy bodies attach a normative component to their "green" definition or bundle the "green" aspects with other desirable job characteristics. For example, the UNEP (2011) defines the green economy as an economy with substantially reduced environmental impact as well as improved fairness and well-being. Another example is the ILO, which defines green jobs as jobs in a number of specific industries which maintain or restore environmental quality while also meeting certain standards of decent work (ILO, 2016)

estimate green employment [48]. Inversely, if a list of pollution-intensive entities can be obtained, then "brown jobs" can also be studied.

Given the broader debate on how to identify green activities [e.g. 49], one issue with the entity-level green job measurement is how to discern green industries/companies. Two main approaches exist [32,48,50]. Green companies can be identified by labelling entire sectors as green (a top-down approach), e.g. based on expert judgement. Alternatively, particular companies could be classified as green (a bottom-up approach). In the case of the bottom-up approach, one can draw on multiple data sources. For example, one prominent stream within this literature relies on green patent data. Other possibilities for bottom-up identification of green companies/establishments include matching a list of green key terms to descriptions from business databases or web scraping.

Some evidence suggests that bottom-up approaches might identify companies as green which are not classified as green using top-down methods, supposedly because not all producers within a "green" sector might be green and vice versa [50]. This explanation for the difference between top-down and bottom-up approaches is corroborated by the substantial within-industry variation with regard to the emission intensity of output (a process-based measure) in the US [51].

Bottom-up identification methods have also been subject to criticism. In particular, patent-based measurements of green activities might (1) capture green invention rather than actual green technology use [17], and (2) disregard particular kinds of green innovation and induce a bias towards green activities in large-scale, technology-focused firms [16,52]. There is some evidence that patent-based approaches identify only a small proportion of eco-innovative green firms [53].

Nonetheless, it has been argued that the entity-level approach could lead to more reliable results than an occupation-based approach for estimating the magnitude of green employment [45]. The reason for this is that in an entity-level approach, employment can be classified as green relative to green output, while in an occupation-based setting such a correction is much harder to make [54]. However, Vona et al. [51] criticise the assumption of proportionality between green jobs and green output found in entity-level studies and argue that an occupational approach is a better way of measuring the fraction of work time linked to green activity and, thus, the actual use of green technology/production.

3.1.1 Entity-level measurement of green jobs in the US

An early output-based industry-level top-down green job measurement approach was implemented by the US Department of Commerce [34]. The Department of Commerce uses highly disaggregated 2007 economic census data to identify green output, based on the NAICS classification system. Output was classified as green according to a narrow definition, including only subsectors for which it was assumed there was a broad consensus on their green character, and a broad definition, additionally incorporating subsectors for which greenness could be more debatable. Since employment data is only available at a higher level of aggregation, employment at the 6-digit NAICS level is classified as green proportional to the greenness of the associated production. In some cases, the economic census output is not granular enough to capture particular green output categories[3], and ad-hoc correction methods are employed.

Following this approach, the Department of Commerce estimated that in 2007, narrow and broad green employment amounted to 1.8 million or 1.5% respectively 2.4 million or 2.0% of total employment.

A number of other US-focused studies rely on the Green Goods and Services (GGS) survey from the US Bureau of Labor Statistics [31]. The GGS provides an output-based industry-level top-down survey approach to estimate green jobs. First, the BLS defined green industries as industries whose output includes one of five green goods and services categories.[4] The BLS's classification of green industries has been criticised as being too conservative, since (1) only firms for which the majority of their output belongs to a green industry were included in the survey (since firms were allocated to industries based on the majority of their output) and (2) certain industries that take up an important position in the value chain for renewable energy, recycling, green chemistry and energy efficiency were excluded [55]. Second, the BLS surveyed a representative sample of companies in these green industries. Third, the BLS then estimated green employment of survey observations as total employment times the share of green production in total revenue. Note that this last step addresses the criticism that top-down approaches might classify non-green companies in green sectors as green, but not the criticism that it disregards green companies in non-green sectors.

The GGS BLS survey has only been undertaken in 2010 and 2011. Based on the aforementioned approach, BLS estimated that in 2011, 3.4 million or 2.6% of US occupations were output-based green.

Apart from the GGS survey, the BLS has also conducted the Green Technologies and Practices (GTP) survey [40]. In contrast to the GGS survey, the GTP provides a process-based entity-level approach. The BLS asked a representative sample of US companies how many of their employees were involved in green technologies or practices for at least half of their time, defined in a very similar way as BLS green industries.[5] The GTP BLS survey was only undertaken in 2011, with the BLS estimating that around 0.9 million or 0.7% of US jobs were process-based green in 2011.

The studies cited above all rely on top-down identification strategies. In contrast, Georgeson and Maslin [56] estimate US green employment using a bottom-up approach. Concretely, they define around 3800 goods and services as green (broadly classified as belonging to the environmental, low carbon and renewable energy sector), which they then try to measure using data from slightly less than 1600 data sources (e.g. company data, government agencies, academic sources) via a complex, somewhat ad hoc/pragmatic collation procedure. They report data for the financial years 2012/13 up to 2015/16. For

[3] This is the case for alternative fuel vehicles and hybrids, green building/construction services, energy efficient appliances, solar photovoltaics, and organic agriculture. See Appendix 2 Section B of US Department of Commerce [34].

[4] These five categories are: (1) energy from renewable sources; (2) energy efficiency; (3) pollution reduction and removal, GHG reduction, recycling and reuse; (4) natural resources conservation; and (5) environmental compliance, education and training, and public awareness.

[5] Green technologies and practices belong to: (1) energy from renewable sources; (2) energy efficiency; (3) pollution reduction and removal, GHG reduction, recycling and reuse; and (4) natural resources conservation.

the financial year 2015/16, they estimated that green US employment amounted to 9.49 million FTEs or about 7.1% of total FTE employment (own calculations based on [57]).

Top-down and bottom-up entity-level measurements can also be combined, as Muro et al. [35] demonstrate. In the first step, they identify green establishments using a list of predefined green industries (top-down identification) and via industry associations, patents, green product lists, government grants, and venture capital investment (bottom-up identification). Muro et al. [35] then derive green employment for these establishments using the Dun-&-Bradstreet company database.[6] The selected establishments fall into five broad categories: agricultural and natural resources conservation; education and compliance; energy and resource efficiency; GHG reduction, environmental management and recycling; and renewable energy. They estimated that 2.7 million workers worked in these green establishments in 2010, about 2.0% of total 2010 US employment (own calculations based on [57]).

US government programmes to identify green jobs such as the BLS GGS have been discontinued for budgetary reasons. Georgeson and Maslin [56] suggest that the lack of recent GGS-like data has forced recent green job estimation efforts to focus exclusively on the renewable energy sector, for which high-quality data is still available. Green job estimates solely based on the renewable energy sector (not reported here) will underestimate the total number of green jobs in the economy.

3.1.2 Entity-level measurement of green jobs in the EU

Since 2017, EU countries are obliged to publish output, export, added value, and employment aggregates for the environmental goods and services sector (EGSS) as defined by Eurostat [58,59].

Green jobs estimates based on the EGSS concept follow an output-based bottom-up and/or top-down entity-level measurement approach [32]. The EGSS is defined in terms of environmental activities or products. Environmental activities are activities aimed at either (1) environmental protection or (2) natural resource management[7], while environmental products are the result of environmental activities. The EGSS includes all producers of environmental goods and services, thus including producers that are not specialised in environmental production or for which environmental production is only a non-primary activity. EGSS uses a direct green employment scope, which means that only employment directly linked to environmental activities/products is reported [32]. Eurostat's EGSS definition has been endorsed by the OECD and UN and is now considered a global standard [23].

Eurostat [32] has produced detailed NACE (CPA/CN) lists of environmental activities (products), which may be of interest to researchers aiming to study green employment.[8] These NACE/CPA/CN codes are linked to specific mutually exclusive subcategories of environmental protection or natural resource management (the two main categories of EGSS activities). As a result, researchers can use these

[6] Muro et al. [35] exclude small firms and correct for mixed green and non-green establishments by using company information, see their study for more information.
[7] For a detailed definition of environmental protection and natural resource management, see Appendix 4 and 5 in Eurostat [32]
[8] See Appendix 2 and 3 in Eurostat [32], and https://ec.europa.eu/eurostat/documents/1798247/6191549/EGSS+list+of+env+products.xlsx

classifications to delimitate precisely their greenness concept and thus enhance cross-study comparability.

An overview of Eurostat green job estimates can be found in Table A1 in the Appendix. Note that EGSS estimation strategies differ somewhat between EU countries due to data availability, a detailed breakdown of these differences can be obtained from the EGSS quality reports published by Eurostat.[9]

Process-based greenness concepts have been applied to the EU as well. In particular, a recent country-level study is Krueger et al. [60] for Sweden. Krueger et al. [60] employ an entity-level measurement approach with low-impact (production-based[10] GHG emissions) and reduction-of-impact ("best-in-class" ESG, ESG news shocks) green job concepts. As mentioned in Section 2, using production-based GHG emissions to measure low-impact process-based greenness might misidentify some sectors as green by disregarding emissions downstream in the supply chain. Additionally, they employ a Prolific survey-based measure (asking respondents whether particular sectors are "sustainable"). Clearly, it is impossible to say whether respondents interpreted "sustainability" according to output, low-impact process or reduction-of-impact process concepts. While Krueger et al. [60] do not attempt to measure green employment, they estimate the effect of firm "sustainability" on wages, working hours, and career opportunities.

"Best-in-class" (i.e. relative to peers) environmental ESG firms pay around 2.1-4.4% lower wages (depending on the econometric specification), compared to one or two firms in the same sector (the ESG data is limited). Following a negative ESG news shock (news coverage indicating a negative environmental impact), wages in the following year increase by 6.8%. Based on survey identification, the top 20% most environmentally friendly sectors are found to pay around 8.7-12.6% less (depending on the econometric specification). Based on GHG emissions, the top 20% most environmentally friendly sectors pay about 5.7% lower wages. Furthermore, labour market mobility data indicates that workers moving to a more sustainable (unsustainable) sector (survey identification) get paid 4.3-6.5% less (more). Further evidence suggests that the negative wage differential associated with increased "sustainability" (survey identification) increases with ability and decreases with age. Lastly, increased "sustainability" (survey identification) is associated with working longer hours in a full-time job and do not seem to be associated with better career opportunities later on. The authors explain their findings through a demand-side channel: workers are willing to accept lower wages to work for a more sustainable firm.

3.1.4 Entity-level measurement of green jobs in the UK

Kapetaniou and McIvor [61] use an entity-level process-based approach to estimate green UK employment. They define green industries as NACE Rev. 2 1-digit industries with a carbon emission intensity below the median. According to their analysis, the UK green sector is responsible for 7% of the UK's emissions and represents 55% of total employment. Compared to the non-green sector, green workers are found to be more likely to be female, older than 40 years, higher-skilled, and receiving adult training.

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[9] These EGSS quality reports can be accessed here: https://circabc.europa.eu/ui/group/b01d2930-990e-44fb-9121-a9a6b00a1283/library/5b8441d7-cdee-4a43-9ac0-9659effd46d3?p=1&n=10&sort=modified_DESC

[10] As opposed to embedded/consumption-based emissions, which would include all emissions embedded in inputs to the production process.

An example of a bottom-up entity-level approach applied in a European setting is the kmatrix [62] study of green employment in the UK. Their approach is very similar to the method used by Georgeson and Maslin [56], as an extensive list of predefined green goods and services are used to identify green activity/employment in specific companies by drawing on a large array of data sources. For the financial year 2010/11, the kmatrix [62] study estimated that green employment reached 0.94 million FTEs.

3.1.5 Entity-level measurement of green jobs in non-Western countries

Only a limited number of studies have measured and/or characterised green employment in non-Western countries [22]. Many studies are situated within the ILO's green job measurement framework [63]. Therefore, these studies share the following characteristics: (1) the ILO's green job definition is often used, which combines both an environment-related component and the requirement that a job is "decent", i.e. meets certain working conditions thresholds – for consistency with the terminology used throughout the article, here we will distinguish between "green jobs" and "decent green jobs"; (2) input-output (IO) tables are used[11], which has the advantage of capturing supply chain employment which is generally not taken into account in other entity-level estimation procedures [48]; (3) combine both output-based and process-based green job concepts.

Sultan and Harsdorff [36] is an example of a study within the ILO framework. They employ a top-down and bottom-up entity-level approach to measure decent green employment in Mauritius. Their estimation method combines the output-based and the process-based green job concepts. For the process-based approach, a relative measure is used to classify the top 10% companies with the lowest environmental impact in each industry as green. Moreover, Sultan and Harsdorff follow the ILO's (2016) green job definition and classify only jobs that meet specific "decency" requirements (as defined by the ILO) as green. Their results indicate that in 2010-11, 6.3% of total employment in Mauritius could be seen as decent green. Using an extended IO model, they find that direct and indirect output and employment multipliers are generally more elevated in green compared to non-green sectors.

Lehr et al. [37] identified green jobs in Tunisia using a top-down entity-level approach following the ILO's measurement framework. Using the output-based and process-based green job concepts as a starting point, green and partially green (sub)sectors were identified in a workshop with stakeholders. Using an extended IO model, Lehr et al. (2018) measured the number of green jobs in Tunisia for 2005-2010. For 2010, they found 0.11 million direct and indirect green jobs or 3.4% of total employment according to ILOSTAT (2023) employment aggregates.

GHK [65] uses a top-down entity-level output-and-process-based approach situated within the ILO's framework to estimate direct and indirect green employment in Bangladesh. Combining data sources with base years ranging from 2005 to 2010, they find direct green employment of 3.54 million or 7% of the job total. Of these jobs, 0.81 million or 2% satisfy the ILO's decency requirement. Green jobs are linked to 4.03 million indirectly green jobs or around 8% of total employment.

[11] For Western countries, studies relying on IO are generally focused on the renewable energy sector and do not include other green economy sectors [e.g. 12,64]

The ILO [66] applies a top-down entity-level output-and-process-based approach to estimate direct and indirect green employment in Mexico in 2011. Using a range of data sources (e.g. case studies, estimated job intensity coefficients per unit of green activity and labour/output ratios from aggregated sectors), direct green jobs amount to 1.81 million in 2011 or 3.8% of total employment (own calculations based on [67]). Using an extended IO table, indirect green employment is found to attain 0.97 million, bringing the direct and indirect green jobs total to 2.19 million in 2011 or 4.6% of total employment (own calculations based on [67]).

3.2 The occupation-specific measurement approach

As mentioned above, two main approaches exist to identify “green jobs”. The previous subsection gave an overview of studies that relied on industry-/company-level measurement techniques. Recently, the occupation-specific approach to green jobs has gained prominence. In contrast to the entity-level measurement method, in this approach, it is not employment in green industries/companies which is classified as green but rather employment in a set of specific green occupations. The task-based method, in particular, has garnered attention. It abolishes the binary green/non-green classification in favour of research aimed at specific green activities/tasks/skills of an occupation.

Tasks should be distinguished from skills. In the literature, Autor's [68] definition of a task is quite prominent: a task is “a unit of work activity that produces output” [e.g. 42,69]. In contrast, a skill refers to the capability of executing tasks [38,68]. Skills are determined by various factors such as education, training, and experience [70]. Hence, green tasks refer to the actual green activity found in a particular job, while green skills can be seen as capturing the degree to which green activities could potentially be performed [71].

The popularity of the task-based method is due to its potential for more helpful policy conclusions [45]. Indeed, how disruptive and (un)just the green transition will be for the labour market, and how much and which policy interventions are desirable to a large extent depends on how much the current skill set of, and tasks performed by, workers will have to change during the transition period [20,54,72,73]. If ‘brown workers’ to a large extent hold the same skills as green workers, then labour market policy is most effective when focusing on matching workers with jobs. On the other hand, if green skills are largely different from brown skills, labour market policy emphasising reskilling and adult learning is most effective.

One notable criticism of task-based methods is that within similar occupations, substantial variation in task content might exist [74], for which no correction is possible if the data are at its most granular at the occupational level.

3.2.1 Occupation-specific green job measurement for the US

US-based occupation-specific green job research is almost entirely based on the ONET dataset. ONET links occupations with, among other things, tasks and skills. In 2009, the ONET database was expanded with a number of “green jobs” [75]. These green jobs were defined following an output-based concept of greenness[12] and are to some extent bounded by an entity-level approach since only jobs in 12 sectors identified as green following a literature review[13] were considered for possible inclusion in the green job list.

ONET subdivides green jobs into three categories:

> (1) Green Increased Demand (GID): jobs for which demand will be higher in a green economy but without changes in occupational task content;
>
> (2) Green Enhanced Skills (GES): jobs whose essential purposes remain the same but whose task content will change significantly;
>
> (3) Green New and Emerging (GNE): new jobs with task content completely different from existing occupations.

Per definition, the task content of GID occupations will stay unchanged. For GES and GNE jobs, the subset of the tasks present in these green jobs that depict "the new kind of working behaviour associated with green economic activities and technologies" were defined as green in ONET [45, p. 17]. The percentage of tasks classified as green for ONET green jobs differs considerably. Therefore, GES and GNE occupations will be impacted differentially by the green transition [76,77].

Based on the ONET database, there are three main pathways for identifying green jobs: (1) using the discrete ONET GID/GES/GNE categories; (2) constructing a continuous green task index for GES/GNE ONET occupations; (3) constructing a continuous green skill index (which requires identification of these green skills – as green skills in contrast to green tasks are not defined in ONET). Regarding (1), discrete green jobs measurements have been criticised for disregarding (a) the heterogeneity among occupations in the same category and (b) the similarity among occupations in different categories [69]. Apart from measuring green jobs according to these three approaches, several ONET-based studies have also characterised the skill differences between green and non-green jobs (without necessarily classifying particular skills as green).

To link the data in ONET about particular jobs and tasks to labour market (survey) data, a crosswalk (a link between two data sources) is required. However, given that the ONET occupational classification is more granular than both the SOC and the ISCO classifications (used in US and EU labour force surveys), ad hoc assumptions need to be made for a crosswalk between ONET and employment data.[14] These assumptions tend to influence green job estimates and need to be considered when formulating conclusions [54]. Additionally, the ONET green job classifications are based on research from around 2010 and might thus

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[12] As evidenced by the ONET definition of a green economy [75, p.3]: "The green economy encompasses the economic activity related to reducing the use of fossil fuels, decreasing pollution and greenhouse gas emissions, increasing the efficiency of energy usage, recycling materials, and developing and adopting renewable sources of energy".

[13] These 12 sectors are: (1) RE generation; (2) transportation; (3) energy efficiency; (4) green construction; (5) energy trading; (6) energy and carbon capture and storage; (7) research, design and consulting services; (8) environmental protection; (9) agriculture and forestry; (10) manufacturing; (11) recycling and waste reduction; and (12) governmental and regulatory administration.

[14] See Scholl et al. [78] for a thorough comparison of different crosswalking options and their implications.

not be up to date with current green job developments [22,44,78–80]. ONET is currently in the process of reviewing and expanding its information on occupational greenness [81].

A measurement study which uses discrete ONET GID/GES/GNE green job classifications is Bowen et al. [77]. They characterise green and non-green occupations based on ONET data and link with BLS employment data using SOC codes. Bowen et al. [77] find that ONET green jobs (including GID) represent 19.4% of the US workforce. Using ONET data on similarity between occupations (jobs related because people with similar profiles start in these careers or people often transit from one career to the other), they classify a further 44.3% of the workforce as capable of transitioning to green jobs.[15] Based on a measure of skill distance, their results indicate that transitioning from non-green to green jobs will likely be easiest in the case of GID occupations. Nonetheless, skill distances with non-green jobs are relatively small for other green job categories as well, which indicates that on-the-job retraining would likely suffice.

Vona et al. [51] harnessed a continuous green task index to study green occupations in the US between 2006 and 2014. The authors calculate a green task index for GES and GNE ONET occupations as follows: # green tasks in occupation k / # all tasks in occupation k. Since GID occupations have no green tasks, using a green task index implies that GID jobs are not considered in their analysis. However, one should note that this implies a somewhat restrictive scope of their output-based approach to greenness. Hence, an ONET green task index does not represent the degree to which a job contributes to green output but rather the extent to which work content has changed or will change due to the green transition.

In the next step, Vona et al. [51] related their green task index to BLS employment data split according to 6-digit SOC occupational codes, 4-digit NAICS industry codes, and 537 geographical areas. Vona et al. [51] find a green job share (defined as the average green task index weighted by employment shares) of 2 to 3% and show that green occupations tend to be associated with higher skills, which require more years of education, are geographically concentrated, are in aggregate pro-cyclical and enjoy a wage premium compared to non-green occupations. Interestingly, Vona et al. [51] relate their green employment estimates to the BLS GGS green employment share figures at the 4-digit NAICS level and find a correlation of 50.5%, indicating a relatively high degree of overlap between these measures.

Two related studies have identified green skills from ONET data. Vona et al. [82] employ a two-step procedure to identify green general skills: in the first step, they regress ONET green tasks on ONET skills. In the second step, they select ONET skills that tend to be particularly and positively associated with green task content and group these in unweighted averages for each occupation. After defining brown jobs as jobs more prevalent in industries with high pollution content, Vona et al. [82] found a small general skill gap between brown and green occupations[16] (smaller than between green and non-green occupations). Moreover, their results indicate that technical skills tend to be associated with green jobs.

Rutzer et al. [69] used ONET task and skill data to identify the green potential of particular occupations. While somewhat similar to the approach taken in Vona et al. [82], Rutzer et al. [69] use a machine learning approach to regress green task content on ONET skills and rely on the (positive or negative) estimated

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[15] Rutzer et al. [69] criticize the Bowen et al. [77] green job similarity measure, since ONET might classify jobs as similar to each other according to aspects which are unrelated to the greenness of these occupations.
[16] Green occupations are defined as occupations with a green task index of 0.1 or more.

coefficients as a basis for identifying green skills, which leads to a more reliable identification.[17] Using a crosswalk between ONET and BLS labour market data[18], Rutzer et al. [69] then construct a continuous measure of the relative green potential (normalised between 0 and 1) of US employment (see Figure 7 p26 in their article). To give an idea of this distribution, the median is 0.23, while around 5% of the US workforce has a relative green potential value of at least 0.6. Environmental engineers have the highest green potential (thus, their relative green potential score is 1). Generally, they find that technical skills contribute to green job potential.

An important drawback of using ONET skills to measure green potential is that ONET skills are fixed [69], whereas new green skills may emerge over time [83]. However, Rutzer et al. [69] argue that this point is of limited importance since ONET skills are rather general and can thus be interpreted as prerequisites for working in any particular occupation.

Apart from the studies concerned with measuring green jobs, Consoli et al. [76] attempted to characterise the skill difference between green and non-green occupations using ONET. They rely on ONET's green occupation list and construct measures of skill distance and technological exposure. According to their findings, green jobs require more high-level cognitive skills, more education, experience, and on-the-job training. These differences with non-green occupations could not be related to differences in technological exposure in green and non-green jobs.

One notable exception to the previously discussed studies based on ONET data is Peters [54]. In this study, ONET data are linked to US Census data (demographics) and BLS data (labour market data). Remarkably, green jobs are defined without using the ONET green jobs list or an ONET-based green task index. Rather, Peters [54] compares task descriptions for all ONET occupations to a list of green key words. Cluster analysis is then used to separate occupations with at least one green task in green and non-green occupations. Using this approach, Peters [54] reports a large variety in the task content of green jobs and finds a green employment share of around 6.4%. According to his results, educational requirements vary considerably according to the type of green job considered. Another interesting finding is that green jobs tend to be male dominated but racially dispersed, and in the US, green jobs tend to be quality jobs (e.g. predominantly full-time with health insurance).

Another idiosyncratic approach to occupation-specific green job characterisation in the US is Muro et al. [84]. The authors aim to characterize jobs in the 'clean energy economy' in the US. Their definition of 'clean energy' is broad (going beyond clean energy) and encompasses (1) clean energy production; (2) energy efficiency (manufacturing and construction); (3) environmental management (including

[17] As they show in their article, using goodness of fit tests. They explain this enhanced goodness of fit by the (1) their use of all ONET skills, rather than only ONET skills which are substantially and positively associated with green task content and (2) the fact that they use estimated coefficients rather than unweighted averages to identify green potential. Rutzer et al. [69] also note that Vona et al. [82] do not necessarily aim to identify green job potential, but rather want to examine whether green skill intensive occupations are differentially impacted by environmental regulation compared to non-green skill intensive occupations.

[18] ONET-BLS skill crosswalks are equivalent in Vona et al. [82]; Bowen et al. [77]; Consoli et al. [76] and Rutzer et al. [69]. ONET 8-digit SOC codes are aggregated to 6-digit SOC codes via simple averages. The correlation between skill values in ONET and skill-values at 6-digit SOC level attains for both median and average 0.99, with 0.79 as the lowest value. This indicates that simple averaging might be a sensible approach [69].

conservation and waste management). Given their broad definition, we believe ‘clean energy economy’ is consistent with what we mean with ‘green economy’ in the context of this review. Industries identified (based on previous studies) as belonging to one of these three categories are classified as green (or part of the ‘clean energy economy’). Hence, as is the case with ONET (see earlier), their approach is to some extent entity-level bounded. Occupations that are more prevalent in green industries with respect to their national employment share are classified as green. In a next step, these green occupations are matched to 2016 US Bureau of Labour Statistics (BLS) and census data on wages, knowledge and skills (from ONET), demographic characteristics, and educational qualifications.

Muro et al. [84] find substantial average hourly wage premia with respect to the national average: 19.1% for clean energy production, 8.5% for energy efficiency jobs, and 15.0% for environmental management jobs. An important determinant of this result is the relatively low share of low-paying green jobs. Moreover, educational attainment in green jobs is lower than the national average. In particular, less than 17% of green jobs in the clean energy production and energy efficiency sectors are held by someone with a bachelor’s degree or more (while for environmental management, the share is close to the national average). Compared to the national average, on-the-job training in the clean energy production and energy efficiency sectors is, on average, considerably more prevalent and more long-lasting. For environmental management, on-the-job training is comparable to the national average. Moreover, clean energy production and energy efficiency occupations tend to require more scientific knowledge and technical skills. Environmental management occupations are again quite close to the national average. Median age of workers is equal (clean energy production, 42.2) to somewhat higher (energy efficiency sector, 42.7; environmental management, 44.3) than the national average (42.2). Compared to a national average of 46.8%, the share of women in employment falls to only 39.0% in the environmental management sector, 18.0% in the energy efficiency sector and 13.2% in clean energy production.

3.2.2 Occupation-specific green job measurement for the EU

Almost all occupation-specific EU-focused studies apply ONET occupational data to EU labour market statistics.[19] As mentioned above, ONET data (using 8-digit SOC codes) needs to be crosswalked (i.e., linked) to ISCO codes (used to classify occupations in EU labour market data). The main difficulty is that multiple SOC codes map to multiple ISCO codes. Crosswalking can either be done using (1) weighted data (weighting can include both departure, in this case, the US, and destination, in this case EU, data) or (2) simple averaging. Most studies apply simple averaging. Scholl et al. [78] provide a thorough comparison of different crosswalking options, and find that weighting leads to similar findings as simple averaging for aggregate employment figures (see below).

As is the case for the US, some studies use the discrete ONET GID/GES/GNE categories to identify green occupations. Hancké et al. [85] link ONET GID, GES, and GNE occupations to EWCS microdata at the 2-digit ISCO level by using a simple averaging ONET-ISCO crosswalk. All occupations that are not classified as green following the ONET crosswalk are defined as brown.

[19] A green skills ISCO mapping was released in 2022 as part of the European Commission’s ESCO framework (see further below).

Hancké et al. [85] then compared green and brown jobs. Job quality differs considerably between European countries, but within-country differences between green and brown jobs tend to be relatively small. Green job quality seems relatively stable over time. Brown and green jobs do not substantially differ regarding job and income security. Brown jobs tend to receive more on-the-job training, while workers in green jobs perceive their employability as higher. Nonetheless, with respect to education and training in green and brown jobs, large differences between countries are accompanied by small differences within countries and a relatively stable relationship over time. Regarding working conditions, there are small differences between green and brown jobs, with brown jobs generally performing better and not much change over time. Finally, work-life balance seems slightly better in brown jobs, while gender balance appears to be substantially more favourable in brown jobs.

Hancké et al. [85] argue that the generally favourable characteristics of brown jobs compared with green jobs might be due to the former's more institutionalised character.

Bowen and Hancké [86] link EU LFS microdata to ONET occupations using a crosswalk at the 3-digit level. For their crosswalk, they classify every ISCO occupational group as green to which at least one ONET GID/GES/GNE occupation links. Following this approach, 35.5% of total employment has been classified as green for 2006, rising to 40% in 2016. A further break-down according to educational attainment reveals that GNE workers tend to have finished tertiary education more often than the average worker, while the reverse is true for GES and GID employees. Moreover, low-skilled workers (i.e. workers who did not finish upper secondary education) are substantially more prevalent in GID occupations compared to total employment. A sectoral break-down and comparison between 2006 and 2016 revealed that green job growth in traditional industrial sectors is mainly driven by GES and GNE jobs growth.

Cambridge Econometrics et al. [87] link ONET GES and GID occupations to 3-digit LFS microdata for the EU27 (including the UK and excluding Croatia). They do not report GNE occupations since at the time of their analysis, no SOC codes had been allocated to these jobs yet. While not explicitly stated, they appear to classify occupations discretely as either green or non-green. According to their analysis, in 2009, there were 18.1% GES occupations and 26.4% GID occupations in the EU27[20].

Valero et al. [22] link ONET GNE, GES, and GID occupations to EU15 (including the UK) LFS microdata for 2011-2019. Their crosswalk procedure consists of assigning to ONET green occupations a greenness score of 1 and to all other ONET occupations a greenness score of 0, and then calculating the greenness of EU occupations as the simple average greenness score of all ONET occupations linked to it. For 2019, they find green employment shares between 17 and 22%. Comparing job characteristics to non-green jobs, they find that green workers are older, male-dominated, higher-skilled, more likely to be on a permanent contract (all of the previous characteristics mainly driven by GNE), and more likely to be full-time.

Scholl et al. [78] link ONET GNE and GES occupation as well as Vona et al. (2018)'s brown job measure (see earlier) to 4-digit ISCO Portuguese employer-employee data for 2011 and 2017. A variety of ONET-ISCO crosswalks are used[21]: (1) binary (ISCO occupation classified as green if at least one corresponding ONET

[20] Note that this includes the UK and excludes Croatia.

[21] As mentioned earlier, a cross-walk is necessary since an ONET occupation may map to several ISCO occupations, and vice versa (many-to-many correspondence).

SOC occupation is GNE or GES); (2) simple averaging (ISCO occupation classified as green in proportion to corresponding ONET SOC occupations that are GNE or GES); (3) weighted averaging[22] (ISCO occupation classified as green in proportion to employment of corresponding ONET SOC occupations that are GNE or GES); (4) green task intensity (per ISCO occupation, the average share of green tasks in the corresponding ONET occupations) using simple or weighted averaging.

Scholl et al. [78] find for 2017 a green (brown) employment share of 17.9% (10.8%) using binary cross-walking, 8.7-10.2% (6.4%) using simple average crosswalking[23], and 10.1-12.1% (5.0%) using weighted average crosswalking. For green task intensity, the results are 2.6% using simple averaging and 1.5% using weighted averaging. Interestingly, there is a downward trend in both green and brown employment over time – which may be an indication that ONET greenness measures do no longer reflect the full set of current green employment. Moreover, they provide evidence that differences between simple and weighted average crosswalking are more pronounced at the sectoral level for both green and brown occupations. Somewhat reassuringly, Scholl et al. [78] find a similar positive association between sectoral productivity and green employment share – which they see as an indication that each cross-walk captures the same underlying 'greenness' characteristic.

Concerning the continuous green task/skill indices approaches for identifying green jobs, a few studies employ these identification approaches in the context of EU studies but somewhat remarkably do not report on the green job estimates these approaches imply. An example of this in the case of an ONET green task index can be found in Elliott et al. [18]. An example in the case of an ONET-based green skill index is Niggli and Rutzer [71]. They link ONET green potential estimates obtained by Rutzer et al. [69] to LFS data at the ISCO-88 3-digit level using an ONET-ISCO crosswalk. Using the OECD's environmental policy stringency index, they then investigate whether labour market responses differ according to green potential. Unfortunately, they do not report on the green potential job distribution for the EU.

Using ONET data for EU-focused studies leads to two main challenges. Firstly, as mentioned above, ONET occupations are classified using SOC codes while LFS microdata reports ISCO codes. While a SOC-ISCO crosswalk (correspondence table) is available, the overlap between SOC and ISCO codes is not one-to-one, meaning aggregations or disaggregations are necessary. Second, the ONET database is constructed based on US data. Similar occupations in the US and EU might have considerably different task content due to differences in organisation and technology [21,86].[24]

[22] A distinction can be made between weighted averaging using only US employment data or weighted averaging using both US and destination employment data (in the latter case weights are determined by allocating US employment proportional to ISCO employment in the destination country/region), see Scholl et al. [78] for more details.

[23] The difference is due to different starting points for the simple averaging. The reason for this is that ONET green jobs are defined at the 8-digit SOC level, while Vona et al. [82] brown jobs are only defined at the 6-digit SOC level, see Scholl et al. [78].

[24] Although Niggli and Rutzer [71] point to research indicating similar occupational skill requirements in the US and other industrialised countries [88,89] and is common in the literature.

For specific countries, occupational databases similar to ONET are available. For example, Cetrulo et al. [90] study the occupational characteristics of the Italian labour market using the ICP dataset. An occupation-specific green jobs study for Italy could rely on the ICP dataset rather than ONET.

For France, Onemev [91] publishes yearly occupation-specific green job estimates. Two green job categories are defined: (1) “green” jobs are jobs whose purpose and/or tasks contribute to measuring, preventing, managing, or correcting negative environmental impacts; (2) “greening” jobs are jobs whose purpose is not environmental but where additional skills have been integrated in such a way that the work content has an important environmental component. Hence, to some extent (1) and (2) seem similar to the ONET GNE and GES respectively occupational categories. The “green” and “greening” green job definitions have been used to identify green occupations in the French ROME job classification database, which via a crosswalk has been linked to labour market data from the French statistical agency.

Onemev [91] estimates for 2018 0.14 million “green” jobs or 0.5% of total employment and 3.79 million “greening” jobs or 14% of total employment in France. “Green” jobs are heavily male dominated, with 82% of the workers being male compared to 52% for the population as a whole. With respect to education, there is no substantial difference between “green” and other jobs. Moreover, “green” compared to non-green jobs seem to have a somewhat higher quality – 88% of “green” jobs are of unlimited duration compared to 74% in the total workforce, while 93% are full-time compared to 83% of all jobs. For “greening” jobs, the situation is largely similar, with 81% men and no substantial difference in education. However, only 73% of “greening” jobs are of unlimited duration, while 90% are working full-time.

In the case of Germany, Janser [42] uses text mining to identify green tasks in the German occupational BERUFENET database for 2006, 2012-2016. BERUFENET links occupations to a set of core and additional requirements. Based on a literature review, he constructs a list of green task keywords – with his definition of greenness closely related to ONET’s greenness concept[25]. After calculating a greenness of task index, Janser [42] links this index to administrative microdata for 2006, 2012-2016. He then goes on to analyse spatial, temporal, and industry distribution.

The shortcomings of ONET might also be overcome by relying on an EU skill database. The ESCO framework is a detailed database developed by EU countries and the European Commission, which describes more than 13,000 skills and their links to 3000+ occupations found in the EU. Recently, the ESCO database has been updated to identify “green skills”. Using both manual labelling and machine learning techniques, 570 ESCO skills have been classified as “green”. For manual labelling, the Cedefop [89] definition of green skills was followed: “the knowledge, abilities, values and attitudes needed to live in, develop and support a society which reduces the impact of human activity on the environment”. To our knowledge, the ESCO database has not yet been used to investigate green skills and occupations.

Another innovative approach to green job measurements is provided by Colijn [92]. An algorithm is used to identify green vacancies in around 117 000 job advertisements collected by Wanted Technologies between December 2011 and November 2012 for the EU27[26] countries, Switzerland and Norway. The

[25] See Janser [42], page 22. His conception of a green economy goes beyond ONET’s by also including as green activity (1) increasing the effiency of material usage; and (2) protecting and promoting biodiversity.
[26] Note that the UK is included while Croatia is not.

vacancy sample is biased towards large-firms and Northern European countries, especially the UK. Colijn [92] distinguishes green jobs as being either dark green (primarily environmental, includes green tasks) or light green (somewhat environmental, includes green tasks). Apart from that, some jobs are seen as near green (not environmental but supporting green occupations). While no detailed explanation of the classification algorithm is given, 0.3% (3.0%) of vacancies were classified as dark (light) green and 3.6% as near green. In a next step, Colijn [92] regresses ONET skills categories (using a crosswalk at the 3-digit SOC level) on (1) green shares per occupational category and (2) the greenness of vacancies and finds strong evidence that technical skills are more prevalent in green occupations, with some evidence that green jobs are generally also higher-skilled with respect to other skill categories.

3.2.3 Occupation-specific green job measurement for the UK

Valero et al. [22] link ONET occupational data to UK LFS microdata for 2011-2019, with the UK LFS data being more granular with respect to ISCO codes and certain variables than the EU LFS. For their crosswalk, they rely on a UK-specific list and take into account uncertainty by implementing two identification strategies: (1) all UK occupations to which at least one ONET GID/GES/GNE is linked are classified as green (likely an overestimation); (2) ONET GID/GES/GNE occupations get a greenness score of 1 and the remaining ONET occupations receive a greenness score of 0, and the greenness of UK occupations is derived by taking the simple average of the greenness scores of all ONET occupations linked to it.

According to approach (1), Valero et al. [22] found that 39% of UK jobs are green, while according to the more conservative crosswalk approach (2) the green job share reaches 17%. Clearly, the precise crosswalk procedure used considerably impacts green job estimates. They find that green workers compared with non-green workers are more likely to be older (driven by GES and GNE), male dominated (across all ONET green categories), completed higher education (driven by GNE, for GID there is a negative correlation), have a permanent contract (driven by GES and GNE), are higher-paid (driven by GES and GNE), tend to be more white (ethnicity), more full-time, and less at-risk of automation. GNE jobs are more likely to have received on-the-job training, while GID jobs are less likely to have participated in training than other jobs. Further analysis of the wage premium reveals that (a) higher wages might be partially driven by older age and higher educational attainment; and (b) correlational evidence suggests that the wage premium controlling for other wage-determining factors and with the sample broken down by skill level is predominantly situated in the middle.

In a next step, Valero et al. [22] analyse online vacancies collected by Burning Glass Technologies (BGT). These vacancies are linked to UK occupational codes, and their results indicate that vacancies are marginally more "green" than current occupations – resulting in 19% (based on the conservative ONET-LFS crosswalk procedure) respectively 49% (based on the expansive ONET-LFS crosswalk procedure) of vacancies classified as green.

To create a rough sense of the magnitude of the green transition, Robins et al. [93] link ONET green job data to UK 2011 census data.[27] They found that 10.5% or 3.2 million jobs would require reskilling, while

[27] For Northern Ireland, the authors rely on 2013 data.

10.4% or 3.1 million of current occupations could benefit without much change in job content. As a result, 21% of the UK's labour force is classified as potentially impacted by the green transition.[28]

3.2.4 International occupation-specific green job measurement

Recently the OECD and the IMF have attempted to measure and characterise green jobs across countries to enhance comparability of findings. The OECD [44] crosswalks[29] ONET data to labour market data at a 3-digit level for 2011-21 in OECD countries[30]. Green jobs are defined as GNE or GES ONET jobs with a green task index (i.e. the number of "green" tasks relative to total tasks in a particular job, see Section 3.2.1) larger than 10%. Using this definition, 18% of OECD employment is classified as green. Brown jobs are defined as in Vona et al. [82] (see Section 3.2.1).

The study focuses on regional/subnational differences. On average, there is a 7 %-point difference between the lowest and highest green regional employment within an OECD country. Moreover, regions which include the capital city tend to exhibit both more green and less brown employment. Additionally, regions with a high share of brown employment tend to have a lower GDP per capita. Regions with a high share of industries such as professional, scientific, and technical activities are prone to have a high share of green jobs. In contrast, regions with a high share of industries such as agriculture or manufacturing record lower green employment shares. For regions with higher R&D investment, both higher green employment shares and higher green employment growth rates are found. Lastly, regions with lower green job share also tend to record lower education/training rates than average.

Another focal point of the OECD [44] study is characterising green employment. Green jobs are disproportionately situated in large firms (250 or more employees), and male-dominated (72% of all green jobs are held by men). However, polluting jobs are also heavily dominated (83% male). To a large extent, these gender differences are industry-related, with manufacturing and construction responsible for high shares of green and brown employment. Green workers are highly educated (56% tertiary education versus 34% in non-green employment) and high-skilled. No difference is found between on-the-job training in green and non-green jobs, but polluting workers tend to report less on-the-job training than average. Using Lightcast vacancy data[31], vacancies tend to have higher shares of green and non-polluting jobs than current employment, demand for green jobs has grown faster than overall labour demand. Using the same vacancy data, a green wage premium of 20% (mostly explained by skills, education, and experience) and a brown wage premium of 12% are found.

The IMF [94,95] applies an output-based occupation-specific approach by weighted-average-crosswalking ONET GNE and GES occupations to US, EU, South-Africa and Mexican labour market data[32] for 2005-19.

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[28] While it seems that the first figure refers to GES and GNE jobs and the second figure to GID occupations, this is not explicitly stated by the authors nor is the ONET-Census crosswalk they employ explained – hence, it is hard to compare these findings to the broader literature.

[29] Using simple averages.

[30] Specifically: the UK, Iceland, Australia, Canada, EU countries, Norway, New Zealand, Switzerland, and the US. Some measurements are based on a more restricted dataset (e.g. only using EU LFS data).

[31] The precise geographical scope of the vacancy data ('for selected OECD countries') is unclear.

[32] Annex Table 3.1.2 in the IMF [95] report gives a detailed break-down of the sample for each estimate.

The IMF relies on a green task index. Brown jobs are identified following Vona et al. [82] (see earlier), once again cross-walked using weighted averaging.[33] In addition, sectoral total (i.e., direct and indirect) emissions per worker are used to measure brownness (in line with the IMF, henceforth 'emission intensity').

The IMF [94,95] finds that green task intensity is on average 2-3%, while brown jobs constitute about 2-6% of total employment. For 2011-2019, green task intensity and brown employment have stayed more or less constant. From 2005 to 2015 (data years differ due to data availability), emission intensity has fallen.

Green task intensity, brown employment, and emission intensity are all higher in industrial sectors, although considerable cross-country heterogeneity exist. A high skill level is positively associated with a high green task index and negatively associated with brown employment and emission intensity, while being an urban worker tends to involve higher green task index levels and lower brown employment (but not less emission intensity). High green task intensity, brown, and high emission intensity jobs are heavily male-dominated, and are associated with permanent, full-time employment. All job categories are associated with routine work and might therefore be more susceptible to automation, although brown and high emission intensity jobs are notably more routinizable. Job tenure is on average higher in brown and high-emission-intensity employment, and both high green task intensity and high emission intensity jobs are more prevalent in larger firms.

Moreover, there is evidence that general green skills (as defined by Vona et al. [82]) – i.e. skills that are associated with high green task intensity jobs – are widely distributed across economic sectors. Furthermore, an average non-zero green task index job has a 6.7% wage premium compared to an average brown job. A novel aspect of the IMF [94,95] work is its use of labour market transition data. Both green task intensity and brown jobs are associated with job stability. Furthermore, moving from brown to high green task intensity jobs is not more challenging than shifting from non-brown, non-green to high green task intensity jobs.

3.3 Comparison of the entity-level and occupation-based approaches

An interesting question is how the different green job estimation approaches compare to each other. Østergaard et al. [70] couple linked country-specific employer-employee datasets with the 2014 EU CIS survey[34] to identify, what they refer to, as jobs with green skills in the four Nordic countries. Their study compares the EGSS Eurostat output-based entity-level measurement approach, two education-based identifications (relying on a list of green key terms[35] linked to ISCED and national educational codes) and an occupation-based classification (using both an ONET crosswalk and a list of ISCO-08 green occupations

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[33] Note that the IMF refers to brown employment as "occupation-level pollution intensity". However, Vona et al. [82] provide a binary brownness measure, which is then cross-walked to ISCO codes (and is therefore continuous between 0 and 1 rather than binary). Therefore, it seems to us more natural to speak about 'brown employment' as we do here.

[34] For Norway, the 2014 CIS survey did not feature an eco-innovation module, but a national survey is available.

[35] Green key terms were: "environ", "energy", "waste", "recycle", "wind" and "solar".

derived from a green key term[36] search of the ILO's ISCO-08 task descriptions[37]). With regard to their ONET task-content measure, they only identify as green those occupations for which the green task index equals 1 (i.e. GNE and GES occupations with only green tasks). Depending on the measure used, they find an employment share of between 0.2-5.3% for green jobs.

One explanation for the relatively minor incidence of green jobs/green skills is that only a few workers require green skills in combination with a larger pool of workers with more generic skills [70]. In fact, this idea is supported by the large share of GID workers found based on ONET.

The overlap between each of these green jobs operationalisations appears rather limited. In particular, of all Danish employees with a green job, only 1.8% is classified as green according to both an occupation-based and the entity-level measurement method (1.2% for occupation-based and education-based greenness, 0.02% for entity-level and education-based), and only 0.01% of green employees is determined to be green by all three approaches (entity-level, occupation-based and education-based). Østergaard et al. [70] interpret these findings as a sign that green jobs are diverse and spread across the economy. In general, the ONET occupation-specific measurement leads to the highest green job estimates but this result might be due to the high level of aggregation required in the crosswalk procedure from ONET to SOC to ISCO codes.

4. Insights from the descriptive green job literature

This article reviews the recent literature on measuring and characterising green jobs. To do so, a simple conceptual framework has been adopted that distinguishes between two green job concepts and two measurement techniques. According to the output-based green job concept, jobs are green if they contribute to the production of green goods or services. The process-based green job concept has two interpretations. In its simple form, process-based green jobs are jobs associated with activities with a low environmental impact. In its more complex form, process-based green jobs are jobs associated with the reduction of environmental impact in production processes. Due to data limitations, which make it hard to identify the environmental impact of production processes, the output-based greenness concept is dominant in the empirical literature.

Regardless of the green job concept one endorses, two measurement techniques are available. On the one hand, green jobs can be measured by identifying green industries/companies and then assuming that (a proportion of) employment in these entities is green (entity-level measurement). To identify green industries and companies, researchers often employ either top-down or bottom-up methodologies. Top-down approaches involve classifying entire sectors as green, whereas bottom-up methods focus on identifying specific companies or establishments as green. However, top-down strategies may overlook green jobs present in non-green sectors, and certain bottom-up methods are similarly prone to disregarding specific green activities. Alternatively, a distinct measurement technique involves the direct classification of particular occupations as green, which is known as occupation-specific measurement.

[36] Idem.

[37] http://www.ilo.org/public/english/bureau/stat/isco/docs/groupdefn08.pdf

Within this branch of the green job literature, occupations are often deemed green based on the environmentally friendly nature of their tasks or the skills they require.

As mentioned in Section 2, the entity-level reduction-of-impact process-based measurement method is required as the entity-level output-based measurement technique may not fully capture all green activity in the economy. To clarify, one might consider (1) a solar panel technician working for a green company but maintaining solar panels of a non-green company; and (2) a solar panel technician maintaining solar panels of a non-green company working for that same company. Following the entity-level job concept, (1) would only be classified as green in an output-based measurement approach, while (2) would only be classified as green in a reduction-of-impact process-based measurement approach. However, following the occupation-specific approach, both (1) and (2) would be classified as green according to the output-based approach since this approach does not distinguish jobs based on the greenness of the entity under which they fall.

Green job estimates differ widely (Table 2). For example, estimates for the share of green employment in the US range from 0.7% [40] to 19.4% [77]of total employment. Rather than only expressing uncertainty about the number of green jobs, the considerable divergence in green employment share estimates could reflect the use of different green job concepts and measurement techniques [77]. If this is the case, then it depends on the purpose at hand which green job estimate one should rely on [22].

Table 2 – Overview of green job estimates

Study	Year	Green job concept	Method/data	Estimate
Bangladesh				
GHK [65]	2005/10	Entity-level output-based and process-based	Using a variety of data sources, extended IO model, ILO decency criterion	direct green: 3.54 million or 7% of total employment direct green + decent: 0.81 million or 2% direct + indirect green: 4.03 million or 8%
Denmark				
Østergaard et al. [70]	2014	Entity-level output-based	Link employer-employee data to EUROSTAT EGGS classifications	0.4% of total employment
		Education-based output-based	Link employer-employee data to ISCED education codes classified as green	0.3% of total employment
		Education-based output-based	Link employer-employee data to national education codes classified as green	0.1% of total employment
		Occupation-specific output-based	Link employer-employee data via crosswalk to specific ONET green jobs	3.7% of total employment
		Occupation-specific output-based	Link employer-employee data to ISCO-08 codes classified as green	0.9% of total employment
EU27				
Eurostat [96]	2020	Entity-level output-based	Eurostat estimate	5.07 million FTEs or 2.8% of total FTE*
EU27+UK				
Bowen and Hancké [86]	2006, 2016	Occupation-specific output-based	Link ONET GID/GES/GNE occupations to EU LFS data	2006: 35.5% of total employment 2011: 40% of total employment
EU26+UK (excluding Croatia), including Norway and Switzerland				
Colijn [92]	2011-2012	Occupation-specific output-based	Algorithm classifies 0.1 million vacancies as green or non-green.	Narrow: 3.3% of total demand Broad: 6.9% of total demand
EU26+UK (excluding Croatia)				
Cambridge Econometrics et al. [87]	2009	Occupation-specific output-based	Link EU LFS microdata to ONET GID/GES occupations	GID: 26.4% of total employment GES: 18.1% of total employment
Finland				
Østergaard et al. [70]	2014	Entity-level output-based	Link employer-employee data to EUROSTAT EGGS classifications	0.3% of total employment
		Education-based output-based	Link employer-employee data to ISCED education codes classified as green	2.4% of total employment

		Occupation-specific output-based	Link employer-employee data via crosswalk to specific ONET green jobs	4.3% of total employment
		Occupation-specific output-based	Link employer-employee data to ISCO-08 codes classified as green	0.3% of total employment
France				
Onemev [91]	2018	Occupation-specific output-based	Link job definition to French job description database, and crosswalk to French labour market data	"Green": 0.14 million or 0.5% of total employment "Greening": 3.79 million or 14% of total employment
Germany				
Janser [42]	2012, 2016	Occupation-specific output-based	Link text-mined green task index with administrative microdata to obtain an estimate of hypothetical full-green equivalents	0.5, 0.6 million FTEs or 1.5, 1.7% of total FTE employment*
IMF (US, EU including UK, South-Africa, Mexico)				
IMF [94,95]	2011-2019	Occupation-specific output-based	Link ONET green task index to labour market data	2-3% green task intensity
Mauritius				
Sultan and Harsdorff [36]	2010	Entity-level output-based and process-based	Variety of data sources used to identify green subsectors, extended IO model, ILO decency criterion	6.3% of total employment decent green
Mexico				
ILO [66]	2011	Entity-level output-based and process-based	Variety of data sources used to identify green subsectors, extended IO model	direct green: 1.81 million or 3.8% of total employment** direct + indirect green: 2.19 million or 4.6% of total employment**
Norway				
Østergaard et al. [70]	2014	Entity-level output-based	Link employer-employee data to EUROSTAT EGGS classifications	0.5% of total employment
		Education-based output-based	Link employer-employee data to ISCED education codes classified as green	0.2% of total employment
		Education-based output-based	Link employer-employee data to national education codes classified as green	0.2% of total employment
		Occupation-specific output-based	Link employer-employee data via crosswalk to specific ONET green jobs	5.3% of total employment
		Occupation-specific output-based	Link employer-employee data to ISCO-08 codes classified as green	0.3% of total employment
OECD				

OECD [44]	2011-21	Occupation-specific output-based	Link ONET GNE/GES occupations to national labour market data	17.6% of total employment
Portugal				
Scholl et al. [78]	2011, 2017	Occupation-specific, output-based	Link employer-employee data to ONET GNE and GES occupations using a variety of cross-walks	17.9% of total employment (binary crosswalk) 8.7-10.2% of total employment (simple averaging) 10.1-12.1% of total employment (weighted average) 2.6% green task intensity (simple averaging) 1.5% green task intensity (weighted averaging)
Sweden				
Østergaard et al. [70]	2014	Entity-level output-based	Link employer-employee data to EUROSTAT EGGS classifications	0.5% of total employment
		Education-based output-based	Link employer-employee data to ISCED education codes classified as green	0.2% of total employment
		Occupation-specific output-based	Link employer-employee data via crosswalk to specific ONET green jobs	3.5% of total employment
		Occupation-specific output-based	Link employer-employee data to ISCO-08 codes classified as green	0.8% of total employment
Tunisia				
Lehr et al. [37]	2005-2010	Entity-level output-based and process-based	Green sectors identified in stakeholder workshop, extended IO model	0.11 million direct and indirect green jobs or 3.4% of total employment**
UK				
kmatrix [62]	2008/9-2010/11	Entity-level output-based	2800 green products and services are used to derive green employment from large number of data sources using triangulation techniques	0.91-0.94 million FTEs or 3.7-3.8% of total FTE employment*
Valero et al. [22]	2019	Occupation-specific output-based	Link ONET GID, GES and GNE occupations to LFS microdata	GNE: 5% GES: 7% GID: 5%
Kapetaniou and McIvor [61]	2018	Entity-level process-based	Define green industries as industries with carbon emissions below median level, link to aggregate Eurostat labour market data	55% of total employment
Robins et al. [93]	2011	Occupation-specific output-based	Link ONET green jobs (precise definition unspecified) to census data	10.5% of total employment requires reskilling 10.4% of total employment will face increased demand
US				

Vona et al. [51]	2006-2014	Occupation-specific output-based	Link BLS labour market data to ONET green task index	3.0-3.1% of total employment
Vona et al. [51]	2006-2014	Occupation-specific output-based	Link BLS labour market data to ONET *core* green task index	2.0-2.1% of total employment
Bowen et al. [86]	2014	Occupation-specific output-based	Link BLS labour market data to ONET GID/GES/GNE occupations	19.4% of total employment, of which GNE: 1.2%
US Bureau of Labor Statistics [31]	2011	Entity-level output-based	Estimated by proportionally relating employment to green production share derived from survey data	3.4 million or 2.6% of total employment
US Bureau of Labor Statistics [40]	2011	Entity-level process-based	Estimated by asking a representative sample how many employees were engaged in green processes for at least half of their time	0.9 million or 0.7% of total employment
Georgeson and Maslin [56]	2015-16	Entity-level output-based	3800 green products and services are used to derive green employment from 1600 data sources using triangulation techniques	9.49 million FTEs or 7.1% of total FTE employment***
Muro et al. [35]	2010	Entity-level output-based	Top-down and bottom-up identification of green establishments, employment identified through company databases	2.7 million or 2.0% of total employment***
Peters [54]	2010	Occupation-specific output-based	Link ONET occupational data to US census data and BLS labour market data	Narrow green job definition: 6% of total employment or 8.1 million
Department of Commerce [34]	2007	Entity-level output-based	Measurement based on products and services classified as green under a narrow and a broad definition	Narrow green job definition: 1.5% of total employment or 1.8 million Broad green employment: 2.0% of total employment or 2.4 million

*Note: *: indicates that % has been calculated using Eurostat* [97] *employment aggregates; **: indicates that % has been calculated using ILOSTAT* [67] *employment aggregates; ***: indicates that % has been calculated using US Bureau of Economic Analysis* [57] *employment aggregates.*
Source: Authors

Regarding measurement methods, it has been argued that industry-level measurement techniques are well-suited to give an indication of the size of the employment effects associated with shifts in green production, while occupation-specific measurement methods may be appropriate if (1) one aims to characterise the occupations affected within particular industries [86] or the economy as a whole [22]; or (2) wants to analyse to what extent work content will change and whether reskilling will be required [75].

Regardless of whether one employs an entity-based or occupation-specific measurement method, divergence might also be due to the scope of green employment one wishes to consider. In the case of entity-level measurement, one may want to count employment in supplying sectors as green. In the case of occupation-specific measurement, one might include occupations for which demand will increase due to green economic activity but, which do not themselves introduce any new tasks associated with green activities (in ONET terms, these are GID occupations). Moreover, in the occupation-specific measurement approach, one might classify a particular job as green in a discrete way or only to the extent in which an occupation is involved in green work activities.

Concerning the choice between green job conceptualisations, the process-based approach seems especially suited to identify (1) highly-polluting sectors where economic transformations are likely to occur [86], as well as (2) aspects of the green transition not captured by the output-based approach, e.g. in the case of an entity-level output-based approach jobs aimed at reducing the environmental impact of production in non-green entities will not be captured [27].

Apart from the chosen measurement method and green job concept, some practical issues introduce uncertainty in green job concepts. In particular, entity-level measurement techniques have been criticised for their imprecision – since not all production in green entities is likely to be green, non-green jobs in green entities are likely to be included as well as some green jobs in non-green entities. To count non-green jobs in green entities, a correction is possible by assuming proportionality between green employment and green production shares [32]. Moreover, the issue of disregarding green jobs in non-green entities may be addressed by supplementing output-based entity-level approaches with process-based reduction-of-impact green job measurements [40].

The occupation-specific measurement approach has practical issues of its own. Concretely, some occupations classified as green might occur in non-green or even brown entities [86], and may not involve any green tasks at all – reflecting the fact that task-content might differ within occupations [74]. Moreover, if one is interested in measuring indirectly green occupations but if those occupations are not expected to increase in demand under a green transformation, the occupation-specific approach may not measure them at all [22].

A further practical issue with occupation-specific green job classifications is that they tend to require a crosswalk in order to match labour market data. For example, the ONET occupational database is more disaggregated than BLS US labour market data. The issue is especially relevant for European occupation-specific studies, which tend to rely on ONET green job classifications, since SOC codes need to be cross-walked to ISCO codes and multiple SOC codes can link to multiple ISCO codes [21]. Valero et al. [22] found evidence that the difference between their 17% green employment share for the UK and Bowen and Hancké's [86] 40% green employment share for the EU is largely due to differences in their crosswalk method. Further evidence of the influence of the crosswalk on final estimates is given by the fact that Bowen et al. [77] estimated a green employment share of 19.4% for the US using a similar approach to

Bowen and Hancké [86]. A rigorous (although not entirely complete[38]) comparison of ONET-ISCO cross-walking options is provided by Scholl et al. [78].

Therefore, it appears that the substantial divergence in estimates of green job shares might to some extent be driven by conceptual/measurement/scope choices of which the desirability depends on the particular purpose at hand, while at least some degree of uncertainty is introduced by shortcomings of individual measurement techniques (see Table 3 for a high-level overview of different conceptual/measurement choice considerations).

Table 3 – High-level overview of green job measurement considerations according to green job concept and measurement technique

		Green job concept		
		Output-based	Process-based	
			Low impact	Reduction of impact
Measurement technique	Entity	• Especially suited to identify scale of employment effects. • Likely to overestimate green employment if no correction for non-green jobs in partially green entities. • Disregards jobs reducing environmental impact in non-green entities. • Requires list of green entities, e.g. via a list of green goods and services coupled to entities.	• Difficult to measure if entire production process taken into account. • Commonly applied to identify brown employment.	• Difficult to measure. • Includes reduction of impact jobs disregarded by output-based entity-level approach.
	Occupation	• Especially suited to characterise green employment or changes in work content/degree of reskilling required. • Could count jobs contributing to brown/non-green production as green. • Disregards indirectly green jobs for which demand will not increase. • Measurement often requires crosswalk. • Requires list of green occupations, e.g. via a list	• Difficult to measure if entire production process taken into account. • Rarely used, and only to identify brown employment	• Not applicable, see Section 2

[38] ONET GID occupations are not included in the comparison.

		of green tasks/skills coupled to occupations		

Source: Authors

Some of the studies in the green jobs' literature went further than merely measuring green employment and have attempted to characterise green jobs (see Table 4 for an overview table). Generally, it is found that workers in green jobs compared to non-green jobs possess more technical skills, are higher-skilled, have more educational attainment, tend to be male, and are more likely to be in quality jobs (higher pay, permanent, full-time). Studies distinguishing between directly green and indirectly green find fewer educational and skill differences for indirectly green and non-green jobs compared to directly green and non-green occupations. Based on these observations Valero et al. [22] draw several policy conclusions. First, there is a clear need for training and skills development for workers in directly green jobs. The education system needs to prepare workers, and on-the-job training is also crucial. Incentives, such as conditional subsidies or tax credits, may be needed to encourage the development of transferable skills, given the externalities involved. Second, given the uncertainty surrounding green jobs, there is a need to strike a balance between specific and general skills. Third, given the distributional impact of green jobs and the existing imbalances (in terms of age, race, and gender), targeted policies are necessary.

Table 4 – Overview of green job characteristics

Study	Year	Green job concept	Method/data	Characteristic of green jobs
EU15 (including UK)				
Valero et al. [22]	2011-2019	Occupation-specific output-based	Link ONET GID/GES/GNE occupations to LFS microdata	Green workers relative to non-green: • Older • Male-dominated • Higher-skilled • More likely permanent contract • More likely full-time
EU26+UK (excluding Croatia), including Norway and Switzerland				
Colijn [92]	2011-2012	Occupation-specific output-based	Algorithm classifies 0.1 million vacancies as green or non-green.	Green jobs relative to non-green: • More technical skills (strong evidence) • Higher-skilled (some evidence)
EU27+UK				
Bowen and Hancké [86]	2006-2016	Occupation-specific output-based	Link ONET GID/GES/GNE occupations to EU LFS microdata	GNE workers compared to total employment: • Higher share of tertiary educated. GES workers compared to total employment: • Lower share of tertiary educated. GID workers compared to total employment:

				• Lower share of tertiary educated. • Higher share of workers without upper secondary education
Hancké et al. [85]	2005-2015	Occupation-specific output-based	Link ONET GID/GES/GNE occupations to EWCS microdata, and classify non-green occupations as brown	Green jobs compared to brown: • No substantial difference in job and income security • Less on-the-job training • Higher perceived employability • Slightly worse working conditions • Slightly worse work-life balance • Male dominated. • Within-country differences of green and brown job quality relatively small compared to between-country differences
France				
Onemev [91]	2018	Occupation-specific output-based	Link job definition to French job description database, and crosswalk to French labour market data	"Green" jobs relative to non-"green": • Male-dominated • No educational difference • Higher job quality (more unlimited duration contracts, more full-time) "Greening" jobs relative to non-"greening": • Male-dominated • No educational difference • Higher job quality (same amount of unlimited duration contracts, more full-time)
IMF (US, EU including UK, South-Africa, Mexico)				
IMF [94,95]	2005-2019	Occupation-specific output-based	Link ONET green task index and Vona et al. (2018) brownness measure to labour market data	High green task intensity jobs compared to neutral jobs: • Concentrated in industrial sectors • High-skilled • Urban • Permanent, full-time • More routine • Larger firms • Male-dominated • Job stability

				High green task intensity jobs wage premium of 6.7% compared to brown jobs
Sweden				
Krueger et al. [60]	1990-2021	Entity-level, various greenness concepts	Link ESG data (reduction-of-impact process-based), production-based GHG emissions (low-impact process-based), and survey classification (green job concept unclear) to Swedish administrative microdata	Top 20% most environmentally friendly to rest wage differential: • -2.1-4.4% (ESG) • -8.7-12.6% (survey) • -5.7%
UK				
Valero et al. [22]	2011-2019	Occupation-specific output-based	Link ONET GID/GES/GNE occupations to LFS microdata	Green workers relative to non-green: • Older • Male-dominated • Higher educational attainment • More likely permanent contract • More likely full-time • Higher paid. • More "white" • Less at-risk of automation
Kapetaniou and McIvor [61]	2018	Entity-level process-based	Define green industries as industries with carbon emissions below median level, link to aggregate Eurostat labour market data	Green workers relative to non-green: • Older • Female-dominated • Higher-skilled • More adult training
US				
Consoli et al. [76]	-	Occupation-specific output-based	Analysis of ONET occupational data, comparing GES and GNE to non-green occupations	GNE jobs relative to non-green: • More high-level cognitive skills • Less routinised • More on-the-job training GES jobs relative to non-green: • Less routinised • Higher educational requirements • More work-experience • More on-the-job training
Bowen et al. [77]	2014	Occupation-specific output-based	Link ONET GID/GES/GNE occupations to BLS labour market data	GES/GNE green jobs compared to non-green jobs: • More on-the-job training

				• Higher educational requirement • More experience • Lower incidence of manual skills GID green jobs compared to non-green jobs: • Only minor skill differences with non-green occupations Transitions from green to non-green jobs: • Relatively small skill distance in general, on-the-job training may suffice
Vona et al. [51]	2006-2014	Occupation-specific output-based	Link ONET GES/GNE occupations to BLS labour market data	Directly green occupations relative to other occupations: • Higher skill level • More years of schooling • Geographically concentrated • Aggregate is pro-cyclical • Wage premium
Vona et al. [82]	-	Occupation-specific output-based	Analysis of ONET occupational data, comparing GES and GNE to non-green occupations	Directly green jobs relative to non-green: • Higher incidence of engineering and technical, operation management, monitoring, and science skills Directly green jobs relative to brown: • Skill distance generally smaller than between green and non-green • Green jobs tend to be higher skilled
Peters [54]	2010	Occupation-specific output-based	Link ONET occupational data to US census data and BLS labour market data	Green jobs relative to non-green: • Educational attainment varies considerably according to type of green job • Male dominated • Racially dispersed • Quality jobs (e.g. full-time, health-insurance)

Muro et al. [84]	2016	Occupation-specific output-based	Identify green occupations as being more prevalent in 'clean energy production', 'energy efficiency' or 'environmental management' sectors compared to national average. Link these occupations to BLS labour market, US census and ONET data	Compared to national average: • Hourly wage premium between 8.5-19.1% (depending on sector) • Lower educational attainment (especially in clean energy production and energy efficiency) • More and longer on-the-job training (especially in clean energy production and energy efficiency) • More scientific knowledge and technical skills required (especially in clean energy production and energy efficiency) • Older • Male-dominated

Source: Authors

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5. Future research suggestions

As argued in the previous Section, the wide divergence in green employment estimates can be partially attributed to differences in the underlying greenness concept, measurement technique, and scope. In addition, some of the variability is due to the shortcomings of individual measurement techniques.

Given the diverse purposes for which green job estimates are required, relying on a range of greenness concepts, measurement techniques, and employment scopes does not strike us as problematic. However, comparability between studies should be enhanced by explicitly stating the underlying greenness concept, measurement technique, and scope. The simple framework in Section 2 of this article might perhaps be of some relevance here.

Furthermore, comparability can be enhanced if future green employment studies would discuss their methodology against some standard. Ideally, any divergence from the relevant standard should be identified (e.g. by ISCO or NACE code), motivated (e.g. data availability or research aims), and assessed in terms of impact (e.g. likely leading to higher/lower employment aggregates). In the case of output-based entity-level measurement, Eurostat's [32]EGSS approach seems an obvious candidate for a literature standard. A detailed conceptual breakdown of EGSS green activities and accompanying NACE codes is available (see Section 3.1.2).

Regarding the output-based, occupation-level approach ONET is dominant in the literature. Hence, it would be desirable if work in this area not relying on the ONET-list would explicitly state (1) how the identified green occupations differ from ONET green occupations; (2) why using ONET is not desirable in the specific context of the research; and (3) what the likely impact in terms of aggregate employment/employment characteristics of this choice implies.

Moreover, even studies relying on ONET differ in how they define green employment (see Section 3.2.1). To some extent, these differences in ONET-based greenness definition are driven by research aims (e.g. a continuous index based on green tasks/skills might be preferable if one is interested in the extent to which the green transition will require reskilling). If the choice for a particular definition is driven by research aims, then this choice should be explicitly motivated. However, some of these definitional differences are driven by seemingly ad hoc methodological choices. For example, Østergaard et al. [70] classify an occupation as green if its ONET-based green task index equals 1, while for Vona et al. [82] an occupation is green if its ONET-based green task index equals 0.1. Future work would likely benefit from carefully examining such choices in previous studies with a similar research purpose (the present article might perhaps be of some help), and motivating/assessing (e.g. by running robustness checks) the impact of methodological differences with previous work.

One last difficulty with using ONET as literature standard is that it requires crosswalking (especially if applied outside the US). Different crosswalking options are possible, and ONET-ISCO crosswalking lists are readily available [78]. In some cases, the choice of a crosswalking option can be guided by research aims. For example, weighted crosswalking could be preferable if one aims to estimate green employment size (rather than employment characteristics) [78]. Given the availability of crosswalking lists, running robustness checks seems fairly straightforward.

Apart from these suggestions to heighten comparability between studies, our review points to specific research opportunities. A number of studies have examined differences between 'brown' and green employment, a topic with high policy relevance. Notably, brown employment is exclusively identified as employment in high emission industries. The dominant approach is to use Vona et al.'s [82] identification, which identifies occupations as brown if they are concentrated in highly polluting US industries. The underlying assumption that the green transition will (only) render obsolete occupations concentrated in high-pollution US industries may not be valid. Future work could focus on validating this brown employment measure.

Relatedly, there is some concern in the literature that ONET green job classifications have become outdated [22,44,78–80]. While ONET is currently reviewing and expanding its green occupational information [81], these revisions may not lead to a review/update of its green occupation list. If ONET does not update its green job classifications, then future green employment research could benefit substantially from external validation or improvement of ONET's existing green occupations list.

6. Conclusion

This article presents a comprehensive review of the literature on measuring and characterising green jobs, focusing on entity-level and occupation-specific approaches in various countries or regions. We adopt a conceptual framework that distinguishes between output-based and process-based greenness, as well as between entity-level and occupation-specific measurement techniques. The variability in green job estimates, ranging from 0.7% to 19.4% of total employment in the US, where most of the studies are situated, is attributed to diverse green job concepts, measurement techniques, and scopes of employment considered. Studies focused on characterising green employment generally find that workers in green jobs compared to non-green jobs possess more technical skills, are higher-skilled, have more educational attainment, tend to be male, and are more likely to be in quality jobs (higher pay, permanent, full-time).

The process-based approach is particularly effective in identifying high-pollution sectors where economic transformations are likely to occur, capturing aspects of the green transition not addressed by the output-based approach.

Both entity-level and occupation-specific measurement approaches have their practical challenges. Entity-level measurements may include non-green jobs in green entities, while occupation-specific measurements may classify some occupations as green that do not involve any green tasks. However, occupation-specific measurements, particularly the task-based method, have gained traction in recent years. This method emphasises green activities, tasks, and skills within an occupation, allowing for more useful policy conclusions by considering the disruption of the green transition in the labour market and the effectiveness of labour market policies such as reskilling and adult learning.

The entity-level measurement approach examines green jobs through the lens of green entities, using aggregate statistics or survey data. However, identifying green industries or companies presents a challenge, with top-down (labelling entire sectors as green) and bottom-up (classifying specific companies as green) approaches often leading to discrepancies. In the US, studies often rely on the Green Goods and Services (GGS) survey or the Green Technologies and Practices (GTP) survey, while in the EU, the Environmental Goods and Services Sector (EGSS) concept is used.

The primary dataset for occupation-specific green job research in the US is the ONET classification, which links occupations with tasks and skills. ONET classifies green jobs into Green Increased Demand (GID), Green Enhanced Skills (GES), and Green New and Emerging (GNE) categories. Studies have used various methods to measure green jobs, such as discrete ONET GID/GES/GNE categories, constructing a continuous green task index for GES/GNE ONET occupations, and constructing a continuous green skill index. However, some limitations to using ONET skills to measure green potential exist, as ONET skills are fixed at the time of classification and may not account for emerging green skills. Moreover, to link ONET data to labour market data, a crosswalk is required, which necessitates ad hoc assumptions that may influence green job estimates. Studies using ONET data have explored the differences between green and non-green jobs, including skill distances and transition potential.

Given the wide range of green employment estimates, comparability between studies is key. To this end, future work could explicitly identify, motivate, and assess the greenness concept, measurement technique, and scope underlying its methodological approach. Moreover, additional work on identifying brown and green occupations would benefit future research concerned with identifying and characterising green employment.

References

1. Steffen W, Richardson K, Rockström J, Cornell SE, Fetzer I, Bennett EM, et al. Planetary boundaries: Guiding human development on a changing planet. Science. 2015 Feb 13;347(6223):1259855.
2. Persson L, Carney Almroth BM, Collins CD, Cornell S, de Wit CA, Diamond ML, et al. Outside the Safe Operating Space of the Planetary Boundary for Novel Entities. Environ Sci Technol. 2022 Feb 1;56(3):1510–21.
3. Calvin K, Dasgupta D, Krinner G, Mukherji A, Thorne PW, Trisos C, et al. IPCC, 2023: Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, H. Lee and J. Romero (eds.)]. IPCC, Geneva, Switzerland. [Internet]. First. Intergovernmental Panel on Climate Change (IPCC); 2023 Jul [cited 2023 Nov 20]. Available from: https://www.ipcc.ch/report/ar6/syr/
4. Geels FW, Sovacool BK, Schwanen T, Sorrell S. Sociotechnical transitions for deep decarbonization. Science. 2017 Sep 22;357(6357):1242–4.
5. Jenkins K, Sovacool BK, McCauley D. Humanizing sociotechnical transitions through energy justice: An ethical framework for global transformative change. Energy Policy. 2018 Jun;117:66–74.
6. Fragkos P, Paroussos L. Employment creation in EU related to renewables expansion. Appl Energy. 2018 Nov;230:935–45.
7. Montt G, Wiebe KS, Harsdorff M, Simas M, Bonnet A, Wood R. Does climate action destroy jobs? An assessment of the employment implications of the 2-degree goal. Int Labour Rev. 2018 Dec;157(4):519–56.
8. University of Cambridge Institute for Sustainability Leadership. Working towards a climate neutral Europe: Jobs and skills in a changing world. Technical Report [Internet]. CLG Europe; 2020. Available from: https://www.corporateleadersgroup.com/reports-evidence-and-insights/Jobs-and-skills-in-a-changing-world
9. Sovacool BK, Evensen D, Kwan TA, Petit V. Building a green future: Examining the job creation potential of electricity, heating, and storage in low-carbon buildings. Electr J. 2023 Jun 1;36(5):107274.
10. Garrett-Peltier H. Green versus brown: Comparing the employment impacts of energy efficiency, renewable energy, and fossil fuels using an input-output model. Econ Model. 2017 Feb;61:439–47.
11. Markkanen S, Anger-Kraavi A. Social impacts of climate change mitigation policies and their implications for inequality. Clim Policy. 2019 Aug 9;19(7):827–44.
12. Markandya A, Arto I, González-Eguino M, Román MV. Towards a green energy economy? Tracking the employment effects of low-carbon technologies in the European Union. Appl Energy. 2016 Oct;179:1342–50.
13. Christie-Miller T, Luke A. Qualifying for the race to net zero [Internet]. Onward; 2021. Available from: https://www.ukonward.com/wp-content/uploads/2021/09/Qualifying-for-the-race-to-net-zero-FINAL.pdf
14. Office for National Statistics. Low carbon and renewable energy economy, UK. 2022 Feb;13.

15. Dechezleprêtre A, Sato M. The Impacts of Environmental Regulations on Competitiveness. Rev Environ Econ Policy. 2017 Jul 1;11(2):183–206.

16. Gagliardi L, Marin G, Miriello C. The greener the better? Job creation effects of environmentally-friendly technological change. Ind Corp Change. 2016 Oct;25(5):779–807.

17. Cecere G, Mazzanti M. Green jobs and eco-innovations in European SMEs. Resour Energy Econ. 2017 Aug;49:86–98.

18. Elliott RJR, Kuai W, Maddison D, Ozgen C. Eco-Innovation and Employment: A Task-Based Analysis. IZA Discussion Paper No. 14028. [Internet]. 2021 [cited 2022 Aug 9]; Available from: https://www.ssrn.com/abstract=3767265

19. D'Alessandro S, Cieplinski A, Distefano T, Dittmer K. Feasible alternatives to green growth. Nat Sustain. 2020 Apr;3(4):329–35.

20. Černý M, Bruckner M, Weinzettel J, Wiebe K, Kimmich C, Kerschner C, et al. Employment effects of the renewable energy transition in the electricity sector: An input-output approach. ETUI Research Paper - Working Paper 2021.14 [Internet]. 2022 [cited 2022 Aug 9]; Available from: https://www.ssrn.com/abstract=4013339

21. Vona F. Labour markets and the green transition: a practitioner's guide to the task based approach. [Internet]. Biagi F, Bitat A, editors. LU: Publications Office; 2021 [cited 2022 Aug 9]. Available from: https://data.europa.eu/doi/10.2760/65924

22. Valero A, Li J, Muller S, Riom C, Nguyen-Tien V, Draca M. Are 'green' jobs good jobs? How lessons from the experience to-date can inform labour market transitions of the future [Internet]. Grantham Research Institute on Climate Change and the Environment and Centre for Economic Performance; 2021. Available from: https://www.lse.ac.uk/granthaminstitute/publication/are-green-jobs-good-jobs-how-lessons-from-the-experience-to-date-can-inform-labour-market-transitions-of-the-future/

23. Bowen A, Kuralbayeva K. Looking for green jobs: the impact of green growth on employment [Internet]. 2015 Mar p. 32. Available from: https://www.lse.ac.uk/granthaminstitute/wp-content/uploads/2015/03/Looking-for-green-jobs_the-impact-of-green-growth-on-employment.pdf

24. Horbach J, Rennings K, Sommerfeld K. Circular Economy and Employment [Internet]. 2015 p. 39. Available from: https://circulareconomy.europa.eu/platform/en/knowledge/circular-economy-and-employment

25. Bowen A. Green' Growth, 'Green' Jobs and Labor Markets [Internet]. 2012. Available from: https://elibrary.worldbank.org/doi/pdf/10.1596/1813-9450-5990

26. Martinson, K., Stanczyk, A. and Eyster, L. 2010. Low-Skill Workers' Access to Quality Green Jobs. Urban Institute. Available from: https://www.urban.org/sites/default/files/publication/32921/412096-Low-Skill-Workers-Access-to-Quality-Green-Jobs.PDF

27. US Bureau of Labor Statistics. green_definition.pdf [Internet]. 2013. Available from: https://www.bls.gov/green/green_definition.pdf

28. Jacob K, Quitzow R, Bär H. Green Jobs: Impacts of a Green Economy on Employment [Internet]. Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ); 2015. Available from: https://energypedia.info/images/f/fc/Green_Jobs_-_Impacts_of_a_Green_Economy_on_Employment.pdf

29. ILO. What is a green job ? [Internet]. 2016 Apr [cited 2022 Aug 22]. Available from: http://www.ilo.org/global/topics/green-jobs/news/WCMS_220248/lang--en/index.htm
30. Bontadini F, Vona F. Anatomy of Green Specialization: Evidence from EU Production Data, 1995-2015 [Internet]. Sciences Po OFCE; 2020. Available from: www.ofce.sciences-po.fr/pdf/dtravail/WP2020-21.pdf
31. US Bureau of Labor Statistics. ggs_technote_extended [Internet]. 2013. Available from: https://www.bls.gov/ggs/ggs_technote_extended.pdf
32. Eurostat. Environmental goods and services sector accounts: manual : 2016 edition. [Internet]. LU: Publications Office; 2016 [cited 2022 Aug 9]. Available from: https://data.europa.eu/doi/10.2785/79114
33. Connolly K, Allan GJ, McIntyre SG. The evolution of green jobs in Scotland: A hybrid approach. Energy Policy. 2016 Jan;88:355–60.
34. US Department of Commerce. Measuring the green economy [Internet]. 2010. Available from: https://www.commerce.gov/data-and-reports/reports/2010/04/measuring-green-economy
35. Muro M, Rothwell J, Saha D. Sizing the clean economy [Internet]. The Brookings Institution; 2011 p. 68. Available from: https://www.brookings.edu/research/sizing-the-clean-economy-a-national-and-regional-green-jobs-assessment/
36. Sultan R, Harsdorff M. Green jobs assessment Mauritius [Internet]. 2014 p. 71. Available from: https://www.ilo.org/wcmsp5/groups/public/@ed_emp/@emp_ent/documents/publication/wcms_317238.pdf
37. Lehr U, Missaoui R, Bockermann A, Marrouki S, Mönning A, Ben Salem G. Green jobs in Tunisia measuring methods and model results [Internet]. 2018. Available from: https://www.ilo.org/wcmsp5/groups/public/---ed_emp/documents/publication/wcms_631705.pdf
38. ILO. Methodologies for assessing green jobs [Internet]. 2013 Feb. Available from: https://www.ilo.org/wcmsp5/groups/public/---ed_emp/---emp_ent/documents/publication/wcms_176462.pdf
39. ILO. Green jobs mapping study in Malaysia [Internet]. 2014 [cited 2022 Aug 23] p. 90. Available from: https://www.ilo.org/wcmsp5/groups/public/---asia/---ro-bangkok/documents/publication/wcms_239640.pdf
40. US Bureau of Labor Statistics. Survey Methods and Reliability Statement for the August 2011 Green Technologies and Practices Survey [Internet]. 2011. Available from: https://www.bls.gov/gtp/survey_methods.pdf
41. Deschenes O. Deschennes 2013 Green jobs.pdf [Internet]. Forschungsinstitut zur Zukunft der Arbeit; 2013. Available from: https://ftp.iza.org/pp62.pdf
42. Janser M. The greening of jobs in Germany The greening of jobs in Germany. First evidence from a text mining-based index and employment register data. (IAB-Discussion Paper 14/2018), Nürnberg, 74 p. [Internet]. Institute for Employment Research; 2018. Available from: https://www.researchgate.net/publication/325763075
43. Burger M, Stavropoulos S, Ramkumar S, Dufourmont J, van Oort F. The heterogeneous skill-base of circular economy employment. Res Policy. 2019 Feb;48(1):248–61.

44. OECD. Job Creation and Local Economic Development 2023: Bridging the Great Green Divide [Internet]. OECD; 2023 [cited 2023 Nov 20]. (Job Creation and Local Economic Development). Available from: https://www.oecd-ilibrary.org/employment/job-creation-and-local-economic-development-2023_21db61c1-en
45. Dierdorff EC, Norton JJ, Gregory CM, Rivkin D, Lewis P. Greening of the World of Work: Revisiting Occupational Consequences [Internet]. 2011 p. 79. Available from: https://www.onetcenter.org/dl_files/Green2.pdf
46. Horbach J, Janser M. The role of innovation and agglomeration for employment growth in the environmental sector. Ind Innov. 2016 Aug 17;23(6):488–511.
47. Elliott RJR, Lindley JK. Environmental Jobs and Growth in the United States. Ecol Econ. 2017 Feb;132:232–44.
48. Allan G, McGregor P, Swales K. Greening regional development: employment in low-carbon and renewable energy activities. Reg Stud. 2017 Aug 3;51(8):1270–80.
49. Furchtgott-Roth D. The elusive and expensive green job. Energy Econ. 2012 Nov;34:S43–52.
50. Shapira P, Gök A, Klochikhin E, Sensier M. Probing “green” industry enterprises in the UK: A new identification approach. Technol Forecast Soc Change. 2014 Jun;85:93–104.
51. Vona F, Marin G, Consoli D. Measures, drivers and effects of green employment: evidence from US local labor markets, 2006–2014. J Econ Geogr. 2019 Sep 1;19(5):1021–48.
52. Dosi G, Grazzi M, Moschella D. What do firms know? What do they produce? A new look at the relationship between patenting profiles and patterns of product diversification. Small Bus Econ. 2017 Feb 1;48(2):413–29.
53. Licht G, Peters B. Do Green Innovations stimulate Employment? Firm-level Evidence From Germany. WWWforEurope Working Paper No.53. Available from: https://www.wifo.ac.at/wwa/pubid/47155
54. Peters D. Understanding Green Occupations from a Task-Based Approach. Appl Econ Perspect Policy. 2014;36(2):238–64.
55. Pollack E. Assessing the green economy and its implications for growth and equity. OC TOBER. 2012;18.
56. Georgeson L, Maslin M. Estimating the scale of the US green economy within the global context. Palgrave Commun. 2019 Dec;5(1):121.
57. US Bureau of Economic Analysis. Data series [Internet]. 2023. Available from: https://fred.stlouisfed.org
58. Eurostat. Environmental goods and services sector metadata [Internet]. 2023. Available from: https://ec.europa.eu/eurostat/cache/metadata/en/env_egs_esms.htm
59. Aldieri L, Carlucci F, Cirà A, Ioppolo G, Vinci CP. Is green innovation an opportunity or a threat to employment? An empirical analysis of three main industrialized areas: The USA, Japan and Europe. J Clean Prod. 2019 Mar;214:758–66.
60. Krueger P, Metzger D, Wu J. The Sustainability Wage Gap [Internet]. Rochester, NY; 2023 [cited 2023 Nov 20]. Available from: https://papers.ssrn.com/abstract=3672492
61. Kapetaniou C, McIvor C. Going Green Preparing the UK workforce for the transition to a net-zero economy [Internet]. Nesta; 2020. Available from: https://www.nesta.org.uk/report/going-green-preparing-uk-workforce-transition-net-zero-economy/

62. kmatrix. Low Carbon Environmental Goods and Services (LCEGS) [Internet]. 2012 p. 66. Available from: http://www.zemo.org.uk/assets/reports/12-p143-low-carbon-environmental-goods-and-services-2010-11.pdf

63. Jarvis A, Varma A, Ram J. Assessing green jobs potential in developing countries [Internet]. 2011 [cited 2022 Aug 23]. Available from: https://www.ilo.org/wcmsp5/groups/public/@dgreports/@dcomm/@publ/documents/publication/wcms_153458.pdf

64. Allan GJ, Ross AG. The characteristics of energy employment in a system-wide context. Energy Econ. 2019 Jun;81:238–58.

65. GHK. Measuring green jobs in Bangladesh [Internet]. 2010. Available from: https://www.ilo.org/global/topics/green-jobs/publications/WCMS_159433/lang--en/index.htm

66. ILO. Evaluation of the Potential of Green Jobs in Mexico [Internet]. 2013 p. 8. Available from: https://www.ilo.org/wcmsp5/groups/public/@ed_emp/@emp_ent/documents/publication/wcms_236143.pdf

67. ILOSTAT. Annual employment in thousands [Internet]. 2023. Available from: https://ilostat.ilo.org/topics/employment/#

68. Autor DH. The “task approach” to labor markets: an overview. J Labour Mark Res. 2013 Sep;46(3):185–99.

69. Rutzer, C., Niggli, M. and Weder, R. 2020. Estimating the Green Potential of Occupations: A New Approach Applied to the U.S. Labor Market [Internet]. WWZ Working Paper 2020/03. Available from: https://www.econstor.eu/bitstream/10419/240412/1/2020-03.pdf

70. Østergaard CR, Holm JR, Iversen E, Schubert T, Skålholt A, Sotarauta M. Environmental Innovations and Green Skills in the Nordic Countries. In: Sedita SR, Blasi S, editors. Rethinking Clusters [Internet]. Cham: Springer International Publishing; 2021 [cited 2022 Aug 9]. p. 195–211. (Sustainable Development Goals Series). Available from: https://link.springer.com/10.1007/978-3-030-61923-7_14

71. Niggli, M. and Rutzer, C. 2020. Environmental Policy and Heterogeneous Labor Market Effects: Evidence from Europe [Internet]. Available at SSRN: https://papers.ssrn.com/sol3/Delivery.cfm/42caeec2-495a-4ac6-9938-0c457a35f08a-MECA.pdf?abstractid=3973664&mirid=1

72. Auktor GV. Green Industrial Skills for a Sustainable Future [Internet]. UN Industrial Development Organization; 2020 Nov p. 50. Available from: https://www.unido.org/sites/default/files/files/2021-02/LKDForum-2020_Green-Skills-for-a-Sustainable-Future.pdf

73. Dicks J, Molnár B. The employment benefits of a green COVID-19 recovery [Internet]. Cambridge Econometrics; 2020. Available from: https://www.camecon.com/wp-content/uploads/2021/01/20210113-Employment-Benefits-of-a-Green-COVID-19-Recovery_Technical-Report_full_revised_CE.pdf

74. Autor DH, Handel MJ. Putting Tasks to the Test: Human Capital, Job Tasks, and Wages. J Labor Econ. 2013;31(2):S59–96.

75. Dierdorff EC, Norton JJ, Drewes DW, Rivkin D, Lewis P. Greening of the World of Work: Implications for O*NET®-SOC and New and Emerging Occupations [Internet]. 2009 p. 49. Available from: https://www.onetcenter.org/dl_files/Green.pdf
76. Consoli D, Marin G, Marzucchi A, Vona F. Do green jobs differ from non-green jobs in terms of skills and human capital? Res Policy. 2016 Jun;45(5):1046–60.
77. Bowen A, Kuralbayeva K, Tipoe E. Characterising green employment: the impacts of 'greening' on workforce composition. Energy Econ. 2018 Apr;72:269–75.
78. Scholl N, Turban S, Gal PN. The green side of productivity: An international classification of green and brown occupations [Internet]. Paris: OCDE; 2023 May [cited 2023 Nov 20]. Available from: https://www.oecd-ilibrary.org/fr/economics/the-green-side-of-productivity_a363530f-en
79. Curtis EM, Marinescu I. Green energy jobs in the US: What are they, and where are they? [Internet]. (National Bureau of Economic Research Working Papers). Available from: https://www.nber.org/system/files/working_papers/w30332/w30332.pdf
80. Sofroniou N, Anderson P. The green factor: Unpacking green job growth. Int Labour Rev. 2021 Mar;160(1):21–41.
81. ONET. Additional Initiatives at O*NET Resource Center [Internet]. 2022 [cited 2022 Aug 22]. Available from: https://www.onetcenter.org/initiatives.html#green
82. Vona F, Marin G, Consoli D, Popp D. Environmental Regulation and Green Skills: An Empirical Exploration. J Assoc Environ Resour Econ. 2018 Oct;5(4):713–53.
83. Strietska-Ilina O, Hoffman C, Haro MD, Jeon S. Skills for green jobs: a global view: synthesis report based on 21 country studies. Geneva: International Labour Office; 2011. 456 p.
84. Muro M, Tomer A, Shivaram R, Kane J. Advancing inclusion through clean energy jobs [Internet]. 2019 [cited 2023 Nov 20] p. 30–5. Available from: https://www.brookings.edu/articles/advancing-inclusion-through-clean-energy-jobs/
85. Hancké B, Van Overbeke T, Neos N. Social situation monitor: quality of green jobs. [Internet]. LU: Publications Office; 2020 [cited 2022 Aug 9]. Available from: https://data.europa.eu/doi/10.2767/001616
86. Bowen A, Hancké B. The social dimensions of 'greening the economy': developing a taxonomy of labour market effects related to the shift toward environmentally sustainable economic activities. [Internet]. LU: Publications Office; 2019 [cited 2022 Aug 9]. Available from: https://data.europa.eu/doi/10.2767/448791
87. Cambridge Econometrics, GHK, Warwick Institute for Employment Research. Studies on Sustainability Issues Green Jobs; Trade and Labour [Internet]. 2011 p. 272. Available from: http://ec.europa.eu/social/BlobServlet?docId=7436&langId=en
88. OECD. Boosting Skills for Greener Jobs in Flanders, Belgium [Internet]. OECD; 2017 [cited 2022 Aug 9]. (OECD Green Growth Studies). Available from: https://www.oecd-ilibrary.org/employment/boosting-skills-for-greener-jobs-in-flanders-belgium_9789264265264-en
89. Cedefop. Green skills and environmental awareness in vocational education and training. [Internet]. LU: Publications Office; 2012 [cited 2022 Aug 9]. Available from: https://data.europa.eu/doi/10.2801/78825
90. Cetrulo A, Guarascio D, Virgillito ME. Anatomy of the Italian occupational structure: concentrated power and distributed knowledge. Ind Corp Change. 2021 Apr 9;29(6):1345–79.

91. Onemev. La mesure de l’emploi par les métiers exercés par les individus [Internet]. 2022 [cited 2022 Aug 23]. Available from: https://www.ecologie.gouv.fr/sites/default/files/Onemev_emploi_metiers.pdf

92. Colijn B. Green jobs in Europe and the increasing demand for technical skills. 2014. Neujobs working paper, no. 4.2. Centre for European Policy Studies, Brussels. Available from: https://www.voced.edu.au/content/ngv%3A67416

93. Robins N, Gouldson A, Irwin W, Sudmant A. Investing in a just transition in the UK How investors can integrate social impact and place-based financing into climate strategies [Internet]. Grantham Research Institute on Climate Change and the Environment; 2019. Available from: https://www.lse.ac.uk/granthaminstitute/publication/investing-in-a-just-transition-in-the-uk/

94. Bluedorn JC, Hansen NJ, Noureldin D, Shibata I, Mendes Tavares M. Transitioning to a Greener Labor Market: Cross-Country Evidence from Microdata [Internet]. Rochester, NY; 2022 [cited 2023 Nov 20]. Available from: https://papers.ssrn.com/abstract=4178907

95. War sets back the global recovery. Washington, DC: International Monetary Fund; 2022.

96. Eurostat. Employment in the environmental goods and services sector [Internet]. 2023. Available from: https://ec.europa.eu/eurostat/databrowser/view/env_ac_egss1/default/table?lang=en

97. Eurostat. FTE data received from Eurostat upon request. 2023.

Appendix

Table A1 – Overview of country-specific green job estimates based on Eurostat EGSS guidelines

Source	Year	Green job concept	Method/data	Estimate
EU27				
Eurostat (2023b)	2020	Entity-level output-based	Eurostat estimate	5.07 million FTEs or 2.8% of total FTE
Belgium				
Eurostat (2023b)	2020	Entity-level output-based	Country-specific calculation based on EUROSTAT EGSS guidelines	0.07 million FTEs or 1.6% of total FTE
Bulgaria				
Eurostat (2023b)	2020	Entity-level output-based	Country-specific calculation based on EUROSTAT EGSS guidelines	0.07 million FTEs or 2.1% of total FTE
Czechia				
Eurostat (2023b)	2020	Entity-level output-based	Country-specific calculation based on EUROSTAT EGSS guidelines	0.14 million FTEs or 2.7% of total FTE
Denmark				
Eurostat (2023b)	2020	Entity-level output-based	Country-specific calculation based on EUROSTAT EGSS guidelines	0.08 million FTEs or 3.3% of total FTE
Germany				
Eurostat (2023b)	2020	Entity-level output-based	Country-specific calculation based on EUROSTAT EGSS guidelines	0.67 million FTEs or 1.9% of total FTE
Estonia				
Eurostat (2023b)	2020	Entity-level output-based	Country-specific calculation based on EUROSTAT EGSS guidelines	0.04 million FTEs or 6.1% of total FTE
Ireland				
Eurostat (2023b)	2020	Entity-level output-based	Eurostat estimate	0.04 million FTEs or 2.0% of total FTE
Greece				
Eurostat (2023b)	2020	Entity-level output-based	Country-specific calculation based on EUROSTAT EGSS guidelines	0.08 million FTEs or 2.2% of total FTE
Spain				
Eurostat (2023b)	2020	Entity-level output-based	Country-specific calculation based on EUROSTAT EGSS guidelines	0.47 million FTEs or 2.7% of total FTE
France				
Eurostat (2023b)	2020	Entity-level output-based	Country-specific calculation based on EUROSTAT EGSS guidelines	0.64 million FTEs or 2.6% of total FTE
Croatia				

Eurostat (2023b)	2020	Entity-level output-based	Country-specific calculation based on EUROSTAT EGSS guidelines	0.04 million FTEs or 2.4% of total FTE
Italy				
Eurostat (2023b)	2020	Entity-level output-based	Country-specific calculation based on EUROSTAT EGSS guidelines	0.53 million FTEs or 2.5% of total FTE
Cyprus				
Eurostat (2023b)	2020	Entity-level output-based	Country-specific calculation based on EUROSTAT EGSS guidelines	0.01 million FTEs or 2.8% of total FTE
Latvia				
Eurostat (2023b)	2020	Entity-level output-based	Country-specific calculation based on EUROSTAT EGSS guidelines	0.03 million FTEs or 3.1% of total FTE
Lithuania				
Eurostat (2023b)	2020	Entity-level output-based	Country-specific calculation based on EUROSTAT EGSS guidelines	0.05 million FTEs or 3.5% of total FTE
Luxembourg				
Eurostat (2023b)	2020	Entity-level output-based	Country-specific calculation based on EUROSTAT EGSS guidelines	0.02 million FTEs or 8.4% of total FTE
Hungary				
Eurostat (2023b)	2020	Entity-level output-based	Country-specific calculation based on EUROSTAT EGSS guidelines	0.05 million FTEs or 1.1% of total FTE
Malta				
Eurostat (2023b)	2020	Entity-level output-based	Country-specific calculation based on EUROSTAT EGSS guidelines	0.00 million FTEs or 1.6% of total FTE
Netherlands				
Eurostat (2023b)	2020	Entity-level output-based	Country-specific calculation based on EUROSTAT EGSS guidelines	0.18 million FTEs or 2.7% of total FTE
Austria				
Eurostat (2023b)	2020	Entity-level output-based	Country-specific calculation based on EUROSTAT EGSS guidelines	0.19 million FTEs or 5.1% of total FTE
Poland				
Eurostat (2023b)	2020	Entity-level output-based	Country-specific calculation based on EUROSTAT EGSS guidelines	0.29 million FTEs or 1.8% of total FTE
Portugal				
Eurostat (2023b)	2020	Entity-level output-based	Country-specific calculation based on EUROSTAT EGSS guidelines	0.12 million FTEs or 2.6% of total FTE
Romania				

Eurostat (2023b)	2020	Entity-level output-based	Country-specific calculation based on EUROSTAT EGSS guidelines	0.14 million FTEs or 1.7% of total FTE
Slovenia				
Eurostat (2023b)	2020	Entity-level output-based	Country-specific calculation based on EUROSTAT EGSS guidelines	0.03 million FTEs or 3.3% of total FTE
Slovakia				
Eurostat (2023b)	2020	Entity-level output-based	Country-specific calculation based on EUROSTAT EGSS guidelines	0.05 million FTEs or 1.9% of total FTE
Finland				
Eurostat (2023b)	2020	Entity-level output-based	Country-specific calculation based on EUROSTAT EGSS guidelines	0.15 million FTEs or 6.4% of total FTE
Sweden				
Eurostat (2023b)	2020	Entity-level output-based	Country-specific calculation based on EUROSTAT EGSS guidelines	0.16 million FTEs or 3.4% of total FTE
Iceland				
Eurostat (2023b)	2020	Entity-level output-based	Country-specific calculation based on EUROSTAT EGSS guidelines	0.00 million FTEs or 2.0% of total FTE
Switzerland				
Eurostat (2023b)	2020	Entity-level output-based	Country-specific calculation based on EUROSTAT EGSS guidelines	0.16 million FTEs or 4.1% of total FTE
North Macedonia				
Eurostat (2023b)	2020	Entity-level output-based	Country-specific calculation based on EUROSTAT EGSS guidelines	0.01 million FTEs or 1.4% of total FTE
Serbia				
Eurostat (2023b)	2020	Entity-level output-based	Country-specific calculation based on EUROSTAT EGSS guidelines	0.04 million FTEs or 1.6% of total FTE

Note: Eurostat estimates are published as time series, most recent data is reported here. % has been calculated using Eurostat (2023c) employment aggregates.