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Labour Markets and the Green Transition: a practitioner's guide to the task-based approach

Author : Vona, F.
Editors: Biagi, F., Bitat, A.

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Contact information

Name: Abdelfeteh BITAT
Email: Abdelfeteh.BITAT@ec.europa.eu
Tel.: +32 229-90546

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Executive Summary

Studies on the relationship between “green policies” and the labour market have been often relegated to the grey literature due to the lack of clear definitions of green jobs and skills. Primarily, uncoordinated statistical efforts across countries did not help build a common set of standardised measures for the green economy that can be used for policy evaluation. With the growing interest in the low-carbon transition and the urgent need to monitor and assess the effect of large-scale post-pandemic green stimuli, it is of paramount importance to build a widely accepted framework that can be used to analyse the structural transformations in the labour market associated with the greening of our economies. This report makes the case that the task-based approach is the best solution to these problems.

The first part of the report examines in depth recent applications of the task-based approach to capture the impact of environmental policies and the green transition on the labour market. These applications are based on an extremely rich, publicly available dataset: the US Occupational Information Network database (O*NET). From a conceptual point of view, the task approach provides a natural definition of occupational “greenness” that can be interpreted either as the proxy of the share of jobs performing green tasks or as the time spent by the average worker on green tasks. Such a greenness indicator provides a working solution to the main problem of defining green jobs, that is: the fact that in most cases a job cannot be classified as entirely green or not green. Looking at tasks rather than at occupations gives more information on the greenness of the technology used by the average worker employed in an occupation. Practically, the use of occupational greenness to reweight employment statistics (what is called here a “task-based measure of green employment”), provides estimates that are in the range of those of the few reliable surveys on green production. Conversely, approaches based on occupation-based, binary definitions overestimate green employment by a factor of 5.

The flexibility of the task-based approach has other key advantages. Notably, it allows identifying skills that are important in green jobs. These skills can be estimated using theoretically-based revealed comparative advantage schedules. Identifying green skills is crucial to inform policymakers on the training investments required by the low-carbon transition. In addition, the concepts of green skills allow shedding light on important issues, such as the effectiveness of green fiscal plans, distributional effects of environmental policies and reallocation costs.

The second part of the report analyses the data constraints that prevent the full implementation of the task-based approach in the EU. Further, it suggests possible ways to overcome these constraints. The main obstacle is the unavailability of fine-grained occupation-level data in the European Labour Force Survey. This obstacle can only be solved using national-level employment data, firm-level data or matched employer-employee data. The second obstacle is the lack of a commonly accepted framework to define green tasks in Europe. However, this obstacle can be overcome in four ways. The easiest, but less precise, is to use cross-walks between the US SOC occupational classification and the EU ISCO classification. The second is to use directly data on the diffusion of green technologies at the firm or sectoral level. The limitation here is that green technologies are produced by a few high-tech sectors only and that the adoption in other sectors, i.e. construction, is difficult to observe. The third consists in using data on the pollution content of productions, an inverse of the greenness measures, which are however incomplete because they often miss indirect pollution impact over the value chain. The final and most promising solution is to use job vacancy data, combined with a reasonable set of “green keywords”, to identify green job ads. This solution would anyway require a common and widely agreed set of “green keywords” used to classify a job vacancy as green.

The report concludes by reviewing existing attempts to improve the data quality on green labour markets in Europe. A key area where additional data are needed is the supply of training and educational programs for the green economy as well as mapping their presence in EU regions. Concerning existing data collection efforts, the report provides three suggestions: i) for new surveys, it is better not to use a binary definition of green jobs; ii) the transparency of the data collection process should be ensured; iii) a coordinated statistical effort to establish standard definitions of green jobs and tasks is required. On the latter point, an essential effort to monitor the greening of the EU labour markets consists of creating clear standards to define occupational greenness also with EU data. By agreeing on such standards while increasing the effectiveness of data collection will increase the usefulness of such data in monitoring labour market transformations linked to the green transition as well as the possibility of conducting credible policy evaluations of green deal plans.

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Authors

Francesco Vona

Editors

Federico Biagi

Abdelfeteh Bitat

Abstract

Studies on the relationship between “green policies” and the labour market have been often relegated to the grey literature due to the lack of clear definitions of green jobs and skills. Primarily, uncoordinated statistical efforts across countries did not help build a common set of standardised measures for the green economy that can be used for policy evaluation. With the growing interest in the low-carbon transition and the urgent need to monitor and assess the effect of large-scale post-pandemic green stimuli, it is of paramount importance to build a widely accepted framework that can be used to analyse the structural transformations in the labour market associated with the greening of our economies. This report makes the case that the task-based approach is the best solution to these problems.

1 Introduction

The European Green Deal (EGD) of the European Commission represents an unprecedented effort to accelerate the transition towards a clean, sustainable and smart economy. The plan unleashes large public investments in several areas of the so-called green economy, including, among others, investments in renewable energy and storage technologies, new grid and transport infrastructures, material reuse and the circular economy. The EGD plan is “*a new growth strategy that aims to transform the EU into a fair and prosperous society, with a modern, resource-efficient and competitive economy where there are no net emissions of greenhouse gases in 2050 and where economic growth is decoupled from resource use*” (European Commission, 2019, p. 2), which will also set the landscape for (and hopefully crowd-in) private investments (Mundaca and Ritcher, 2015). The funding for the EGD has been increased to respond to the Covid-19 crisis, as a response to both the climate and the pandemic crises (e.g. Helm 2020, Agrawala et al., 2020; Chen et al., 2020).

Achieving the ambitious goal of reconciling economic growth, employment and environmental sustainability through massive green spending requires a careful assessment of the effectiveness of several components of the EGD, as well as its impact on both environmental and socioeconomic outcomes. Of primary importance for policymakers is the impact of the EGD on jobs, especially in regions that heavily rely on polluting sectors and fossil fuels. Technological and organizational changes induced by the EGD plan will be accompanied by a massive reallocation of labour towards greener activities, such as renewable energy technologies, retrofitting buildings, recycling, and new infrastructures for the energy and transport sectors. Given the scale of the EGD plan, green investments could be used to reemploy both workers who lose their jobs in polluting sectors, including the fossil-fuel value chain, and those who have been displaced by the Covid-19 crisis.

Labour research has shown that reallocation costs are proportional to the distance in the skill sets between “origin” and “destination” occupations (e.g., Kambourov and Manovskii, 2009; Gathmann and Schönberg, 2010; Guvenen et al., 2020). Consequently, the essential element for the success of the reallocation process induced by the EGD plan is the presence of the appropriate workforce skills to develop and use green technologies. In the context of the smaller green stimulus enacted during the Obama Presidency in response to the 2008 financial crisis, Popp et al. (2020) show that the job creation effect of the green stimulus is positively correlated with the fraction of workers with the skills most needed in green activities, basically engineering and technical skills (Vona et al., 2018). Overall, in a scenario of generous green spending, skill mismatches and thus reallocation costs will be lower in local labour markets with a larger share of workers with the appropriate skills.

There is an additional reason to consider skill development for green and low-carbon technologies as a key strategic investment of the EGD plan: the building and reinforcement of a comparative advantage in sectors where demand is expected to grow very rapidly in the near future (batteries, wind turbines, electric vehicles, bikes, trains, etc.). However, European regions may differ in the endowment of competences that are required to build or reinforce such green comparative advantage. Recent studies document that the local endowment of certain skills is one of the main drivers of the diffusion of the technologies that use these skills intensively (e.g., Beaudry et al., 2010). Further, labour research invariably found that spatial and personal inequalities are associated with differences in skill endowments across regions and workers, respectively (e.g., Moretti, 2004). Identifying the set of skills that are important to favour the development and diffusion of green technologies is a crucial step of an ambitious plan to accelerate the transition towards a low-carbon, sustainable and fair economy and, at the same time, monitor its progress. Note that, with increasing technological complexity, the “race” between technology and education is now played at a very granular level (Goldin and Katz, 2010; Acemoglu and Autor, 2012). The key policy question is thus no longer to simply increase the supply of tertiary-educated students, but to precisely identify which types of qualifications, educational and training programs, including on-the-job training, are better suited to provide the skills specifically required in expanding technologies (Vona and Consoli, 2015). Green technologies are no exception to this pattern: identifying the skill specific to the various green technologies is of utmost importance to design the appropriate educational responses and integrate green policies with existing educational and training policies (Cedefop, 2019).

Several conceptual and measurement issues limit the possibility to analyze how labour markets respond to environmental policies and, more in general, to the large scale diffusion of green technologies, environmental management system and environmentally-friendly organizational forms. The key measurement issue consists in assessing the extent to which a worker is involved in activities that produce negative effects for the environment or performing tasks that can reduce such negative effects. In other words, measurement is complicated by the fact that there are two dimensions of *green* exposure that matters. On the one hand, a worker or a job can be considered “green” if she is engaged in activities that do not pollute or pollute less than a given benchmark. These jobs are normally in the service sector, such as catering, tourism and education. On the other hand, a worker or a job can be considered “green” if she is engaged in the development, production

and maintenance of technologies (e.g., renewables) and organizational forms (e.g., recycling and reusing) that have the potential to reduce or eliminate environmental impacts. In addition to the possible environmental benefits, this second dimension of greenness is particularly interesting for policymakers because it is often associated with net job creation, by building comparative advantages in fast-growing exporting sectors, such as renewable energy equipment, storage technologies and electric vehicles.

This report discusses the statistical and conceptual challenges to conduct rigorous research on green jobs and skills, especially for the dimension related to green technologies and productions. In particular, the focus of the report will be on the main data constraints that limit such a research line in Europe. Note that, while estimating the greenness of a job in terms of pollution generation requires data on emissions that are increasingly available at various levels of aggregation, it is more difficult to measure to what extent a job belongs to green technologies, production and diffusion. Surely, some EU datasets, such as the Community Innovation Survey (CIS) or databases on green production (PRODCOM), allow to quantify the number of workers employed in companies or sectors that develop green technologies or produce green goods. However, the coverage of these datasets is often limited to the manufacturing sector. Therefore, a researcher would miss out all non-manufacturing jobs that are related to the production or diffusion of a green technology. For instance, the production of PV panels represents a small part of the total employment in the solar energy sector, which mostly require installers.

The report proposes to use the task-based approach as a flexible solution to build an index of occupational greenness that allows to monitor the progress made by countries, regions and sectors in building economic activities that are able to reduce environmental impacts. The first part of the survey describes how to extend and apply the task-based approach (Autor et al., 2003; Autor, 2013) to examine environmental issues. In particular, it contrasts a continuous task-based index of occupational greenness and a binary definition of a green job. The main conclusion of this part is that the task-based approach provides the most reliable and accurate estimate of the size of green employment, which is in the range of previous estimates obtained through specific, but infrequent, surveys on green production. In turn, using a binary definition of green jobs provides far less accurate -and thus credible- estimates. More in general, to become credible, research and policy analyses of labour markets in the green transition urge to agree on a clear, robust and widely accepted definition of occupational greenness, which, as this report suggests, should go beyond a binary classification of occupations (i.e. fully green vs non-green). This survey builds the case for the task-based approach to become the standard in this rapidly growing field. Importantly, the advantage in measurement accuracy is matched with other advantages, discussed extensively in the report: i) the identification of green skills (i.e. the skills that are prevalent in green jobs); ii) the assessment of distributional effects of environmental policies and green technologies; iii) the assessment of reallocation costs linked to reskilling, especially for workers in polluting industries.

In the long term, it is important to identify some areas where new data can be collected in order to enhance our understanding of both the demand-side (tasks, occupations) and the supply-side (educational programs, on-the-job training) of the labour markets related to the green economy. For future data collection efforts, this report offers a few insights.

First, it discusses how job vacancy data could potentially help in identifying green tasks, which is especially useful in countries lacking detailed datasets on the task content of occupations.

Second, given the lack of granular data at the EU level, it proposes to use national-level data, including matched employer-employee datasets. However, to ensure across-country and time comparability, a joint effort should be carried out to have a common conceptual definition of green tasks and how they can be used to define green occupations.

Third, some existing data collection efforts, such as ESCO (European Skills, Competences, Qualifications and Occupations), adopt the task-based approach, but are probably not yet ready to provide reliable estimates of the green economy. In addition, ESCO data are collected through a process that has to be refined to be consistent with usual statistical standards.

Statistical offices and EU agencies, such as the European Centre for the Development of Vocational Training (Cedefop), are in an ideal position to start collecting data on educational and training programs for green jobs. In particular, more information is required to map the actors that are involved in the educational and training system aimed at increasing the supply of green skills at different levels of education.

The remainder of the report is organized as follows. Section 2 presents the task-based approach and how to use it as a measurement framework in empirical research on green jobs and skills. Section 3 discusses in details the empirical implementation of this approach. Section 4 illustrates the main constraint (i.e. data availability)

to conduct empirical research on the green economy outside the US. Section 4 also provides some suggestions on how to overcome such data limitations. Section 5 concludes by providing some policy insights.

2 The task-approach to green labour

This section begins by presenting the task-based approach to labour markets. It then showcases three possible applications to environmental problems.

2.1 The task approach to labour markets

The task approach has become an important tool to study the impact of structural transformations on the labour markets thanks to the pioneering contributions by David Autor and co-authors (Autor et al., 2003; Autor, 2013) and the literature that has followed those early contributions. This approach originated with the aim of assessing the impact of computers and digital technologies on the labour markets ⁽¹⁾. Theoretically, the approach has been consolidated by Acemoglu and Autor (2011) and Acemoglu and Restrepo (2017) within the logic of the Ricardian model of comparative advantage. These models highlight the important distinction between tasks and skills, which becomes essential for the identification of green (or brown or any “technology-specific”) skills.

In the task-based model, the organization of production is divided into different functions, called tasks, which are complements in producing final output. That is: a firm requires both tasks requiring physical strength and tasks requiring abstract thinking to produce output. Obviously, the degree of complementarity between tasks depend on the particular sector or production method used.

In this approach, the existing task composition of the economy reflects the current state of the technology. To illustrate, in a subsistence economy, most tasks require physical strength, endurance and informal know-how on plants, animals and weather events. In a knowledge-based economy, problem-solving, verbal and writing abilities become valuable economic inputs. These examples also suggest that the process of socio-economic development involves both the modification of existing tasks and the emergence of new tasks (Vona and Consoli, 2015; Acemoglu and Restrepo, 2017). *Increasing task variety* is the first margin of technological change in the task-based approach: it captures the emergence of new functions to match the requirement of new technologies. The task “coding” did not exist before the invention of computers. The task “test electrical components of wind systems” did not exist before the wind turbines started to be used to produce electricity. Lin (2011) empirically shows that a greater incidence of new jobs, an empirical proxy for new tasks, is associated with a more rapid adoption of new technologies in US regions.

The second key element of the task-based model is that productive factors (e.g. capital, energy, labour with different skills) compete to perform a given task. The aggregate demand of a productive factor depends on the extent to which it is relatively more efficient in performing several tasks. In turn, a productive factor can become obsolete if it becomes less efficient than another productive factor in performing several tasks. The classical case studied by a burgeoning literature (see footnote 1) is that of automation, whereby new equipment (robots, computers, etc.) replace various types of human labour. Among productive factors, skills are particularly important because they mediate both the efficiency and distributional impact of any structural transformations, including the green one. Workers’ skills are basically the tacit know-how to perform a task. Over time, some worker’s skills can be eventually codified, and thus performed by a machine (Vona and Consoli, 2015), leading to a reduction of labour costs.

The substitutability among productive factors in performing a given task (or set of tasks) illustrates the second margin of technological change in this model: *task-replacing technological change*. Indeed, a subset of tasks previously performed by humans or animals are now performed by power engines or robots. In parallel, workers displaced by machines have been reassigned to other tasks. It is worth noting that these replacement and reorganization effects are muted in a standard “production function” framework, while they can be appreciated in the task-based model that creates a functional distinction between tasks and productive factors, including skills.

¹ The path-breaking paper of Autor, Levy and Murnane (2003) applies an important result of early research in artificial intelligence to economics: computers have a comparative advantage over humans in performing routine tasks, while humans retain a comparative advantage in complex abstract and social tasks as well as in physical tasks requiring coordination. Bringing this simple and powerful idea to data (see section 3 for details), the authors find that new technologies replace workers in the middle of the wage distribution which uses routine tasks more intensively, i.e. clerks or manual workers in manufacturing. Well-known patterns of wage and employment polarization are straightforward consequences of using the working hypothesis of routine-replacing technological change. Indeed, abstract tasks used intensively by workers at the top of the distribution can (or could) not be replaced by intelligent machines, while non-routine manual tasks at the bottom are (or were) not affected by new technologies, i.e. a robot cannot yet replace a waitress or a bus driver. Several following-up papers confirm these patterns, with obvious differences related to the time period, the phase of the economic cycle and the country coverage (Autor et al., 2006; Spitz-Oener, 2006; Goos and Manning, 2007; Acemoglu and Autor, 2011; Autor and Dorn, 2013; Goos, Manning and Salomons, 2014; Deming, 2017; Atalay et al., 2020).

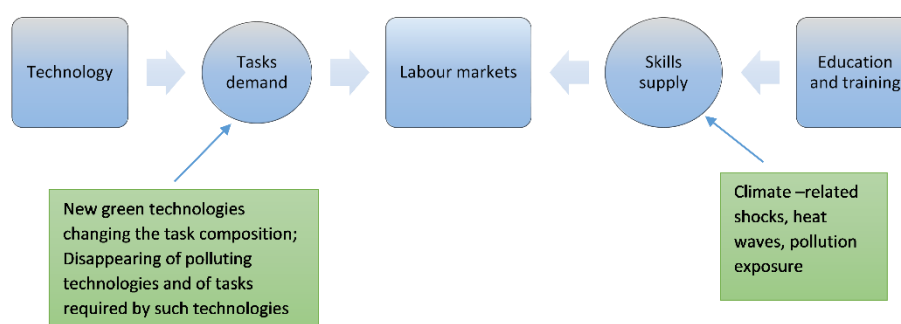
The assignment of a productive factor to a given task depends on a task-specific matching function $\alpha(s, i)$, which defines the efficiency of factor s in performing task i ; that is: the absolute advantage of productive factor s in performing task i . However, in the logic of the Ricardian model, the assignment of productive factors to tasks follows a comparative rather than an absolute advantage logic. Indeed, time constraints prevent a super-efficient productive factor (e.g. Magic Johnson or Larry Bird) from carrying out all tasks in the economy (e.g. playing in all positions of a basketball team). What matters for task assignment is then the relative gap $\alpha(s, i)/\alpha(k, i)$ in the efficiency schedule of productive factors s and k ⁽²⁾. Such gap captures the comparative advantage of a productive factor in a certain task with respect to other productive factors and, as we will see, it is important to identify the skills that are prevalent in green tasks. At the macroeconomic level, the assignment rule of tasks to productive factors determines the aggregate demand of each factor. Returns to factors are set at their equilibrium levels, but extensions with unemployment are possible, assuming the presence of matching frictions or downward wage rigidities.

The task-based approach presented here is over-simplified to highlight the main ideas. In reality, tasks are bundled together in what we call a “job” and often performed by more than one productive factor. Dynamic aspects of job tenure also matter as workers become more efficient in performing a specific task through learning-by-doing, reinforcing the strength of a specific task-skill matching. Moreover, the supply of each productive factor is endogenous. Notably, skills are formed through educational and training programs, and labour supply can be affected by exogenous events. Finally, on a more substantial level, some argue that the task approach prevailing in the labour economics literature suffers from a sort of “technological reductionism”. Indeed, the dominant version of such an approach neglects the social embeddedness and the organizational aspects that contribute to determine the assignment of tasks to jobs (e.g., Fernandez-Macias and Bisello, 2021). While this sociological critique to the dominant version of the task approach is particularly relevant in relation to the study of automation, where, as Marxian scholars have noted long ago, the assignment of tasks to jobs largely reflect the class conflicts between workers and capitalists (Braverman, 1974), there are no clear-cut theoretical reasons to think that it is also relevant for the green transition.

2.2 From theory to empirics: applications to environmental and resource economics

This section illustrates the relevance of the task-based approach for research questions at the intersection between environmental and labour economics. To illustrate the two main applications, Figure 1 summarizes a broader conceptualization of the task-based approach in relation to labour inputs, focusing on the functional distinction between tasks (e.g. what workers are expected to do at the workplace – the ‘demand side’) and skills (e.g. the abilities and competences that workers should possess to perform work tasks – the ‘supply side’). On the demand side, the task composition is affected by technological change, and green technologies are no exception. Taking the example of the energy transition, new tasks related to the installation of wind turbines (e.g., climb wind tower to inspect and repair) replace tasks related to coal mining jobs (e.g., operate mining machines to gather coal). On the supply side, the availability of the appropriate training programs allows workers to become proficient in tasks demanded by green technologies.

Figure 1. Representation of the task-based model, focus on the distinction between tasks and skills



² Usually, assignment is solved by first ranking the complexity of both tasks and productive factors (e.g., skills) and then imposing some monotonicity in the comparative advantage schedules, i.e. the ratio $\alpha(s, i)/\alpha(k, i)$ for two different productive factors s and k . In Acemoglu and Autor (2011), the comparative advantage schedule between high-skill and low-skill labour ($\alpha(h, i)/\alpha(l, i)$) is strictly decreasing in task complexity i , thereby high-skill workers have a comparative advantage in complex tasks.

The remainder of this section illustrates the flexibility and salience of the task-based model for environmental and resource economics by developing three examples.

Example 1: Labour supply and climate change

The first application is on the impact of climate change on labour supply and productivity. Heatwaves are well-known to reduce the productivity of workers employed in outdoor tasks (Graff Zivin and Neidell, 2012; Hsiang et al., 2018; Graff Zivin and Neidell, 2013 for a survey). A straightforward implication is that the profitability of automating tasks performed outdoors by humans should increase together with the incidence of hot temperatures. Concomitantly, heatwaves could temporarily impair cognitive functions required to perform abstract tasks (e.g., Graff Zivin et al., 2018). As a result, performing abstract tasks in these conditions will require the combination of capital (air conditioning) and skilled labour, thus increasing the capital intensity in performing such tasks.

Labour supply is also affected by extreme climate events and hot temperatures (e.g., Hanna and Oliva, 2015). The task model is able to highlight an important dimension of heterogeneous labour supply effects, which depends on the task in which a worker is specialized. For instance, labour supply may decrease in occupations with outdoor exposure because a unit of effort will be less productive in outdoor tasks. Put differently, the supply of skills depends on task-specific matching productivities, which are unevenly affected by climate shocks. The green box in the bottom right of Figure 1 represents the effect of climate shocks on labour supply. In other words, climate shocks can be seen as another way to endogenise labour supply choices in the task-based framework. Importantly, considering the effect of climate shocks as mediated by tasks' characteristics would allow to expand the scope of research on the distributional effects of climate change by differentiating spatial exposure to high temperatures across workers performing different tasks, i.e. outdoor vs. indoor.

Example 2: Distributional effects of environmental policies

A second application concerns the literature on distributional effects of environmental policies using computational general equilibrium and other quantitative models (Araar et al., 2011; Rausch et al., 2011; Fullerton et al., 2012; Goulder et al., 2019). In these models, distributional effects typically depend on the change in the relative demand of capital and labour induced by an environmental policy.

Two margins of adjustment are relevant here. On the one hand, environmental policies increase the cost of polluting inputs such as coal or steel relative to the cost of capital and labour. Such change in relative costs may make polluting inputs too expensive in certain tasks, so that labour and capital will compete to replace them. On the other hand, dirty tasks may disappear altogether. Trivially, coal mining is a task that is expected to disappear in a low-carbon economy. Capital and labour previously assigned to coal mining tasks can be reallocated to other tasks. Reallocation costs will be proportional to the extent to which such inputs are specific, that is: easily adaptable to other tasks. The case of the re-employment of coal miners in other activities is well-known, but a similar reasoning applies to power plants that can or cannot be reconverted to clean fuels. These two adjustment margins, which can be jointly identified using the task-based model, will shed new light on how input substitution induced by an environmental policy occurs, linking it directly to the costs of factor reallocation.

Example 3: New green tasks

The third application is on labour markets and the green transition. Imagine that new green tasks are created by a low-carbon technology, such as a smart grid (see Figure 1). These new tasks are usually ill-defined, difficult to express in rules and thus require tacit knowledge to be gradually improved and performed. In such ill-defined tasks, humans usually retain a comparative advantage over machines (Autor, 2013; Vona and Consoli, 2015).

However, on the supply side, the education curricula providing appropriate skills for these new, ill-defined tasks do not exist yet since it is impossible to acquire them through existing educational programs. As the development of green technology unfolds, a skill shortage is likely to emerge and the price of the most closely related skills (i.e. aerospace engineering for wind turbines) will go up until the skill supply does not adjust. Eventually, new educational and training programs will be needed to expand the supply of new skills required to operate and develop green technologies. Note that the type of adjustment required in this case may be very different from an incremental adjustment in training programs required to reallocate workers from brown to green jobs. Interestingly, the task-based approach allows to examine both types of adjustments of the skill supply (Vona and Consoli, 2015).

The remainder of the report focuses on applications related to the adjustment of labour market to green technologies and production methods, both through the creation of green jobs and the destruction of brown jobs. The task-based approach to study these issues has been successfully used in a burgeoning empirical literature that, by providing rigorous definitions of green employment and skills (Vona et al., 2018; Vona et al., 2019), allows to uncover the labour market distributional impacts of environmental taxes (Marin and Vona, 2019) and green subsidies (Popp et al., 2020; Chen et al., 2020) on different types of workers.

3 Measurement framework and applications of the task-based approach

This section explains the empirical implementations of the task-based approach in details. Section 3.1 discusses the key conceptual issue mentioned in the Introduction: what is a green job? Section 3.2 presents the main data source to study the greening of the labour market: the Occupational Information Network (O*NET). It also contrasts a binary definition of green jobs with a task-based indicator of occupational greenness. Section 3.3 shows how the task-based indicator allows to improve the measurement of green employment. Section 3.4 presents the second main empirical application of the task-based model, namely the identification of green skills. Section 3.5 showcases how the task-based approach can be used to estimate reallocation costs.

3.1 Defining what is “a green job”

Establishing a clear definition of what is a green job has always been a major obstacle to conduct rigorous research on the labour market responses to environmental policies and to the adoption of green technologies. This depends on the fact that there is no widely accepted definition of what is green. Indeed, there are several ways of defining what a green production or service is and there are specific environmental problems that require *ad hoc* solutions. There are two broad approaches to define “what is green” (e.g., Bontadini and Vona, 2020): i) the “*process definition*”; ii) the “*output definition*.” These approaches are also inspiring existing and on-going research on the labour market effects of environmental policies.

The *process definition* emphasizes the effective pollution content of production and thus indirectly of a job. The approach is intuitive: it uses data on direct and indirect pollution generated in producing a good as a measure of the inverse of the product greenness. A job associated with the production of A can be defined as greener than a job associated with the production of B, if the pollution content of A is lower than that of B. The main issue with the process approach is that data limitations make it virtually impossible to obtain a measure of the pollution content of products for multiple environmental problems and across several countries, sectors and years (Sato, 2014). So far, the available datasets, such as the World Input-Output Tables, are very aggregated at the sectoral level, available for a few developed countries and for air pollution only (Rodrigues et al., 2018). Research assessing the labour market impacts of environmental policies consider the pollution intensity of a sector as the key measure of the extent to which a job is exposed to the effect of environmental policies through an increase in production costs (Morgenstern et al., 2002; Walker, 2011; Kahn and Mansur, 2013).

The *output definition* is based on the potential of a product or a service to generate harmful impacts on the environment. This is the preferred approach for most lists of green products or activities (e.g., Bontadini and Vona, 2020). For instance, both the Green Goods and Services Survey of the Bureau of Labor Statistics in the US (Becker and Shadbegian, 2009; Elliott and Lindely, 2017) and the Eurostat definitions of green products (Eurostat, 2016) use the output approach³. One obvious reason for this choice is that tracking the pollution content of a job is almost impossible in the absence of detailed data on the entire life-cycle of production (including at the granular level of the plant) and consumption. Another important reason is that the process approach highlights the job destruction effect of environmental policies –that is: on polluting sectors and companies—rather than the job creation effect—i.e. on sectors developing green technologies and goods. Bontadini and Vona (2020) show that there is no overlap between polluting sectors (e.g., chemicals, cement and steel) and sectors developing green products and technologies (e.g., various machinery and equipment industries). Thus, it is important to use both the process and the output definitions to understand the structural transformations associated with the green transition.

A strand of research uses the *output definition* to infer the share of green jobs in a sector from the share of green production in that sector (Becker and Shadbegian, 2009; Elliott and Lindely, 2017). Such an approach has three main limitations. First, it imposes a proportionality assumption between green production and green employment, neglecting the fact that green productions can have different labour intensity than non-green productions, also within the same sector. Second, it does not allow to identify the specific types of workers and tasks that complement green activities, limiting the possibility to analyze distributional impacts. Third, data on green production are only available for the manufacturing sector, while several (if not most) green jobs are created outside manufacturing in construction, waste management and power generation. However, as discussed extensively in section 4.4, this approach represents a solid alternative to the recommended task approach.

³ In turn, defining an international list of green products is particularly difficult as testified by the failures at the World Trade Organization to find a list of goods entitled to benefit from reduced trade tariffs.

While this report uses a definition of “what is green” that is conceptually tied to the green technologies needed to reduce environmental impacts (and thus to the *output definition*), it shows that a more granular task-based approach, in which tasks rather than products are the building blocks, allows to disambiguate the definition of what is “green” in the context of labour (Consoli et al., 2016; Vona et al., 2018, 2019).

3.2 Using the O*NET dataset to define green jobs

Besides a suitable definition of what is green, implementing the task-based approach to study green jobs and skills requires appropriate data. More specifically, researchers need data containing detailed information on the task and skill content of occupations, where an occupation is defined as a bundle/vector of tasks and skills. Data with such characteristics are well established only for the United States. Indeed, the oldest one is the US Dictionary of Occupation and Titles (DOT), developed in 1939 by the United States Employment Service in order to facilitate the matching of unemployed workers to job vacancies after the Great Recession (Gray, 2013). Experts rated the extent to which a particular task (e.g. handling and moving objects) or skill (e.g. math) is important in an occupation. Rates were assigned either on a 1-to-5 scale or as a dichotomous variable (yes/no).

After reaching its revised 4th edition in 1991, the DOT was replaced by the online Occupational Information Network (O*NET) in 2000 (4). Not only O*NET has dramatically expanded the range of skills and work activities (from around 44 in DOT to more than 400 in O*NET), but it has also added detailed text descriptions for a subset of tasks specific to each occupation (5). More specifically, O*NET contains information on both tasks (e.g. what workers are expected to do at the workplace – the ‘demand side’) and skills (e.g. the abilities and competences that workers should possess to perform work tasks – the ‘supply side’). Skills are defined for all occupations with a 1-5 importance score attached, while tasks are text descriptions unique to each occupation and thus can be represented as a binary piece of information. The downside of O*NET is that occupational descriptions are available for only 900 occupations (6). In turn, DOT defines skill contents at the level of approximately 12,000 job titles, where a job title can be seen as the most granular sub-level of an occupation. The O*NET data have been used in countless applications in labour economics, published in both top general and field journals in the discipline.

O*NET has a special section devoted to identify green jobs and tasks: the ‘Green Economy Program’ (maintained together with the US Department of Labor), developed to provide a definition of what is green and is mostly inspired by the *output definition* (see Dierdorff et al., 2009; 2011; Peters et al., 2011).

The information contained in the ‘Green Economy Program’ can be used to identify green jobs based on two types of definitions: i) a binary definition where an occupation is considered either green or non-green; ii) a continuous definition of occupational greenness that, as we will see, exploits information on the greenness of the task content of occupations. We will discuss and compare these two alternatives in what follow.

A binary definition of green occupation

The ‘Green Economy Program’ of O*NET identifies three groups of green occupations: (i) existing occupations that are expected to be in high demand due to the greening of the economy (*Green Increased Demand*); (ii) occupations that are expected to undergo significant changes in task content due to the greening of the economy (*Green-Enhanced Skills*); and (iii) new occupations in the green economy (*New & Emerging Green*). Occupations belonging to any of these groups can be considered as “green” in a binary fashion, thus a clear advantage of a binary approach is that it is closely linked to the standard occupational classifications.

Table 1. Examples of green occupations in O*NET

	Green enhanced skills	Employment share (2011-2012)	Description
11-1021.00	General and Operations Managers	1.50%	Plan, direct, or coordinate operations of organizations; formulate policies, plan the use of materials and human

4 The interested reader can explore the online resources of O*NET: <https://www.onetonline.org/> and the entire database: <https://www.onetcenter.org/database.html#individual-files>.

5 O*NET also changed the methodology to collect the data from using only expert judgement to the combination of expert judgment and incumbents’ surveys.

6 For the 17.0 O*NET edition, tasks and skills information were available for 912 occupations. This roughly corresponds to the 6/8-digit level of Standard Occupational Classification (SOC).

resources. Diverse and general in nature, with respect to functional area of management.

53-3032.00	Heavy and Tractor-Trailer Truck Drivers	1.23%	Drive a tractor-trailer combination or a truck with high capacity. May be required to unload truck. Requires commercial drivers' license.
49-9071.00	Maintenance and Repair Workers, General	0.98%	Keep machines, equipment, or the structure of an establishment in repair. Duties include: pipe fitting; insulating, repairing electrical or mechanical equipment; installing, aligning, and balancing new equipment.
47-2061.00	Construction Laborers	0.64%	Perform tasks involving physical labor at construction sites. Duties include: operating hand and power tools of all types; cleaning and preparing sites; cleaning up rubble, debris and other waste materials.
43-5071.00	Shipping, Receiving, and Traffic Clerks	0.54%	Verify and maintain records on incoming and outgoing shipments. Prepare items for shipment. Duties include: assembling, shipping merchandise or material; receiving, unpacking; arranging for the transportation of products.

Green emerging		Employment share (2011-2012)	Description
51-9199.01	Recycling and Reclamation Workers	0.17%	Prepare and sort materials or products for recycling. Identify and remove hazardous substances; dismantle components of products.
13-1199.05	Sustainability Specialists	0.15%	Address organizational sustainability issues, such as waste management, green building practices, and green procurement plans.
13-1199.01	Energy Auditors	0.15%	Conduct energy audits of buildings, building systems, or process systems. May also conduct investment grade audits of buildings or systems.
41-4011.07	Solar Sales Representatives and Assessors	0.14%	Contact new or existing customers to determine their solar equipment needs, suggest systems or equipment, or estimate costs.
17-2051.01	Transportation Engineers	0.10%	Develop plans for surface transportation projects, according to engineering standards and construction policy. Prepare designs, specifications and modification for transportation facilities.

Green demand		Employment share (2011-2012)	Description
53-7062.00	Laborers and Freight, Stock, and Material Movers, Hand	1.72%	Manually move freight, stock, or other materials or perform other general labor. Includes all manual laborers not elsewhere classified.
43-4051.00	Customer Service Representatives	0.91%	Interact with customers to provide information in response to inquiries about products and services and to handle and resolve complaints.
51-2092.00	Team Assemblers	0.80%	Work as part of a team having responsibility for assembling an entire product or component of a product. Can perform all tasks conducted by the team in the assembly process and rotate.
51-1011.00	First-Line Supervisors of Production and Operating Workers	0.45%	Directly supervise and coordinate the activities of production and operating workers, such as precision workers, machine setters and operators, assemblers, fabricators.
47-2111.00	Electricians	0.42%	Install and maintain electrical wiring, equipment, and fixtures. Ensure that work is in accordance with relevant codes. May install or service street lights, intercom or electrical control systems.

Source: adapted from Consoli et al. (2016).

The group of *Green Increased Demand occupations* include very general occupations such as Software Developers (SOC 15-1133.00), Customer Service Representatives (SOC 41-4011.00) and Chemical Plant and System Operators (SOC 51-8091.00). Although indirect job creation is one of the goals of green subsidies, the procedure used by O*NET to identify occupations indirectly affected by the green transition is not transparent (see section 4.3). *Green Enhanced Skill occupations* are directly involved to develop solutions to various

environmental problems although not exclusively so. Examples are Electro-Mechanical Technicians (SOC 17-3024.00), Roofers (SOC 47-2181.00) and Urban and Regional Planners (SOC 19-3051.00). Finally, the group of *New & Emerging Green* occupations includes new jobs involved in the development and diffusion of green innovations such as Weatherization Installers and Technicians (SOC 47-4099.03), Recycling Coordinators (SOC 53-1021.01) and Solar Energy Systems Engineers (SOC 17-2199.11).

Excluding *Green Increased Demand* occupations is not enough to deal with ambiguities generated by binary green job definition, which also persist in the two sub-groups of *Green Enhanced Skill* and *New & Emerging Green* occupations (Vona et al., 2018). However, as we will see in the next section, the O*NET dataset allows for a much finer distinction of the importance of green tasks within an occupation.

A continuous, task-based definition of occupational greenness

Because some occupations in the list of *New & Emerging Green* and *Green Enhanced Skill* cannot be considered as fully green, Vona et al. (2018) proposes to overcome this problem by exploiting the very rich information on the task and skill content of occupations in O*NET. As anticipated above, each occupation is defined as the combination of two vectors: i) a vector of scores in general skills (defined for all occupations); ii) a vector of dummies for the presence of text-rich, specific tasks (defined for each occupation only). For *Green Enhanced Skill* and *New & Emerging Green* occupations, 'Green Economy Program' of O*NET contains information on green tasks. Thus, the vector of specific tasks can be further divided into a vector of green and a vector of non-green specific tasks. Importantly, green tasks are not collected for *Green Increased Demand*, reflecting the fact that such occupations may benefit only indirectly from green policies

Figure 2 provides a visualization of the structure of O*NET dataset. The Figure emphasizes the empirical counterparts of demand (specific tasks) and supply (general skills) presented in Figure 1. Each box gives a few examples of tasks and skills, distinguishing tasks into green and non-green. For instance, the occupation Supply Chain Managers (SOC 11-9199.04) has 29 specific tasks of which 9 are green (e.g. investigate or review the carbon footprints and environmental performance records of current or potential storage and distribution service providers) and 20 non-green (e.g., negotiate prices and terms with suppliers, vendors, or freight forwarders). As with all other occupations, the occupation Supply Chain Managers has a score in each general skill such as engineering, problem-solving or manual dexterity. Another example of mixed green/non-green occupation is the occupation Sheet Metal Workers (SOC 47-2211.00) that has 6 green tasks such as 'constructing ducts for high-efficiency heating systems or components for wind turbines' and 18 non-green tasks such as 'developing patterns using computerized metalworking equipment'.

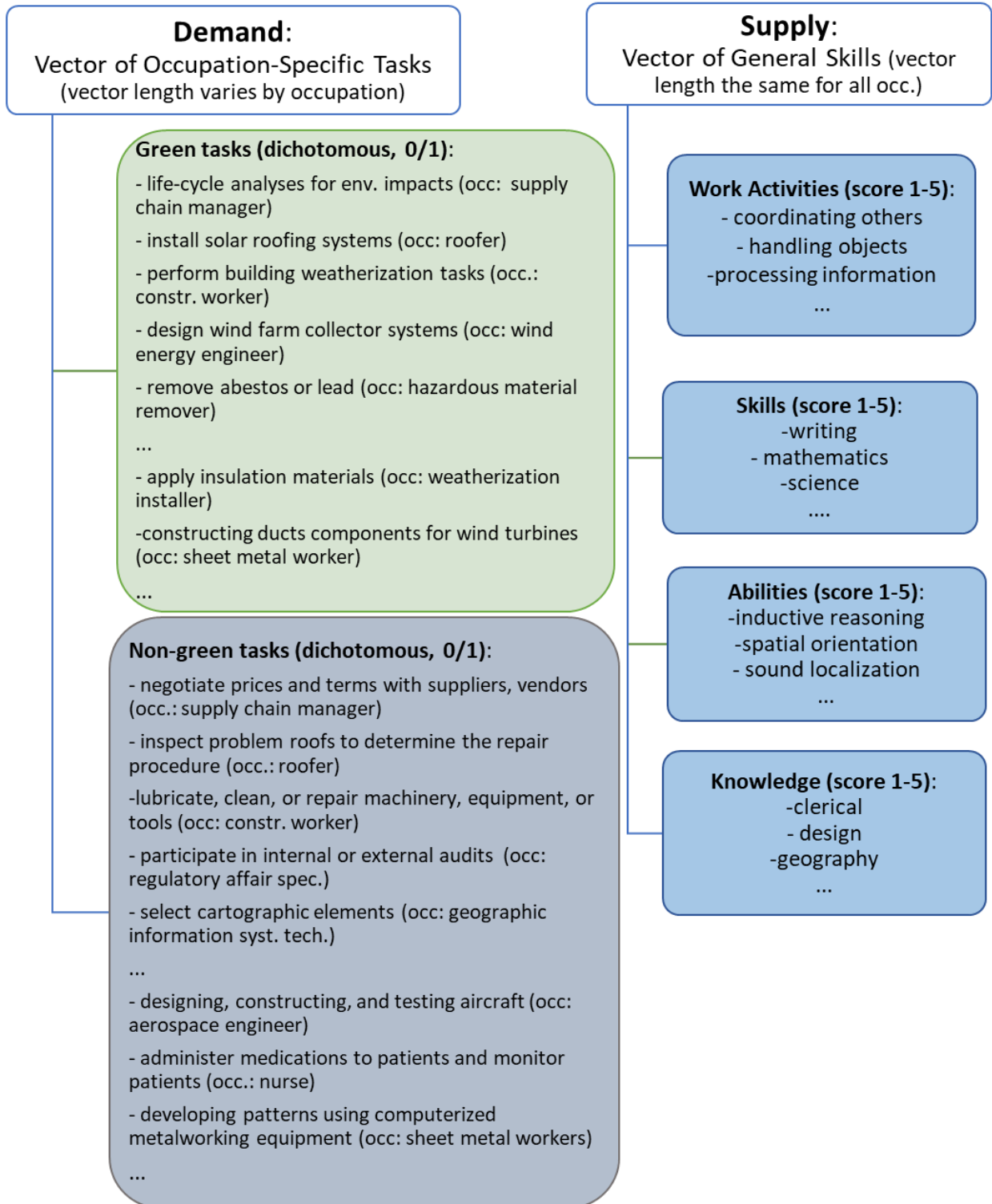
Exploiting the information on green and non-green tasks, Vona *et al.* (2018, 2019) construct a continuous measure of occupational *Greenness*, which places greater weight on occupations with a larger share of green tasks. In particular, the *Greenness* indicator is defined as the ratio between the number of green specific tasks and the total number of specific tasks done in occupation k :

$$Greenness_k = \frac{\#green\ specific\ tasks_k}{\#total\ specific\ tasks_k} \quad (1)$$

The *Greenness* index varies continuously between zero and one. As said above, the greenness index takes values greater than zero only for *Green Enhanced Skill* and *New & Emerging Green* occupations; that is: for approximately 130 out of more than 900 occupations at the SOC 8-digit level (⁷). Further, O*NET provides a measure of the coreness of the occupation-specific tasks, thus the *Greenness* indicator can be built in a more restrictive way by including core tasks only (Vona et al., 2019). Finally, O*NET also provides importance weights for each specific tasks. However, the correlation between the unweighted (equation 1) and the weighted greenness is extremely high, making the use of such weights unnecessary.

Figure 2. Structure of O*NET data, selected tasks and occupations

⁷ Note that new occupations are constantly added to the list of jobs to reflect changes in technology and the organization of work. However, the total number of green jobs has remained constant to date. A reader can consult the SOC occupational structure here: https://www.bls.gov/oes/current/oes_stru.htm.



Source: Authors own elaboration.

There are two possible interpretations of the *Greenness* indicator. First, consistent with the fact that tasks are units of work, and recalling the definition of an occupation as a bundle of tasks, occupational *Greenness* can be interpreted as the amount of time spent on green activities and technologies in the average job post within a certain occupation. Importantly, the indicator captures the fact that most occupations are neither green nor non-green, and often transitioning towards greener task configurations. Second, the *Greenness* indicator is related to the underlined aggregation of job posts in an economy. Indeed, a job post can be either green or non-green within a broader 8-digit SOC occupation. For instance, Maintenance and Repair Workers (SOC 49-9042.00) can specialize either on a hybrid car (a green technology) or on a diesel car (a “brown” technology). At the aggregated level, the *Greenness* indicator captures the share of Maintenance and Repair job posts that are associated with the use of green cars. This second interpretation makes the link between task and technology adoption more transparent (see also Figure 1).

Table 2 illustrates the increase in accuracy that can be obtained by shifting to the granular task-level when measuring green employment. The Table includes two dozen occupations that were classified “green” in the binary occupation-level definition of O*NET. When occupations are re-classified on a continuous *Greenness* scale, only the most uncontroversial occupations like Environmental Engineers, Solar Photovoltaic Installers or Biomass Plant Technicians are fully green (*Greenness* score=1). Conversely, occupations that, on average, encompass both green and non-green tasks have an intermediate *Greenness* score, such as Electrical Engineers, Automotive Specialty Technicians or Roofers (*Greenness* score between 0.3 and 0.5). Finally, there is a group of occupations for which, on average, green tasks are marginal, such as traditional Engineering occupations, Marketing Managers or Construction Workers. To illustrate, 14% of tasks performed by a US electrical engineering technician is green, 100% of the task performed by a wind energy project manager is green and 0% of tasks performed by a clerk is green.

Table 2. Examples of green occupations by level of “Greenness”

	<i>Greenness</i> =1	<i>Greenness</i> btw 0.5 and 0.3	<i>Greenness</i> <0.3
Green Enhanced Occupations	Environmental Engineers, Environ Science Technicians, Hazardous Material Removers	Aerospace Engineers, Atmospheric and Space Scientists, Automotive Specialty Technicians, Roofers	Construction Workers, Maintenance & Repair Workers, Inspectors, Marketing Managers
New and Emerging Green Occupations	Wind Energy Engineers, Fuel Cell Technicians, Recycling Coordinators	Electrical Engineering Technologists, Biochemical Engineers, Supply Chain Managers, Precision Agriculture Technicians	Traditional Engineering Occupations, Transportation Planners, Compliance Managers

Source: adapted from Vona et al. (2018)

3.3 Measuring green employment: task-based vs. binary definition

Consistent with the two interpretations of the occupational greenness indicator above, Vona et al. (2019) propose a task-based measure of green employment that reweigh occupational employment shares by their greenness:

$$Task – based Green Emp Share_t = \sum_{k=1}^K Greenness_k \times \frac{L_{kt}}{L_t} \quad (2)$$

The L_{kt}/L_t is the share of employment of occupation k from the Bureau of Labor Statistics (BLS) Occupation Employment Statistics. The authors show that the share of green employment, based on the continuous occupational *Greenness* indicator ⁽⁸⁾, closely matches the share of green employment obtained with the Green Good and Service Survey of the BLS, that is: approximately 2-3% of total employment. Remarkably, Bonatidini

⁸ In Vona et al. (2019), the greenness measure is refined by using a version of O*NET release 18.0 of July 2012, which provides weights on the importance of occupation-specific tasks.

and Vona (2020) and Cedefop (2019) find very similar shares of, respectively, green production and green jobs using different data sources. In turn, the green employment share using the O*NET binary measure would be:

$$\text{Binary Green Emp Share}_t = \sum_{k=1}^K 1_{k \in \text{O*NET green}} \times \frac{L_{kt}}{L_t} \quad (3)$$

is always larger than the task/greenness-based measure (as $\text{Greenness}_k \leq 1$) and it is defined for a larger set of O*NET green occupations, which include *Green Demand* occupations. The share of green employment computed using equation (3) is approximately 20%. Excluding *Green Demand* occupations, Consoli et al. (2016) estimate a share of the green employment in the US economy of approximately 11%. Importantly, even the latter estimate is clearly off-target being four times larger than that obtained using the Green Good and Services survey of the Bureau of Labor Statistics.

In an extension, Vona et al. (2019) also use BLS employment statistics at a more disaggregated level to construct industry-level and region-level measures of green employment. For instance, the regional-level counterpart of equation (2) is:

$$\text{Task – based Green Emp Share}_{jt} = \sum_{k=1}^K \text{Greenness}_k \times \frac{L_{jkt}}{L_{jt}} \quad (2')$$

where j index regions, and the employment shares are adapted accordingly. A key advantage of these very granular measures is that they vary across time and sectors/regions, thereby they can be used to estimate the distributional effect of green policies across locations. The granularity of the task-based information is a clear advantage compared to the “pure” *output definition*, which can only be binary. The main idea is that the more granular the definition, the more information on the nature of the technology are revealed and thus the more precisely the researcher can distinguish green and non-green workers within the same definition. Therefore, the task-based approach is the most accurate to define what a green job is.

A related advantage of the task-based measure rests on the rich text content of occupation-specific tasks. Looking at such text allows to check both the credibility of the green task classification by means of selected keyword searches or sophisticated text analyses (e.g., Janser, 2019). Moreover, the text content of green tasks can be used to distinguish jobs in different subsectors of the green economy as done already in some spreadsheets provided by O*NET⁽⁹⁾. This feature of the O*NET data makes the task-based approach suitable to analyse the labour market impacts of specific green technologies, especially when the share of green employment will increase up to a level that allows detailed analyses by green subsectors without incurring in large sampling errors⁽¹⁰⁾.

Finally, another key advantage of the greenness indicator, and of the task approach in general, is that it is dynamic, since it is easier to track the within-occupation task and skill changes without waiting for updates in the occupational classification. To understand this, note that the official occupational classifications (i.e. the SOC and ISCO classifications) are updated only rarely, typically every decade or so, thus they are not well suited to track the onset of structural transformation⁽¹¹⁾. In turn, occupational tasks are updated by O*NET more frequently, usually every 3 to 5 years. Because most occupations are transitioning towards greener tasks, this dynamic aspect is of paramount importance to track the patterns. In the future, green occupations will enter the occupational classifications and this will make the binary definition more reliable, especially for certain green technologies that are unquestionably green such as renewable energy. However, the task-based definition

⁹ O*NET divides the green occupations into the following sectors: agriculture and forestry, energy efficiency, manufacturing, renewable energy generation, environmental protection, government regulation, green construction, recycling, R&D and consulting, transportation. More detailed distinctions are limited by the relatively small number of green occupations. Burger et al. (2019) use O*NET to study the circular economy, but they do not use a task-based approach to classify circular economy green tasks. Instead, they arbitrarily assign an industry as belonging to core or enabling circular economy functions. For instance, “Automotive body, paint, interior, and glass repair” is considered a core circular economy industry as well as “waste collection”. Clearly, this approach is misleading as both industries can or cannot implement circular economy recommendations.

¹⁰ For instance, one can search in the text description of the green tasks to define tasks relevant for specific green technologies, such as electric vehicles or recycling.

¹¹ Recall that updates of occupational classifications have been used in labour economics as a way to measure new technologies (Linn, 2011; Acemoglu and Restrepo, 2017), but over a longer time period.

of occupational greenness encompasses the case of fully green occupations as a special one, thus it is still more general than a binary approach.

All these advantages do not imply that the measure of green employment obtained through equation (3) is reliable for highly disaggregated analyses. First, the average greenness may hide substantial heterogeneity, especially across locations. Indeed, construction workers can be greener in regions with large scale weatherization and renewable energy programs than in regions allowing hydraulic fracking. Note, however, that research in labour economics makes the same assumption to measure the distribution of exposure to routine or other technology-related tasks across locations (e.g., Autor and Dorn, 2013). To be precise, regional task-based measures of green employment should be interpreted as measures of exposure to the green transition. Second, the aggregations through equation (2) and (2') still poses problems related to the granularity of employment data. These problems will be discussed in details in section 4.2 as they are the main constraint to use this methodology in Europe. Third, the accuracy in collecting green tasks' data in O*NET, although exceptional and unique compared to the data available for Europe, may need to be improved. To illustrate this, the *Greenness* indicator does not have full support, but it is defined between 0 and 0.5 and above 0.5 can be only equal to one. Finally, the notion of task may appear very abstract for policymakers and practitioners, in spite of the development of new datasets at the task level also in Europe ⁽¹²⁾.

3.4 Identifying green skills

Another important application of the task-based approach is in the context of the identification of the competences and skills relevant for specific jobs, including green ones. Skills are important to assess both the distributional and aggregated effects of environmental policies. For instance, regarding distributional effects, workers with the appropriate skills will be more productive in green occupations than workers without such skills. Thus, they are likely to benefit relatively more in terms of wages and employability from ambitious green fiscal plans. The opposite occurs to workers with a skill set far from that required in green jobs. However, the concept of "green skills" remains elusive in the existing policy literature (e.g., Cedefop, 2010, 2019; ILO-Cedefop, 2011)

This section explains how green skills can be precisely identified using the task-based approach, following the very general methodology introduced by Vona et al. (2018). The idea is to use the task-based approach to reveal "coarse" comparative advantage schedules, searching for the skills or productive factors that are better suited to perform certain tasks. The matching function between tasks i and productive factor s introduced in section 2 (i.e., $\alpha(s, i)$) can be estimated using O*NET. Intuitively, this can be done exploiting the partition of the vector of occupational characteristics into tasks (specific to each occupation) and skills (defined for all occupations) – recall again Figure 2 ⁽¹³⁾.

To give the main insight of the data-driven methodology of Vona et al. (2018), let us begin with a general example, unrelated to the green economy. A researcher or a policymaker is interested in the skills that are more prevalent in a specific occupation, i.e. financial analyst, or a particular group of occupation, i.e. finance occupations. In order to assess if, e.g., mathematical skills are relatively more important in finance occupations than in other occupations, the simplest way is to regress the skill score in mathematics (defined for all occupations) ⁽¹⁴⁾ on a dummy equal to one for finance occupations (which is then zero for all other occupations). Mathematics is more important in finance than in the rest of the economy if the estimated coefficient for the dummy "finance occupation" is positive and statistically different from zero. The procedure can be repeated for all skills, or for a subset of skills of interest for the particular research question. In O*NET, it is natural to focus on 'Knowledge' (32 items), 'Work activities' (41 items) and 'Skills' (35 items), ⁽¹⁵⁾ which reflect more closely the actual know-how applied in the workplace. Going back to the finance example, a researcher will run 108 (32+41+35) regressions to reveal which skills are important in finance occupations.

¹² For instance, the Italian national institute for the analysis of public policies (so-called INAPP) has developed the counterpart of O*NET using a similar methodology: <https://www.inapp.org/it/dati/Audit>, the so-called INAPP-ISTAT Survey on Italian Occupations (ICP). The well-known German Qualification and Career Survey, developed by the Federal Institute for Vocational Education and Training (BIBB) and the Institute for Employment (IAB), has been used in several influential papers in labour economics and it is exceptionally rich as tasks varies within occupations, i.e. the task content of an electrical engineer can be different in two different companies. However, in both cases, no clear definition of green jobs or tasks is provided, thus the analysis should proceed using external sources to identify what is green.

¹³ Figure 2 also exemplifies what is defined as skills and what is defined as tasks in this context.

¹⁴ As shown in Figure 2, O*NET partitions the skill space in sub-groups. All of them are considered as "Skills" in the conceptual framework used in this paper, but only one is properly named "Skills". Others are labeled as "Knowledge", "Work Activities" or "Attitudes".

¹⁵ Recall that all occupations are assigned a Likert score (normally 1-5) for the relevance of certain skills (e.g. engineering, problem-solving, manual dexterity, etc.). See again Figure 2 for further clarifications.

Applying this method to the skills most relevant for the green economy is straightforward, but with some important adjustments. In line with the discussion of previous section, Vona et al. (2018) use the greenness indicator rather than a dummy equal to one for green occupations. Because using the greenness indicator increases the accuracy in the definition of green occupations, it also improves the accuracy in the identification of the skills that are prevalent in greener occupations. Practically, the procedure is implemented by fitting the following equation:

$$score_o^s = \varepsilon_o + \beta^s greenness_o + \phi_o \quad (4)$$

ε_o is an error term, $score_o^s$ is a score for skill s that is defined for all occupations (see Figure 2) and normalized to vary between zero and one, $greenness_o$ is the greenness indicator defined in the previous section (equation 3). The regression is repeated for all the 108 skills mentioned above. The estimated coefficient $\hat{\beta}^s$ are defined for each skill. A positive and significant (at 1% level) $\hat{\beta}^s$ indicates that the general skill s is used more intensively in greener occupations and thus it is a *green skill*, precisely defined. Equation (3) also includes occupational dummies (ϕ_o , at the SOC 3-digit level) (¹⁶). Adding occupational dummies at the three-digit SOC level allows to reveal comparative advantage schedules within similar occupations (e.g., environmental engineer and chemical engineer). In contrast, without adding occupational dummies ϕ_o , a researcher would confound both variation across broad occupations, which can be understood using an occupation-based analysis, and specific within-occupation changes, which require the task-based model to be appreciated.

Using this procedure, Vona et al. (2018) obtain 16 green skills (i.e. with a positive and significant $\hat{\beta}^s$), which are ranked and clustered together using principal component analysis (¹⁷). The resulting four groups of green skills are: i) Engineering and Technical, ii) Operation Management, iii) Monitoring, and iv) Science. Importantly, the share of the variance explained by the Engineering and Technical principal component is much larger (34.9%) than the share explained by the other three principal components. Operation Management is next in importance, with 24.5% of the variance explained. Monitoring and Science are marginal green skills, explaining respectively only 8.2% and 6.2% of the variance.

The detailed list of the 16 green skills is provided in Table 3. *Engineering and Technical skills* encompass skills required in several stages of technology, including design, construction and installation. As shown in Vona et al. (2018), these skills are very important also in low- and middle-skills occupations such as Solar Installers, Weatherization Workers and Technicians. *Operation Management skills* are associated with new organizational practices needed in greener activities; in particular, with continuous assessment and adaptive business practices. Relevant examples of professions intensive in Operation Management skills are Sustainability Specialists, Chief Sustainability Officers and Supply Chain Managers. *Monitoring skills* include legal, administrative and technical activities necessary to comply with regulatory standards. Key occupations using these skills intensively include Environmental Compliance Inspectors and Emergency and Management Directors and Legal Assistants. *Science skills* are obviously important in the first stages of the innovative process. Occupations with high scores in this skill can either have specific knowledge applicable to environmental issues, such as Materials Scientists or Hydrologists, or be more general know-how, such as Biophysicists and Biologists.

As already clear in the example of finance occupations, this data-driven approach to identify green skills can be used for several other purposes relevant for environmental problems. For instance, a researcher can be interested in identifying “brown” skills by replacing brown with green tasks. Also, it is possible to partition the set of green tasks by the type of green technology using the rich text contained in the definition of specific tasks. Finally, other functional forms and estimation methods are worth to be explored, but the results appear very robust to variations in the preferred statistical model (see the appendix of Vona et al., 2018 for details).

Table 3. Green Skills

<i>Engineering & Technical</i>

¹⁶ Vona et al. (2018) estimate equation (6) using only three-digit SOC occupations containing at least one job with greenness greater than 0. This implies eliminating broad occupational groups, such as i.e. Personal Care and Service, which are not relevant following the output definition of what is green as it is implicitly done by O*NET. However, because they control already for 3-digit SOC dummies, the results of the procedure to identify the green skills are not affected by excluding irrelevant occupational groups.

¹⁷ Principal component analysis builds a linear combination of the original variable ranked by the share of the total variance across occupations that they can explain.

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

Source: adapted from Vona et al, (2018)

Green skills are found to be important to mediate the economic effect of green policies, such as subsidies to renewable, energy efficiency, brownfield redevelopment and low-carbon infrastructure. Popp et al. (2020) show that the net job creation of the green part of the US American Recovery and Reinvestment Act (ARRA) was much larger in US commuting zones with a larger fraction of workers with the appropriate green skills (measured as the share of workers in the upper quartile of the nation-wide green skill distribution), which also received a larger fraction of green spending and were growing relatively faster before the 2008 financial crisis. The next section explores two key applications of green skills: i) to estimate the cost of re-employing a worker from a brown to a green job; ii) to estimate the distributional effect of environmental policies.

3.5 Estimating reallocation costs and distributional effects

Politicians and policy makers are interested in policies that allow overcoming the resistance of brown lobbies against climate and environmental policies. Among those lobbies, low-skilled workers employed in polluting industries represent a particularly thorny case as they are at the bottom half of the income distribution, but earn more than low-skilled workers in several service sectors. Because much-needed climate policies will eventually destroy “brown” jobs (i.e. jobs in polluting industries) and create green ones, the key question is: how easy is it to reallocate these brown workers into green occupations?

A strand of research in labour economics uses the task-based approach to answer the broader question of which are the consequences of job-to-job transitions and reallocations in terms of earning, employability and other labour market outcomes (e.g., Kambourov and Manovskii, 2009; Gathmann and Schönberg, 2010). The central finding of this research strand is that workers’ reallocation costs mostly depend on the skill similarity between origin and destination occupations. Moreover, skill specificity is more correlated to occupational characteristics than to sectoral characteristics. Researchers use various measures of skill similarity (i.e. the angular separator distance as in Gathmann and Schönberg, 2010) for two paired occupations or groups of occupations (brown vs. green). Note that, without the detailed information on tasks and skills, it would be impossible to build measures of occupational similarity and thus to assess the size of the reallocation costs linked to retraining.

Applying these measures of skill proximity to the green transition is straightforward if a researcher is able to clearly identify green and brown occupations. The discussion of section 3.2 highlights that this is not an easy task. However, using the task-based approach can be helpful to select a sub-set of occupations with greenness

index greater than a certain threshold, which can be considered more affected by the use and development of green technologies than others. In doing so, the greenness indicator can be used to go back to a binary, but more accurate, definition of green occupations. For instance, Vona et al. (2018) define as “green” an occupation with greenness greater than 0.1, while Popp et al. (2020) consider “green energy” only occupations with greenness equal to one and with wind and solar in the job description.

To define brown occupations, there are no datasets collecting information on brown tasks as O*NET does for green tasks. Consequently, a researcher has to resort to a *process definition* that considers brown an occupation primarily employed in polluting industries or firms. In practice, it is possible to use well-known definitions of polluting industries and then search for the occupations that have a particularly high probability of being prevalent in such industries. For instance, Vona et al. (2018) consider brown an occupation that has a probability of being found in polluting sectors higher than a certain threshold¹⁸. By contrast, Popp et al. (2020) define a subgroup of brown energy occupations using occupational titles related to oil, gas, coal and mining.

Four practical points should be made to use skill proximity measures in this context. First, skill distances can be computed using the sub-set of 16 green skills defined in the previous section (i.e. the skills that are most important in destination occupations) or using all the possible skills defined in O*NET. The choice depends on the specific research question. To study reallocation costs related to the brown-green job transition, looking at differences in green skills seems more appropriate to avoid the noise created by irrelevant skills. Second, skill distances have no clear metrics, thus a researcher should establish a benchmark for comparison or try to quantify the cost required to change job in terms of foregone earnings. For the brown-green transition, the logical benchmark is the skill distance between any occupation (excluding brown ones) and green occupations. Third, computing skill distances makes much more sense across similar occupations. For instance, it makes sense for two pairs of 6-digit occupations belonging to the same 2-digit SOC groups, e.g. construction and electric engineers. The reason is related to the adaptation in the supply of education described in Figure 1. Indeed, moving from one broad occupational group to another usually requires acquiring a new degree, which may take several years of education and substantial upfront investment. In contrast, moving within the same occupational group only requires on-the-job training or relatively shorter courses to fill specific skill mismatches, being feasible through relatively shorter training programs. Fourth, there are demographic aspects that should be considered: educational programs available for younger cohorts are very different from those available to older cohorts. The skill distance should be adjusted to include these cohort-specific effects that may limit the effectiveness of training programs for workers of different ages.

Going back to the iconic brown-green job transition, the analysis of Vona et al. (2018) reveals that, relative to the benchmark of all other occupations in the same SOC 2-digit group, green and brown jobs are quite similar in terms of green skills. The only relevant exception is that of construction and extraction workers (i.e., SOC-27). The skill gap in these occupations is very relevant for climate policy: miners are likely to be among the main losers of carbon taxation while roofers and solar photovoltaic installers among the main winners. Indeed, Popp et al. (2020) show that the green stimulus package of Obama benefited mostly low-skilled manual workers in construction. Marin et al. (2020) give a broader view using the same approach to ask the question of whether green stimulus plans can be used to easily re-employ low-skilled workers highly exposed to the Covid-19 crisis or to automation, which are identified using previous indicators also based on O*NET, and thus on the task-based approach¹⁹. These two groups contain a much larger number of workers (compared to just brown workers, which represent approximately 2.5% of total employment even using a broader definition than that of Vona et al. (2018)). The main result is that skill distances with green jobs are much larger for workers exposed to automation and to the Covid-19 crisis than for brown workers.

Not only skill proximity measures are useful to estimate reallocation costs, but also to identify the potential winners and losers of the green transitions. In a nutshell, the task-based approach can help identifying occupations that would benefit or lose from specific environmental policies. The “winning occupations” are those that use intensively green skills, which are not exclusively green occupations. Indeed, the green skill index is defined for all occupations. There can be non-green or marginally green occupations, such as construction engineers, mining machine operators and some transportation workers. By analogy, workers having skills in high demand in the winning occupations will also benefit. In contrast, workers who possess only skills specific to “losing occupations” will be those more at risk of losing their job. In other words, they are more vulnerable because of their low degree of similarity with other occupations.

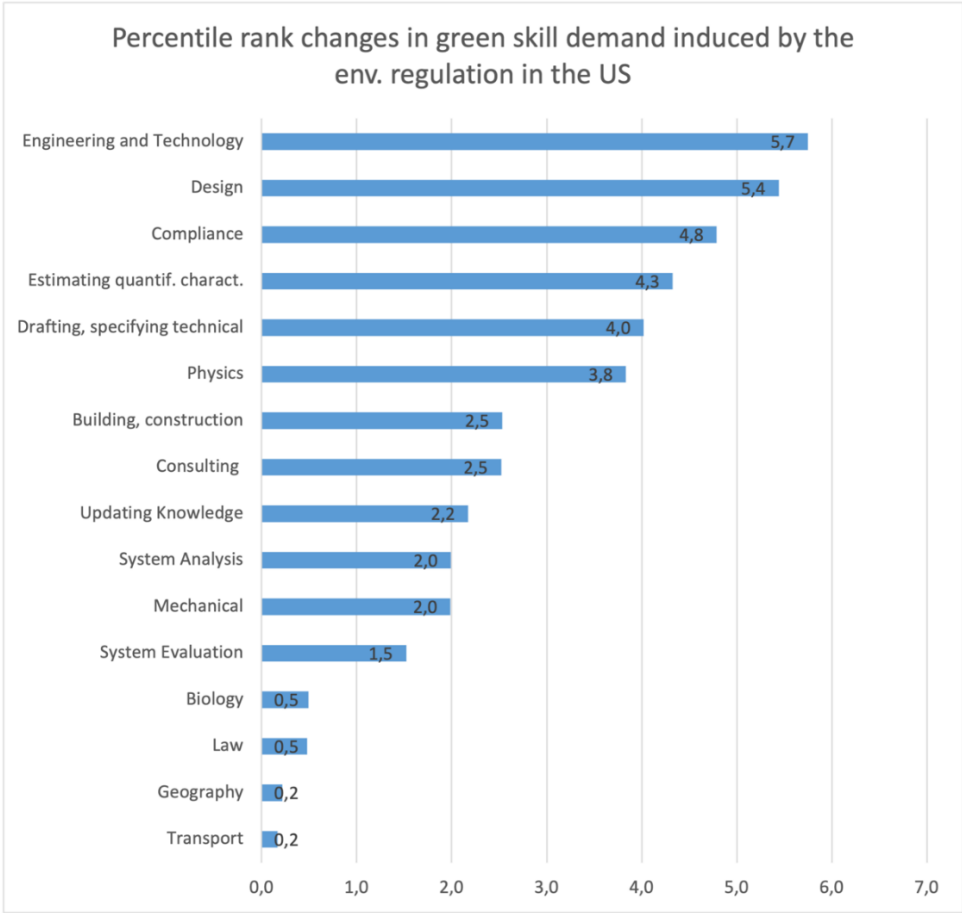
¹⁸ In particular, such probability should be seven time higher than the probability of being found in other sectors. Sectoral pollution is defined based on six criteria pollutants regulated by the US Environmental Protection Agency.

¹⁹ See Marin et al. (2020) for details on these indicators.

To estimate induced changes in the demand for green skills (and implicitly distributional effects), Vona et al. (2018) use a Clean Air Act Amendment in the mid-2000s. The local demand for green skills is constructed for US metropolitan and non-metropolitan areas using a formula similar to that of equation (2')⁽²⁰⁾. The authors find that the demand for workers with green skills, especially engineering and technical skills, increases in areas exposed to a more stringent environmental regulation relative to a counterfactual. The quantified effects by detailed skill items are summarized in Figure 3: this provides an example of how O*NET data can be used to study distributional effects of environmental policies⁽²¹⁾. Following the logic of the task-based approach, if the demand for engineering and technical skills increases, workers who are specialized in occupations using those skills intensively will experience a wage increase and/or an increase in their employability⁽²²⁾.

The next section will discuss the data issues that make the use of the task-based approach difficult in countries different from the US, where databases similar to O*NET have not been developed.

Figure 3. Effect of the clean air act amendments 2009-2011 on the demand of green skills



Source: adapted from Vona et al. (2018)

²⁰ More precisely, denoting with GGS a green general skills (e.g., engineering), the demand of a green general skill in local labour market j is: $GGS_{jt} = \sum_{k=1}^K GGS_k \times \frac{L_{jkt}}{L_{jt}}$, where the GGS score is reweighted by the employment share of occupation k in local labour market j at time t .

²¹ As skill scores have no natural scale, the effects are reported in terms of percentile rank changes of the metropolitan areas relative to the initial position.

²² Wage impacts have been extensively studied by papers on the impact of computers and digital technologies (Autor, Katz and Kearney, 2008; Acemoglu and Autor, 2011; Deming, 2017; Atalay et al., 2020), but not yet in the context of the green economy.

4 Data issues: limitations, solutions and unexplored avenues

Data limitations prevent to conduct similar analyses in most European countries where O*NET is not available. We highlight in this section the main data constraints and how to overcome them. Intuitively, there are two main data constraints to monitor green employment and skills over time. Equation (2) illustrates these two constraints:

$$\text{Task – based Green Emp Share}_t = \sum_{k=1}^K \text{Greenness}_k \times \frac{L_{kt}}{L_t} \quad (2)$$

The first constraint is on the availability of accurate data to measure occupational greenness on a continuous scale. The second constraint concerns the granularity of employment shares (L_{kt}/L_t). As long as green occupations are a small portion of the overall economy, having employment shares at a too aggregated level leads to large measurement errors.

This part of the report is organized as follows. Section 4.1 illustrates the simple idea of imputing O*NET data from SOC occupations to EU occupations, grouped using the International Standard Classification of Occupation (ISCO) classification. Section 4.2 discusses the issue of the level of aggregation in the European Labour Force Survey data that make it difficult to build accurate measures of green employment described above. Section 4.3 discusses how to measure indirect job creation triggered by the uptake of the green economy, which would require the use of national EU Labour Force Survey statistics. Section 4.4 briefly illustrates other approaches to measure what is green and thus identify green jobs. Section 4.5 presents recent data projects and the new frontier of job vacancy data.

4.1 Imputing O*NET scores through cross-walking

Since O*NET and the Green task classification are only available in the US, it is difficult to conduct similar analyses in European countries. For instance, Germany has an excellent task monitoring survey repeated for several decades starting from 1979 and with task constructs varying at the job-post level (see footnote 12), which however does not contain a definition of green job or task. Moreover, the German survey collects information on 19 tasks only (e.g., Gathmann and Schönberg, 2010). The Italian task survey has been developed more recently, with the first wave dating back to 2007. The survey closely replicates the structure of O*NET and thus contains a wider list of skills (e.g., Cirillo et al., 2020). However, also in this case, there is no definition of green tasks or jobs.

To overcome these limitations, research on the effect of computers and digital technologies on the labour markets has assumed that the tasks performed by two similar occupations are the same on both sides of the Atlantic (e.g., Goos et al., 2014). Two conditions should be jointly verified to justify this assumption. First, the tasks performed in a certain occupation primarily reflects technology adoption. Second, the same frontier technologies are adopted in both markets at roughly the same time. While the former assumption seems justifiable in light of the task-based approach (Autor et al., 2003), the latter is more questionable. Already in the case of general-purpose technologies such as computers, it is reasonable to assume that there exists a dominant technology, but much less that this technology is adopted at the same speed in all geographical areas. For the case of green technologies, it is even more difficult to define a dominant technology and it is very likely that technology differences persist depending on long-term strategies in the energy and transport sector. The power sector is a good example of persistent technological diversity. Note also that technological specificity is likely to be much more pronounced for green technologies, as highlighted by the importance of “engineering-type” knowledge (documented in section 3.3) that is intrinsically more sector or firm-specific than general-purpose knowledge, such as coding.

In spite of these obvious limitations, using O*NET skills and tasks for EU occupations remains a promising second-best option to overcome data limitations. The practical implementation relies on the quality of available crosswalks between the US SOC classification and the EU ISCO classification (²³) A few recent papers have followed this approach (Rutzer and Niggli, 2020; Elliott et al., 2021), but without validating it carefully. The report of Gilli et al. (2020) highlights some drawbacks of using this ISCO-SOC cross-walking because ISCO occupational data are aggregated at 3-digit. While the authors of the report did not conduct an extensive

²³ Crosswalk tables are available at the Bureau of Labor Statistics: https://www.bls.gov/soc/isco_soc_crosswalk. Some technical issues have to be solved to apply the crosswalk to a long panel as both the ISCO and SOC classifications evolve over time. Obviously, a researcher should face the usual problems in cross-walking different classifications, such as the fact that there are many-to-many matchings. For instance, a given 6-digit SOC occupations not always belong to a unique 3-digit ISCO occupation.

validation exercise by comparing greenness scores for aggregated occupational groups in ISCO and SOC, some startling results emerge (see Table 4). For instance, the highest greenness score is for managerial occupations in ISCO, while it is for professionals in SOC. In general, the authors conclude that the quality of the crosswalk is not sufficient to use it to measure green employment in Europe, although this conclusion also depends on the level of aggregation in EU employment data that will be discussed in the next section. Rutzer and Niggli (2020) build their own index of occupational green potential, which is however closer to a proximity measure à la Gathmann and Schönberg (2010) than to a real greenness indicator à la Vona et al. (2019). Thus, a detailed cross-validation is not possible in their application. Elliott et al. (2021) use the crosswalk to assign a greenness score to 4-digit ISCO occupations in Dutch firms, thus benefiting from a higher level of disaggregation of ISCO occupational data. Even in this case, detailed cross-validations are not performed, but the size of green employment appears much larger in the Netherlands than in the US, which is a red flag on the poor quality of the crosswalk with the aim of measuring green employment.

Table 4. Top-10 ISCO 3-digit occupations by greenness

ISCO 3digit	ISCO Tiltte	Greenness
961	Refuse Workers	0.692
314	Life Science Technicians and Related Associate Professionals	0.268
932	Manufacturing Labourers	0.231
711	Building Frame and Related Trades Workers	0.230
122	Sales, Marketing and Development Managers	0.202
214	Engineering Professionals (excluding Electrotechnology)	0.198
132	Manufacturing, Mining, Construction and Distribution Managers	0.168
332	Sales and Purchasing Agents and Brokers	0.166
211	Physical and Earth Science Professionals	0.142
215	Electrotechnology Engineers	0.136
213	Life Science Professionals	0.135
142	Retail and Wholesale Trade Managers	0.118
311	Physical and Engineering Science Technicians	0.107
962	Other Elementary Workers	0.099
216	Architects, Planners, Surveyors and Designers	0.092
313	Process Control Technicians	0.092
723	Machinery Mechanics and Repairers	0.077
243	Sales, Marketing and Public Relations Professionals	0.069
241	Finance Professionals	0.068
242	Administration Professionals	0.064

Source: adapted from Gilli et al. (2020)

Two main conclusions can be drawn from this on-going research. First, using a task-based measure of green employment requires very detailed data at the finest level of occupational disaggregation. Recall that the correct task-based approach to measure green employment indicates that only 2-3% of the US workforce is green and it is in line with accurate survey-based measures. When *the devil is in the details*, cross-walking at a more aggregated level always adds measurement error, making it difficult to obtain an accurate task-based measure of green employment outside the US. However, the error in using an occupation-based measure would be even larger. A way to improve the accuracy of the crosswalk would be to use the occupational greenness of SOC occupation at the same level of aggregation of the available ISCO occupation (i.e. both at 3-digit level). Other improvements can involve performing a manual correction of the greenness scores of certain problematic occupations as exemplified in Table 5 (and discussed in the Appendix of Vona et al., 2019).

Second, this imputation approach is more reliable when a researcher uses it to attribute green or other skill indexes (rather than the greenness indicator) to ISCO occupations. The higher reliability stems from the fact that two similar occupations belonging to the same broader group (i.e. electric engineers and telecommunication engineers both belong to the ISCO 215 3-digit group) share a similar set of skills, but a very different greenness (respectively 0.25 and 0). This implies that the green skill scores should be more robust to the measurement error created through the cross-walking.

In light of these difficulties, an alternative approach consists in performing an occupation-based analysis, and then interpret the result using O*NET by looking at the task and skill content of occupations that emerge as “winners” and “losers”. Such an approach is used by Marin and Vona (2019) to study the heterogeneous response to a large and persistent increase in energy prices, a proxy of carbon taxation, on the demand of workers with different skills in EU countries and sectors. Their findings confirm that technical skills complement green and energy-saving technologies adopted in response to increases in energy price. However, the level of data aggregation reduces the policy relevance of these results, as we will see in the next section.

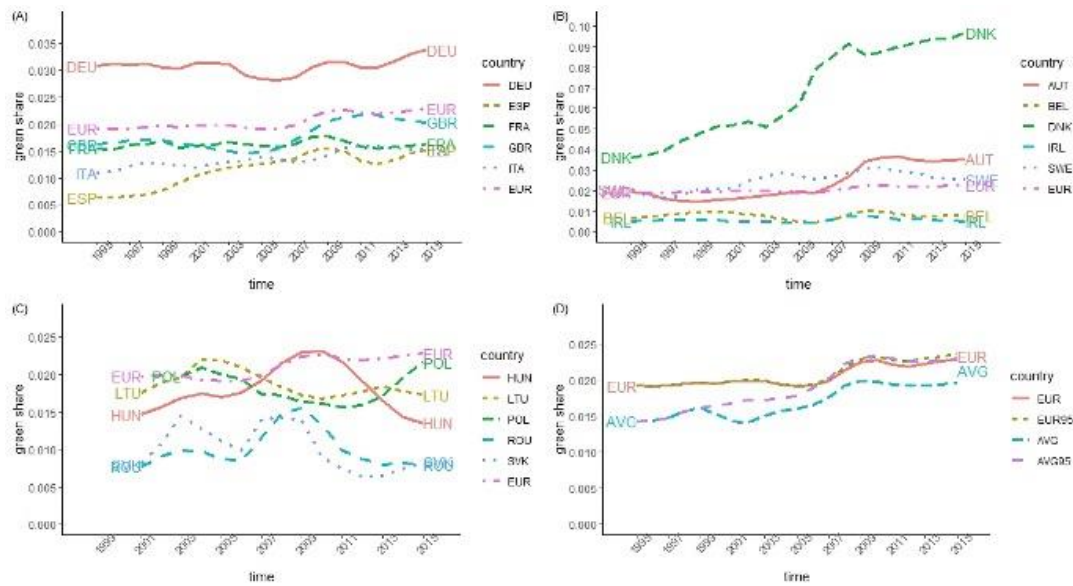
4.2 Level of aggregation in available occupational data

The study of Marin and Vona (2019) is limited by the level of aggregation of available employment statistics in the European Labour Force Survey. This problem is so relevant that it deserves a separate section to be discussed in details.

Let us begin this discussion by noting once again a very important feature of the green economy: its size is very small. Recall that the accurate task-based measure of green employment of equation 4 gives a share of green employment of 2-3% in the US over the period 2006-2014 (Vona et al., 2019). Previous research using the BLS Green Good and Service Survey also for the US provides an estimate in the same range for the years 2010 and 2011 (e.g., Elliott and Lindley, 2017). For Europe, Bontadini and Vona (2020) build a conservative list of green products merging and cleaning the lists used for the international negotiations on green product tariffs at the World Trade Organization (WTO). The authors estimate an average share of green production of 2-2.5% in the manufacturing sector in Europe over the period 2000-2015. Assuming proportionality, as done in works using green production data, the share of green employment is then in the usual range and is significantly higher only in countries that have a comparative advantage in certain green technologies such as Germany (3-3.5%) and Denmark (up to 10%). Saussay et al. (2021) estimate a share of climate-related green job vacancies of approximately 1% over the last decade using the universe of US online job vacancies from Burning Glass Technologies data. The estimated share does not change substantially by reweighting for BLS employment shares at the 6-digit occupation level to increase the representativeness of low-skilled occupations, which are usually under-represented in job vacancy data.

Note that the EGD and the infrastructure plan proposed by the Biden administration will increase the green job share substantially. This will also entail a change in the official occupational structure through revisions of the SOC and ISCO classifications. Presumably, some green occupations that are now relegated at the 6-digit (wind turbine service technician, SOC 49-9080) or 8-digit (chief sustainability officer, SOC 11-1011.03) will be upgraded to a higher level of aggregation where employment statistics are more abundant and available at a detailed sector-region level. Think of the case of computer occupations that, through several SOC revisions, climbed the hierarchy reaching the 3-digit SOC level (15-1). However, changes in the occupational classifications are very slow, while monitoring the progress of the green economy in different regions is a pressing priority for policy-makers.

Figure 4. Share of Green Production in EU countries (from Bontadini and Vona, 2020)



Source: adapted from Bontadini and Vona (2020)

Although the future of research on green employment may be bright (see also section 4.4), the present is darker, especially if a researcher wants to conduct analyses for all European countries. For EU countries, EU Labour Force Survey data are available only at the 3-digit ISCO level, with a limited level of sectoral aggregation (1-digit NACE), or at 1-digit ISCO level and 2-digit NACE level, as for the data used in Marin and Vona (2019). Employment data for regional statistics are even more aggregated in the EU. The comparison with US data is striking: employment statistics at the metro-area or commuting zone level (the equivalent of a NUTS-2 region for Europe) are available for 4/6-digit occupations and approximately 3-digit sectors. This has a simple and obvious implication for the study of the green economy. Even if a researcher had a perfect EU-crafted measure of occupational greenness at the 6-digit ISCO level, it would have to aggregate it at 3-digit level in order to obtain a reliable measure of green employment by using uniform weights (i.e. taking the simple average). To reiterate the main point of this section, such uniform aggregation creates a very large measurement error with the coarse occupational data available in the EU LFS. In particular, it leads to a large over-estimation of the real size of the green economy because occupations with higher greenness are usually much smaller than occupations with lower or zero greenness within a 3-digit ISCO code. The only way to correct this aggregation bias is to use employment statistics at the adequate level of aggregation, i.e. 6-digit ISCO in our example, which are not provided by Eurostat.

To understand the salience of this problem, it is worth noting that it was already present with the much more granular US occupational data when aggregating 8-digit SOC occupations into 6-digit ones. The issue is discussed in details in the Appendix of Vona et al. (2019). To give an example of the type of aggregation error, Table 5 is an extract of Table 1A of Vona et al. (2019). This Table illustrates how the authors treated “problematic occupations”; that is: occupations that have different greenness scores at 8-digit SOC level but belong to the same 6-digit SOC occupation (i.e., the lower level for which employment data are available). In these specific cases, an assumption has to be made to build an “operational” greenness measure at a higher level of aggregation (i.e., 6-digit SOC) that will be used in the analysis. The most natural assumption of using the simple average is very often wrong, as illustrated by the first example of Table 5. Taking the simple average of the greenness of chief sustainability officers and of chief executives, a researcher would obtain that the aggregated “chief executive” occupation has a 0.5 greenness. That is: 50% of chief executives are engaged in green investment! Because chief sustainability officer represents a small fraction of all chief executives, Vona et al. (2019) set the greenness level to zero. For the case of “sales representatives of technical products”, which is partially green and contains the fully green occupation “solar sales representatives”, Vona et al. (2019) choose the minimum of the two greenness levels since solar representatives are a small fraction of all sales representatives. Importantly, the total employment share of sales representatives is large, so the error in using an uncorrected measure of greenness is very large also in this case.

Table 5. Problematic Occupational Shares

SOC 8-digit	SOC 6-digit	Name of the occupation	# tasks	# green tasks	greenness	uniform weight greenness	greenness adopted in the paper
11-1011.00	11-1011	chief executives	32	0	0	0.5	0
11-1011.03		chief sustainability officers	18	18	1		
11-3051.00	11-3051	industrial managers	14	0	0	0.7	0
11-3051.01		quality control system man.	27	0	0		
11-3051.02		geothermal managers	17	17	1		
11-3051.03		biofuels managers	14	14	1		
11-3051.04		biomass managers	18	18	1		
11-3051.05		methane/landfill managers	21	21	1		
11-3051.06		hydroelectric managers	19	19	1		
19-3011.00	19-3011	economists	12	0	0	0.5	0
19-3011.01	19-3011	environmental economists	19	19	1		
41-4011.00	41-4011	sales represent., technical products	38	4	0.11	0.56	0.11
41-4011.07	41-4011	solar sales represent.	13	13	1		
53-1021.00	53-1021	first-line super. help, mat. movers	23	0	0	0.5	0
53-1021.01	53-1021	recycling coordinator	23	23	1		

Source: adapted from Vona et al. (2019)

The main takeaway of this section is that the aggregation error becomes easily large because green occupations are small compared to similar occupations even within a 6-digit occupational group. The error of using uniform weights (i.e. simple averages) is obviously magnified in Europe where the level of occupational aggregation is even coarser, thus making any attempt to use O*NET greenness to infer the size of green employment in Europe useless or misleading (Gilli et al., 2020). A first alternative is to use smaller-scale dataset such as the European Working Condition Survey (EWCS), which collects occupational data at 4-digit ISCO, but suffers from small sample sizes⁽²⁴⁾. Probably a better alternative is to use firm-level or matched employer-employee microdata that, for certain countries like the Netherlands, France and Germany, offers granular occupational splits, usually at 4-digit ISCO level, and are more statistically representative than the EWCS survey. However, even in this case, the aggregation bias is likely to be large without some additional, often manual, cleaning. Moreover, there is no real need to measure green employment at the firm level where it is more interesting to explore directly how investments in green technologies and environmental policies affect the workforce composition (i.e. the share of technicians or manual workers) and the distribution of revenues (i.e., the labour share or the wage premium for engineers)⁽²⁵⁾.

4.3 Assessing indirect employment effects

Recall from section 3.2 that O*NET classifies certain occupations as “*Indirect Green Demand*”, but the procedure used is not fully transparent. The issue is very relevant because green industrial policy might create jobs in

²⁴ The survey is maintained by the European Foundation for the Improvement of Living and Working Conditions (Eurofound). For further details: <https://www.eurofound.europa.eu/data/european-working-conditions-survey>.

²⁵ Marin and Vona (2021) examine the effect of energy prices on workforce composition in French manufacturing establishments, also finding a skill-bias in favour of technicians and against manual workers. Elliott et al. (2021) use O*NET-based measures of green employment at the firm level for the Netherlands and explore their correlation with eco-innovation. The aggregation bias is evident in the very large green employment share they obtain in their estimation sample.

industries, regions and occupations not directly affected by the policy. The literature has developed two approaches to estimate indirect job creation that are independent from the task-based approach, but becomes more effective once direct job creation is accurately estimated. Ergo, they become more effective in combination with the task-based approach to measure green employment. This section briefly discusses these approaches.

The key element of the first approach is that job creation and destruction should be evaluated along the entire life-cycle of the technology, combining the unit labour requirement in all stages of production (²⁶). This life-cycle perspective allows to decompose the labour market effects of environmental policies into effects that may offset each other in aggregate. Notably, job losses in downstream polluting sectors, such as power generation, can be offset by jobs created in upstream sectors such as suppliers of clean machinery. To account for complex upstream-downstream linkages, an active strand of policy-oriented papers used Input-Output (IO) models augmented with assessments of the technology-specific labour requirements, e.g. between renewable and fossil-fuel technologies. Technology-specific assessments of the labour requirements are obtained using a combination of real data or on experts' elicitation. For the important case of the low-carbon transition, Wei et al. (2010) conducted a meta-analysis that summarizes the main results of this strand of research. IO models generally find a positive employment effect when clean technologies replace fossil-fuel ones (²⁷). As discussed in Berck and Hoffmann (2002), a further advantage of IO models is to allow simulating the effect of export shocks, for instance, in the natural resource sector or in renewable energy equipment, on the local economy via job multiplier.

Local job multipliers bring us directly to the second approach to estimate indirect effects: to what extent they are spatially localized. The literature on local job multipliers pioneered by Moretti (2010) contributes to the understanding of the geography of indirect effects. Using a shift-share Bartik instrument (Bartik, 1991), this literature estimates the number of non-tradable or IO-linked jobs created by one new tradable job in a certain sector. The question is: what would happen to the rest of the economy if a particular segment of tradable activities experienced a positive demand shock, i.e. a green fiscal push? The size of the local multiplier varies depending on the type of tradable activities that will expand. Using the task-based measure of green employment described in section 3.3, Vona et al. (2019) are able to track how many jobs are created by a new green job in the local labour market. Importantly, the task-based measure allows to precisely identify what is green and thus to estimate indirect effects on what is non-green. The authors show that the green job multiplier is between 2 and 4, thus in the upper range together with high-tech activities, while Black et al. (2005) and Marchand (2012) find much smaller multipliers, often lower than 1, for oil and gas in Canada. Popp et al. (2020) qualify the Vona et al. (2019) results by isolating the policy-driven component of the green job multiplier. The green job multiplier is smaller suggesting that part of the job creation effect was not driven by a policy push, but by the structural characteristics of greener areas.

Similar analyses are difficult to conduct in Europe for the problem mentioned in the previous section regarding the level of data aggregation in the EU labour force survey. However, there are good surrogate strategies: researchers can either perform by-country analysis using richer labour force surveys available at the national level. Even better, several European countries have excellent firm-level and matched employer-employee datasets that can be linked to data on environmental policies (i.e. energy prices or the EU-ETS) or to data on emissions (i.e. CO₂ emissions). As we discuss in the next section, these data can be used to study the green economy using a different, process-based approach.

4.4 Other approaches to identify green employment

What to do when task-based measures of green employment cannot be built due to lack of the appropriate data? In answering this question, recall first that the definition of green tasks used in O*NET is primarily based on the *output definition*, capturing the potential of a product or a service to minimize the harmful impacts of production and consumption on the environment. Therefore, in the absence of information on green tasks, a researcher can simply use a direct proxy of green technologies or productions as done in seminal papers using the US Green Good and Service Surveys (Becker and Shadbegian, 2009; Elliott and Lindely, 2017). This approach is intuitive as it looks directly at the use of green technologies in the workplace to measure green employment. As already said, the share of green jobs is assumed to be equivalent to the share of green production in that sector (Becker and Shadbegian, 2009; Elliott and Lindely, 2017). However, as already discussed, such an approach does not allow to assess which occupations are more exposed to environmental policies or more

²⁶ That is: the upstream construction phase, the selling and marketing phase, the maintenance phase and the recycling and reuse phase.
²⁷ Markandya et al. (2016) use a multi-regional input-output model to estimate the net employment effect of the change in the energy mix in Europe between 1995-2009. According to their estimates, an increase in total employment of 0.24% can be attributed to the increase in the share of gas and renewables in the energy mix.

involved in green productions. Basically, all occupations involved in green production can be considered as green regardless of their direct involvement in green tasks.

In Europe, there are no direct surveys on the greenness of production, but alternatives are available and have been pursued by few recent papers. First, Horbach and Rennings (2013) take this road by using special modules of the Community Innovation Survey (so-called CIS) containing information on the adoption of green process or product innovation at the firm-level. The recent work of Elliott et al. (2021) makes a step forward in this strand of literature by using a task-based approach to differentiate between green and non-green employment. The problem of this survey is that data are self-reported and thus firms may overstate their innovation effort. Second, Gagliardi et al. (2016) use green patents to identify green activities. The wide and comprehensive coverage of green patents allows to apply this approach in all countries where rich firm-level data are available. Here, the problem is that green patents may be filled by firms and sectors (i.e. upstream suppliers of wind turbines) that sometimes do not produce them and very often do not use them (i.e. power generators). However, both the types and the sizes of the job creation effect may be concentrated in these downstream stages rather than where innovative activities occur. Therefore, it is difficult to have a clear understanding of the job creation effect of a green patent. Finally, Bontadini and Vona (2020) show that very detailed EU production data (the so-called PRODCOM⁽²⁸⁾) can be used to study the green economy. In particular, the authors build a list of green products using PRODCOM, starting from the green products discussed at the World Trade Organization to reduce tariffs and promote the diffusion of green technologies globally. This approach permits overcoming some of the problems raised by the use of patents. Indeed, production captures technology adoption and diffusion better than patents. However, the job creation effect in downstream sectors is not accounted for by the green production approach⁽²⁹⁾. Overall, all these technology-based approaches to green labour markets share a common problem as they are able to shed light on a specific part of the green economy only. That is: the small part of the economy devoted to develop green innovation. However, it misses out other, important, creators of green jobs such as waste management, construction and power generation. These missed sectors are also those that will benefit the most from the green spending packages planned by the EU commission (Popp et al., 2020). This is yet another reason to develop datasets inspired by the task-based approach in EU countries.

Another route consists in going back to the *process definition* of what is green (see section 3.1). By assessing the pollution content of certain activities, it is also possible to infer the inverse greenness of the jobs required to carry out these activities. In other words, the inverse greenness of a job is the pollution intensity of that particular job. A researcher can even construct the “process-based” counterpart of green skills by regressing skills over the pollution content of production as in equation (7). In doing so, a researcher can uncover the skills that have a comparative advantage in performing less polluting tasks controlling for firm-level characteristics. Indeed, pollution is usually measured at the firm and not at the occupational level (e.g. Marin and Vona, 2021). As already mentioned in section 3.1, the main problem of this approach is to track pollution over the entire life-cycle of a product, which is difficult to compute given the high fragmentation of production across countries and companies. Sato (2014) explores the engineering literature on product life-cycle and retrieves a measure of the carbon content (direct and indirect) of detailed products, but only for one year and without cross-country variation. Overall, the approach using life-cycle assessment of pollution content at the product level is very far from providing a reliable measure of the inverse greenness of a product line and thus of the jobs needed in such production.

In sum, compared to the problematic SOC-ISCO crosswalk, CIS, patent and PRODCOM data as well as of pollution intensity measures represent interesting alternatives to study green labour markets for EU countries. Unless a researcher has ISCO occupational data at a granular level of aggregation so that the crosswalk delivers accurate greenness measures, it may be better to use such alternatives rather than an imprecise task-based measure. However, these direct approaches remain a second-best with respect to the task-based approach, especially to assess and to monitor the effects of green fiscal push affecting non-innovative sectors, such as construction and waste management.

4.5 Data projects with long-term impacts.

Several ongoing data projects are trying to overcome the difficulties in measuring green tasks and skills in European countries. Prestigious institutions are involved in long-term data projects on green labour, including

²⁸ PRODCOM is available since 1995 for manufacturing at the 4-digit sectoral level and for all EU countries. An entry point to start exploring the PRODCOM dataset is: <https://ec.europa.eu/eurostat/web/prodcom/data/database>.

²⁹ An interesting extension of this work would consist in using the PRODCOM data to assess the job multiplier effects of green production for the rest of the economy following the approach of Moretti (2010). The job multiplier effects can be further investigated at the occupational or task level using more detailed data from national labour force surveys. For instance, German and Italian data allow a fully-fledged task-based analysis at the provincial level.

the European Centre for the Development of Vocational Training (Cedefop), the European Commission with the innovative ESCO project (European Skills, Competences, Qualifications and Occupations) and the Organization for Economic Co-operation and Development (OECD). All these organizations have extensive expertise in measuring skills⁽³⁰⁾. Finally, some countries have developed specific projects to classify and identify green occupations that are similar in spirit to that of the Bureau of Labor Statistics in the US. For instance, two classifications of green occupations are provided by the French National Observatory for Jobs and Occupations of the Green Economy (Onemev) and the German Federal Agency for Labour. However, these lists of occupations suffer from the “binary definition problem” described for O*NET in sections 3.2 and 3.3⁽³¹⁾. As it was clear from these sections, the real frontier of data development is to use a more granular, task-based definition of occupational greenness.

Concerning the OECD data, some waves of the PISA project included additional questions to assess the environmental awareness of adolescents. These are interesting data to explore as they capture another essential dimension of the green transition that is associated with changes in individual behaviours, attitudes and values (also called soft skills). This dimension is, for instance, very important to issues related to the circular economy, household impacts and recycling behaviour as well as to prevent rebound effects of energy efficiency programs. In one of the rare analyses using these data, List et al. (2020) show that green awareness at 15 is correlated with science-related competences, thus with some of the skills that were considered green using the task-based approach. As briefly discussed in section 2, the mainstream task approach overlooks the organizational aspects of production that can be very relevant for the study of the green transition and its impact on labour markets. Recent research proposes different conceptual taxonomies of tasks that accounts for organizational and social aspects of work with recent applications to automation and AI (e.g., Bisello et al., 2019; Fernández-Macías et al., 2021; Fernández-Macías and Bisello, 2021). However, there is so far no research using the task approach to understand how the organization of work changes in greener companies.

Going back to the OECD data, the PIAAC project provides standard human capital measures for a representative sample of workers in OECD countries, including training and educational requirements, problem-solving, physical, linguistic and social skills. The main problem of PIAAC is that the occupational and sectoral dimensions are not granular enough to identify green jobs, or link the data with green production data. The OECD Centre for Skills has also developed an O*NET-type dataset on skill needs, combining secondary data sources to obtain skill measures equivalent to the O*NET ones. Data are available at the sectoral and regional levels, but momentarily only for a cross-section (2015). Because the skill constructs are the same as the O*NET ones, the green skills identified in Vona et al. (2018) are available in this OECD dataset and can be used to conduct descriptive analyses across countries. However, no work so far has been done to develop new and original datasets with direct measures of green skills for each country and sector.

Cedefop has built several useful datasets on skills and educational requirements. Cedefop is also a leading actor in the study of how labour markets adapt to the green transition. It has conducted influential case studies, supported by descriptive statistical evidence, on green skills and the Vocational and Educational Training to fill potential skill mismatches in green jobs and sectors (Cedefop, 2010, 2019; ILO-Cedefop, 2011). Working in close proximity with local training providers and social actors, Cedefop is in an ideal position to act as the leading actor to monitor green skill development and start ambitious data project at the EU level, especially to track how the supply side of education and training needs to adapt to favour the diffusion of green technologies. In terms of existing data, Cedefop has developed an influential survey on skill forecast combining existing datasets, institutional reports and expert judgements. Another innovative project is the so-called real-time labour market information on skill requirements that exploit the rich text of online job vacancies to extract skill and task requirements.

The European Commission, with the support of Cedefop, is also undertaking a large-scale effort to build a European O*NET, the so-called ESCO, with again an active involvement of several actors to reach a pan-European definition of the task and skill content of occupations⁽³²⁾. One of the main goals of ESCO is to remove linguistic frictions preventing workers’ mobility across EU members as well as creating harmonized job titles

³⁰ The OECD has developed and manages the two largest cross-country projects to measure general skills for students (the so-called Program for International Student Assessment, PISA) and the adults (the so-called Programme for International Assessment of Adult Competences, PIAAC). Please see the devoted pages for further information: and <https://www.oecd.org/skills/piaac/>, <https://www.oecd.org/pisa/> and <https://www.oecd.org/skills/piaac/>.

³¹ To illustrate the problem, in the French classification of green jobs all engineers in the energy sector are considered as fully green. See https://www.ecologie.gouv.fr/sites/default/files/Onemev_emploi_metiers_PCS.pdf

³² These actors are representatives from social partners, employment services, employers, professional associations, sector skills councils, education and training institutes and statistical offices as well as experts in employment and education, related standards and classifications. See the ESCO website for more information: <https://ec.europa.eu/esco/portal/home>.

across European countries. However, there is also a plan to create a supplement of the dataset devoted to green jobs and skills. In doing so, it is essential to establish a common and widely recognized definition of green tasks and jobs, overcoming the existing differences across EU countries that developed their own definitions of green jobs. In light of this survey and given the ambiguity in the green job definitions, looking at a definition of green tasks appears far more promising than merely classifying certain jobs as green. The fact of starting from scratch in this endeavor can be an advantage, possibly building upon the insights of this report.

One problem of both the ESCO and Cedefop methodologies to construct occupational skills is that it is not very clear how the data are collected and aggregated. Because skill and task information are obtained from heterogeneous sources (job vacancies, experts, stakeholders, reports, existing datasets, scientific articles, etc.), it would be very useful to release the exact procedures, sampling and weighting schemes through which all these sources are aggregated. A virtuous example is given by the OECD indicators of product market regulation and environmental policy stringency. Otherwise, the lack of transparency will make it difficult to use these data for research purposes and decreases their reliability for monitoring the evolution of green jobs and skills in Europe. Moreover, the ESCO skill measures are invariant across countries, sectors and time, hence excluding one of the most interesting sources of data variation—the within-occupation changes in tasks and skills—to study effects of environmental policies and monitor differences in skill development policies. Also, access to the ESCO data is not as intuitive and easy as for the OECD datasets or O*NET, making it difficult to assess its best uses. Finally, the ESCO and Cedefop projects are subject to the main constraint of the EU LFS data, which are too coarse in terms of sectoral and occupational breakdown. Were the best measure of occupational greenness and skills available for Europe, it would be anyway impossible to build credible measure of the evolution of green employment across EU regions.

In light of these limitations, the most promising data projects to date remain those of specialized companies scraping and processing job vacancy data. Burning Glass Technologies (BG) is the main player in the field of data-intensive measures of skills based on job vacancies and a close collaborator of Cedefop. The data cover nearly the universe of online job vacancies for the US since 2010, while, for the EU, the data collection process started later and momentarily cover only a few (3/4) years. Interestingly, BG data are organized using the O*NET task and skill classification. However, they present some key features that make them preferable even to O*NET, as recently shown in influential labour economics research (Hershbein and Kahn, 2018; Deming and Kahn, 2018; Azar et al., 2020; Deming and Noray, 2020). The first advantage of BG data is allowing for very precise within-occupation differences in the skill content. That is: two job ads belonging to the same occupation can be compared in terms of skill content. This aspect is crucial to understand to what extent green and non-green job ads are different within a narrow occupation. The second advantage is improving the precision in measuring skill differences across regions and time. In particular, job ad data allow occupational greenness to vary across regions, states and countries. For instance, California may have a larger share of construction workers involved in building retrofitting than another U.S. state, thus a constant greenness across states would underestimate the size of green employment in California. Saussay et al. (2021) use these data to extend the analyses of Vona et al. (2018) focusing on climate-friendly green jobs. Using natural language processing techniques as in Atalay et al. (2020), the authors identify the climate-friendly green job vacancies and then a set of occupation-specific green skills. Note that this is a remarkable improvement with respect to Vona et al. (2018), who were able to identify a general set of green skills that were not occupation-specific.

Overall, several exciting data projects are on track to significantly improve our understanding of the impact of the green transformations on labour markets. Job vacancy data are certainly the most promising avenue among those explored by several institutions and private organizations. The development of such data outside the US would permit assessing also cross-country, within-occupation differences in the skills that are required by green productions and technologies. However, job vacancy data are not representative of the entire working population and tend to over-report job vacancies in high-skilled occupations. Therefore, it remains essential that official statistical offices provide occupational data at a highly granular level of disaggregation to adjust for the lack of representativeness.

To fix the main points, Table 6 summarizes the conclusions of the assessment of methodology and the data that can be used to study the greening of labour markets. It can be seen as a sort of brief practitioner's guide for doing research and monitor the progress of the green economy and the labour market impacts of environmental policies.

Table 6. Summary, practical guidelines to conduct research in green labour markets

Measuring green jobs	pros	cons	suggestions for EU analyses
1. binary definition	Available in several countries	Very imprecise definition of green job. Not coherent across countries	Not very promising, unless for specific sectors such as renewable energy
2. task-based greenness	Very precise, allow to identify green skills and thus policy for reskilling	Data available only for the US with O*NET, but cross-walks possible	It is the conceptual benchmark. Crosswalk SOC-ISCO problematic
3. green job vacancy	As task-based (2), additional pro: greenness varies within occupation, by companies and regions	Data availability still limited for EU countries. Need to agree on a precise list of green keywords to identify green job post	Very promising, but underrepresentation of low-skilled occupations, still need good employment data
4. information on green tech and productions	Important to study green comparative advantage and frontier technologies	No ideal measure. Limited to manufacturing and a few sectors	Very promising for specific analyses when combined with firm-level data
5. pollution content of jobs	Effective greenness of an occupation, at least for a specific environmental dimension (e.g. carbon content)	Very difficult to track the carbon content of production along the whole life-cycle	Very promising for specific studies when combined with firm-level data with information on pollution
Employment data	pros	cons	suggestions for EU analyses
US Bureau of Labor Statistics, Occupational Employment Statistics	Very detailed occupation-by-industry or occupation-by-region data	None	Not EU data
EU Labour Force Survey (LFS)	Available for all EU countries, so it can be used for cross-country comparisons	Very coarse occupation-by-industry details. Impossible to capture "small" green occupations	Not promising: more granular data should be provided by Eurostat
Nation-level Labour Force Surveys	More detailed occupation-by-industry or occupation-by-region data compared to the EU-LFS	No definition of occupational greenness, use crosswalk ISCO-SOC to import O*NET greenness	Very promising, especially if joint effort in several countries
Matched employer-employee data, firm-level data	Often detailed occupational classifications; observe green technology usage or pollution at the firm-level	No definition of occupational greenness. Using crosswalk ISCO-SOC to import O*NET greenness with adjustments	Very promising, but depending on the quality of firm-level data especially on information on pollution and occupations

Source: author's own elaboration

5 Conclusions and Policy Recommendations

This report offers a practical guide on how to use the task-based approach to study and monitor the evolution of green jobs and skills. It sheds light on the key advantages of this approach using studies conducted with US data, especially the US Occupational Information Network, O*NET. First and foremost, it shows that a task-based measure of green employment allows to conceptually disambiguate some of the problems associated with defining green occupations. More specifically, rather than using a coarse and imprecise binary measure of green occupation, the concept of occupational greenness is based on the share of green tasks (or job posts) that are green within an occupation, thus it is continuous and allows occupations to have different shadows of involvement into green activities. Using occupational greenness to estimate the share of green employment improves dramatically the reliability of the estimates departing from rosier, but unrealistic, accounts of the size of the green economy. The increase in the reliability is tested against survey data on green production and it is probably the most important achievement of the task approach, particularly, to monitor the effect of the large green stimulus package planned by the European Commission.

Second, the task-based approach is extremely flexible, meaning that it can be used in several interesting applications. This report focuses on the identification of green skills, which can be empirically derived from a simplified version of the task model. In particular, green skills can be retrieved by estimating revealed comparative advantage schedules. Importantly, the demand for green skills that are identified through the task-based approach (i.e. mainly technical and engineering skills) positively responds to changes in environmental policy stringency. This result further corroborates the approach proposed for identifying green skills, as it provides another external validation of the reliability of the task-based approach using O*NET data.

Third, the report showcases applications of the task-based approach to the study of equity and efficiency effects of environmental policies. The key concept here is that of reallocation costs that is captured by the powerful measurement tool of “skill proximity” measures, which is again conceptually addressed using the task-based approach. This indicator of proximity allows to assess the employment prospects of workers displaced by environmental policies in polluting sectors, tackling a key aspect of the distributional effects of such policies. However, and possibly due to the limited number of studies published so far, the application of the task-based approach to distributional effects opens up even more questions than it answers. Further research is thus required to assess distributional effects of environmental policies, possibly using matched employer-employee data (which help in reducing biases due to sorting). This is a natural application of the task-based model that has been developed to study the distributional effects of information and communication technologies in several influential papers (e.g., Autor et al., 2003; Acemoglu and Autor, 2011).

Fourth, the second part of this report discusses the key data limitations for empirical analyses in EU countries. One main recommendation of our data assessment is that European countries should accelerate their joint effort to build a common statistical framework to measure green jobs and tasks. Some countries already developed task-based surveys (e.g., Germany and Italy), but they are not directly aiming at capturing green tasks. Other countries have rich occupation-level data that can be used to impute O*NET-based measures through cross-walking (France and Netherlands). Further, some efforts have been made to provide lists of green occupations (e.g. France and Germany), which is, however, binary and thus suffers from the limitations discussed in the conceptual part of the survey. In the future, the ISCO occupational classifications will change to make more space for unquestionably green jobs, such as those related to renewable energies, making it easier to monitor the greening of labour markets. However, no European country has so far developed a task-based definition of green employment, by clearly identifying a set of green tasks. This additional effort is of paramount importance in light of the results obtained for the US. To insist on one of the main points of this report, a binary measure of green jobs does not suffice to monitor the evolution of the part of employment that is truly devoted to reduce harmful environmental impacts and, at the same time, reflects the structural transformations induced by environmental policies on the labour markets.

The ESCO dataset is a suitable and promising tool to build such a measure for all EU countries, but it seems that ESCO is planning to adopt a binary rather than a task-based definition of what is green. Moreover, ESCO should provide more transparent information on the data collection and aggregation process in order to make these data appealing for research purposes. The priority is opening the black box of how different data sources in ESCO are aggregated, including experts, stakeholders, union and industry representatives, etc.

For future research, the general trend towards the use of job vacancy data will help overcome some of the limitations discussed in this survey. However, the use of job vacancy data should also be disciplined through the building of common and widely accepted definitions of a green job vacancy. Indeed, while the use of job posting data is very promising and cost-saving, the methodology and the definitions should be transparent as

well. For instance, Burning Glass Technologies introduced a clear methodology to map the rich text of a job ad into a vector of skills and tasks inspired by the O*NET classification. Similar efforts should be put by other institutions that plan to develop job posting measures of green jobs and skills. An early attempt in this direction is made by Saussay et al. (2021), but the methodology used to identify green job ads in this paper represents only one possibility. Researchers and policy-makers should discuss and possibly agree on a common set of definitions and standards for these very rich data.

Another important point on data collection effort concerns the evolution of the supply side of labour markets, namely the changes in the education and training programs to adapt or even anticipate the evolution of green technologies. Institutions such as Cedefop and the OECD have already conducted excellent studies in this direction. However, there is a clear gap in the data space. In particular, there is no systematic assessment of the supply of green educational and training programs, nor of the actors involved in such training. Obviously, the expertise of Cedefop is essential to conduct such assessment, filtering false positives or discharging low-quality programs. A survey on green training and educational programs can also be the occasion to develop a European green certification scheme for training and educational programs. Mapping the supply of education together with the demand for green jobs, e.g., using job vacancy data, will allow enhancing our understanding of how labour markets adapt to the large structural transformations that will be accelerated by the ambitious decarbonization objectives of the European Commission.

Finally, the involvement of different social actors is highly beneficial to sustain a coordinated effort towards a monitoring system of green labour markets at the European level. However, data on green skills and tasks should be developed using independent statistical agencies, mobilizing experts and conducting surveys on incumbent workers as for O*NET. The direct involvement of social parties, such as industrial and labour associations, is likely to be a problem rather than an advantage for data development. When social parties are involved, conflicts of interest may emerge preventing the establishment of clear and rigorous definitions of a green activity or task. The failure of the negotiations at the WTO for a common list of green products is a classic example of the difficulties related to political negotiations aimed at defining a common framework to measure the green economy. Another example is the blurred concept of green jobs proposed by the International Labor Organization, which includes job dimensions unrelated to environmental problems, such as job stability and the pay scale. The involvement of social parties is of paramount importance for the success of the green transition by creating broad political constituencies, but it may be counterproductive when the issue is to develop a new dataset to monitor the greening of labour markets in Europe.

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