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Why Look at Tasks When Designing Skills Policy for the Green Transition?

A Methodological Note on How to Identify Green Occupations and the Skills They Require

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Abstract

The coexistence of several definitions of green jobs and measurement instruments gives room for mismatches between those concepts and their application to research questions. This paper first presents an organizing framework for the existing definitions, measurement instruments, and policy frameworks. It then delves into discussing two appropriate approaches for identifying green occupations to guide skills development policy: the task-content and the skills approaches. In the process, it introduces a novel methodology with a dictionary of green terms for identifying green tasks and occupations. This methodology, utilizing text analysis, demonstrates superior performance compared to the well-known O*NET Green Economic Project classification, particularly for developing countries. Lastly, the paper applies this methodology to Indonesia, a middle-income country, and utilizes various data sources to showcase the utility of the dictionary and text analysis exercise.

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Why Look at Tasks When Designing Skills Policy for the Green Transition?

A Methodological Note on How to Identify Green Occupations and the Skills They Require

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1. Motivation

The greening of the economy, like other mega-trends, is changing the world of work. Identifying the occupations that will be in demand in the green economy—often simply referred to as green jobs or green occupations—and the skills they require is paramount to supporting and enabling an environmentally sustainable planet while contributing to economic development. New industries that produce environmentally friendly goods and services for intermediate or final consumption are emerging. Moreover, the greening of the economy requires highly polluting industries not necessarily to disappear, but to transform by implementing different technologies to become more sustainable. This economic transformation is impacting occupations to varying degrees, and it becomes critical to identify which ones are changing and what skills they require to make the green transformation possible.

Despite the importance of having a common definition of green jobs to be used by researchers and policy makers, there is currently no consensus on a single concept yet, let alone how to identify them in practice. On the one hand, there is agreement that green jobs aim to reduce environmental impact by both producing environmentally friendly outputs and promoting environmentally friendly production processes. On the other hand, the scope of what green jobs should encompass varies. For some, a definition of green jobs should include all jobs that are somehow associated with the greening of the economy, regardless of whether the job itself contributes to reducing the impact on the environment. Supporters of this view include all environmentally neutral jobs, that is, jobs that do not harm the environment even if they do not help to preserve it. Others include what is usually referred to as "greening jobs" or jobs for a greener economy or indirect green jobs. These are jobs that do not directly contribute to preserving the environment but might be in-demand as part of the green transformation. Lastly, some institutions like the ILO add the "decent job" layer to the definition: a green job not only needs not to damage the environment, but it also needs to pay adequate wages and provide worker protection.

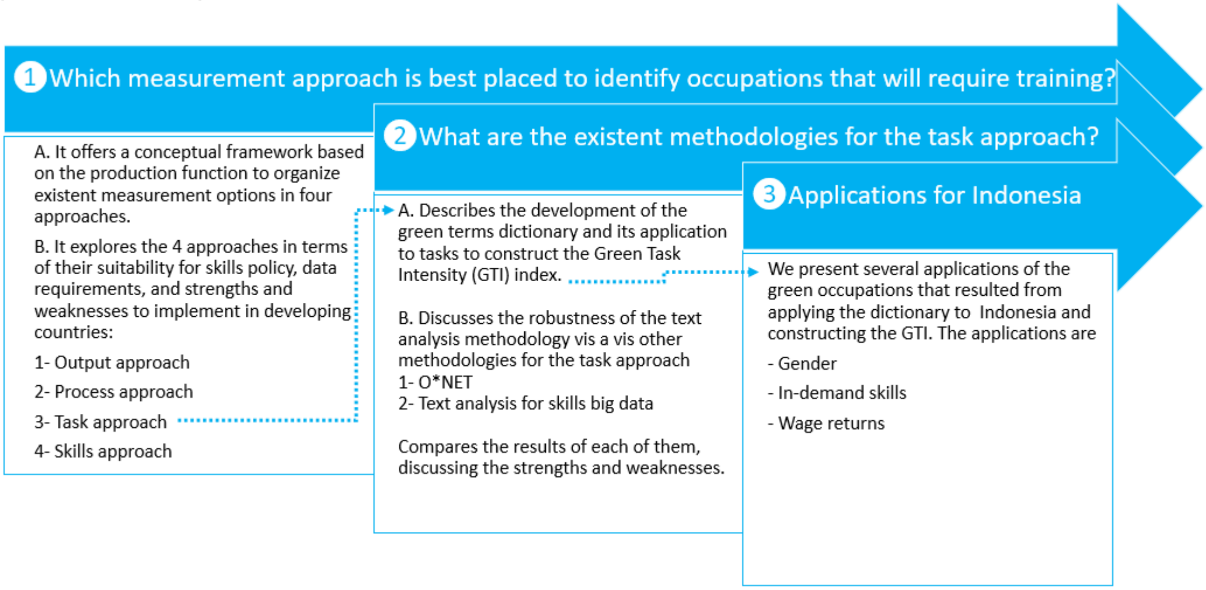
The lack of convergence stems from the unfeasibility of translating the concepts into a single measurement methodology that suits existing data (or cost-effective, collectible new data) and different policy questions. Many policy makers prioritize supporting workers moving out from brown jobs to other green jobs. Researchers instead have a broader set of questions, for which they use different definitions and deploy very different specialized surveys. These surveys are usually a good tool for specific questions at hand, but generalizing their use to other policy questions creates important biases.

As a single definition may not be possible—or even desirable—in view of the multiple policy questions, this paper seeks to identify which occupations and skills should be the focus of skills development policies needed to support the greening of the economy. Put simply, it aims to identify which occupations may require new skills training to support the green economy. With this objective in mind, this paper shows that green jobs should be understood as those that have specific tasks assigned to lessen consumers' and/or firms' environmental impact. These green tasks can either be assigned with the goal of producing greener outputs or of reducing the firm's environmental footprint. The proposed methodological approach helps to identify the skills that will be needed to carry out such tasks. Some of these jobs will require core skills, some of which will be transversal, while others would be specific technical green skills. This paper leaves out of consideration those indirect or neutral jobs, as it is assumed that advanced labor market information systems would provide the signals to the workforce of which jobs are in demand and hence worth pursuing. This paper also excludes the worker's protection layer from the definition since it is not the main objective of the skills policy, and it is addressed by another set of policy instruments.

This note contributes to the understanding of skills policy in the context of the green transition as follows. Section 2 presents a conceptual framework to identify green jobs, departing from the state-of-the-art definition of the production function and resulting in four measurement approaches. Then, it discusses their suitability for skills policy along with their data requirements and limitations when applied in advanced and developing countries, becoming a reference point in the literature. Section 3 discusses the methodologies that can be used to identify green occupations under the task approach and introduces one based on text analysis. Specifically, the proposed methodology constructs a dictionary of green terms and applies text analysis to an occupational database containing task statements with the objective of measuring the green task intensity of occupations. This section also discusses the strengths and weaknesses of the methodology vis-à-vis relying on the O*NET Green Economy Program, a well-recognized list of green occupations in the U.S. Finally, section 4 presents analytic applications of the green occupation taxonomy obtained to the case of Indonesia to illustrate the potential of the proposed methodology. More specifically, it describes selected green occupations' characteristics: gender, education, in-demand skills, and wage premium. Figure 1 visually summarizes the organization of this note.

The intended audience of this paper is analysts and policy makers working on skills policy around the world. The proposed definition and measurement methodology can be deployed in any country that relies on ISCO-08 or any other country that uses an occupational classification system containing task statements. We are making available to the community of analysts a toolkit that includes: (i) a readme file; (ii) the dictionary of green terms, which can be easily modified to reflect the country's green economic development; (iii) the STATA do files that classify green tasks and create the green task intensity index for each occupation – with minor modifications, this do-file can be applied to any occupational database with task statements; and (iv) an excel file with the classification of all task statements in ISCO-08 into green, green potential, and non-green, as well as all 4-digit occupations with their respective green task intensity index. The recommendation to analysts is to directly use the excel with the classification if working with a database of occupations that uses ISCO-08 at the 4-digit level. However, if using an occupational database with task statements at a more disaggregated level, running the toolkit to get a more accurate description of the occupation is preferred.

Figure 1. Visual organization of the note



2. Green jobs and methodologies to measure them

A. A conceptual framework to understand how to align measurement with policy questions

Green jobs are being widely discussed in academic literature and among policy makers. Although there is no consensus yet on a definition or on how to measure them, it is widely agreed that green jobs aim to reduce negative environmental impact by both producing environmentally friendly outputs (goods and services) and promoting environmentally friendly production processes. The term 'environmentally friendly' is usually applied and denotes reducing and limiting energy and raw materials consumption, greenhouse gas (GHG) emissions, waste and pollution, protecting and restoring ecosystems, and enabling adaptation to climate change.[4] The scope of the definitions also varies. For example, some envision that all jobs will eventually be green and therefore use definitions that encompass jobs with zero environmental footprint—that is, jobs that neither pollute nor have a negative impact on the environment—and/or jobs that are in demand due to the greening of the economy, even if the job itself does not directly contribute to reducing environmental impact.[5] Others, however, aim for more focused definitions that specifically include jobs that directly contribute to reducing the environmental footprint. This paper follows the latter approach with the objective of advising governments on priority areas.[6]

[4] Vidican Auktor (2020), ILO (2016), ILO (2019), Eurostat (2009), and BLS (n.d.). Gregg, C.; Strietska-Ilina, O.; Büdke, C. (2015). Appendix A contains each institution's definition.

[5] See Ruppert Bulmer et al. (2022) and Stoveska (2017).

[6] It should be noted that countries are endorsing to ILO's definition of green jobs. For example, ASEAN countries and ILO have agreed on a series of recommendations to promote green jobs (ASEAN and ILO 2021), starting by having ASEAN Member States to work together to agree on common and workable definition of green jobs, using a

From here on, the term 'green' is used to indicate the proposed definition of jobs, and more broadly, to refer to output, technologies, tasks, or skills that contribute to reducing environmental impact. In the subsections that describe a specific measurement approach, 'green' will refer to the specific definition of that subsection.

Accurately identifying green jobs is challenging since a green job involves two different dimensions: the firm and the worker. The firm and worker dimensions complement each other, and both contribute to making a job green. These dimensions sometimes, but not always, overlap.

The *firm-level dimension* relates to the **output** (goods or services) that the job contributes to producing, and the **technologies** applied to do so. The firm's environmental footprint naturally relates to the outputs produced. At one end, firms with a negative environmental footprint produce highly polluting or high carbon-intensive outputs (e.g., coal). At the other end, firms with a positive environmental footprint produce environmentally friendly outputs (here on green outputs or environmental goods and services, EGS) (e.g., solar panels). Green outputs include those that may have carbon-intensive production processes but still contribute to the greening of the economy (e.g., a firm manufacturing electric cars). In the middle, there might be firms that have a neutral environmental footprint, with zero or low carbon-intensive outputs (e.g., a leasing firm). In addition to the firm's output, the job may be performed at a firm that intentionally utilizes technologies[7] to reduce its own environmental footprint. These are usually referred to as green or environmental technologies. The adoption of green technologies could be triggered by different objectives: increasing profits, compliance with regulations, social responsibility, accessing new market opportunities, or raising consumer awareness on climate change issues (e.g., a paperless office or a firm reducing hazardous waste in the environment).

The *worker-level dimension*, instead, relates to the **task-content** of the job and the **skill requirements** to perform it well. Following Acemoglu and Autor (2011), "[…] *a task is a unit of work activity that produces an output. In contrast, a skill is a worker's endowment of capabilities for performing various tasks. Workers apply their skill endowments to tasks in exchange for wages, and skills applied to tasks produce output."* The technological feasibility and the economic cost ultimate determine the combination of capital and skills into tasks that will produce output. This dimension considers whether the job entails carrying out specific tasks that aim to lessen the environmental impact either by contributing to the production of green products and services, or by reducing the firm's environmental footprint. It also examines the skills required and whether they involve specific knowledge or abilities related to the environment.

Figure 2. Approaches to measure green jobs in terms of their relationship with the production function.

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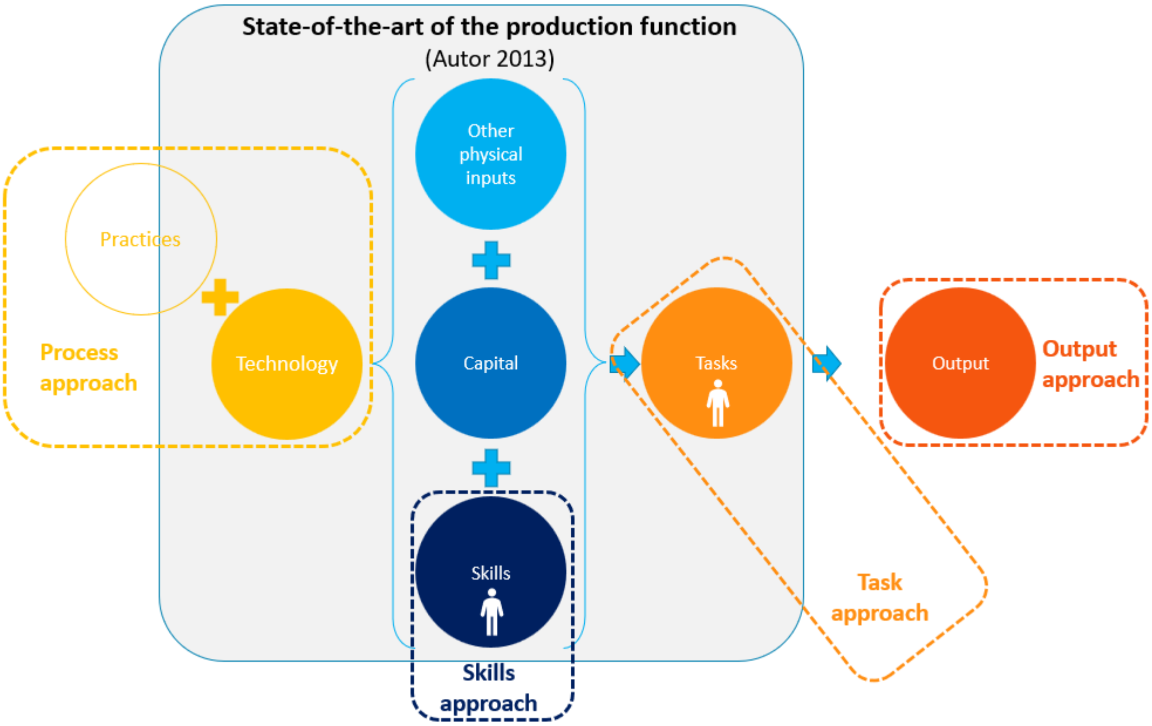
spectrum approach to identify core green, indirectly green, and non-green occupations across different sectors and geographies. This paper proposes a narrower definition that comes close to what ILO and ASEAN refer as core green occupations. It is consistent with the range of activities that ILO considers as green jobs (see Figure 1 of ASEAN and ILO 2021).

[7] Eurostat (2009) defines technologies as technical processes, installations and equipment, and methods or knowledge, the nature or purpose of which is environmentally friendly.



Notes: the visualization represents the production function as described in Autor (2013), where the output Y has a production function such as $Y = \left[\int_0^1 y(i)^{\frac{\eta-1}{\eta}} di\right]^{\frac{\eta}{\eta-1}}$, where $y(i)$ is the production level of task $i$and $\eta$is the elasticity of substitution across tasks. For simplicity, the Autor assumes there are three types of skill levels (but the production function could be generalized to n varieties of skills), each of which when combined with capital produce the task that will generate output. The task production function can be represented as $y(i) = A_L\alpha_L(i)l(i) + A_M\alpha_M(i)m(i) + A_H\alpha_H(i)h(i) + A_K\alpha_K(i)k(i)$ where A is the factor-augmenting technology, $\alpha_{L,M,H}(i)$ are the factor productivity schedules for skills low, medium and high, $l(i)$ is the number of low skill worker units dedicated to produce task i, and $k(i)$ is the number of physical capital units dedicated to produce task i. Distinct from the canonical model, however, a factor-augmenting technological change need not increase the wages of all factors in this setup. Hence, the greening of the economy can influence the technology used, the physical capital, the skills, altering tasks and/or outputs.

There are efforts to measure each of the mentioned dimensions. These efforts can be grouped into four approaches, according to the role they play in the production function, as visualized in Figure 2.[8] One of the reasons likely influencing the lack of agreement on a definition of green jobs is that each approach matters to a different extent depending on the research or policy question. The objective of this paper is to inform skills policy and hence, for this purpose, a green job is one which has specific tasks assigned to lessen consumers' and/or firms' environmental impact. These green tasks can either be assigned with the goal of producing greener outputs or of reducing the firm's environmental footprint. They help to reduce and limit energy and raw materials consumption, greenhouse gas emissions, and waste and pollution, or they protect and restore ecosystems, or enable adaptation to climate change. A green job involves specific green tasks and can be at any firm regardless of its economic activity, including at firms with a negative environmental footprint (e.g., a water treatment specialist at a coal mine). And the level

[8] See Autor (2013) for a full discussion of the task approach and the state-of-the-art representation of the production function.

of greenness of a job can vary depending on the importance of green tasks. Not all jobs in a firm producing a green output are green jobs involving green tasks.

Some examples help to better understand the multiple dimensions and how they relate to classifying a job as green or non-green, depending on the question at hand. First, there are jobs that, given green technologies established at the firm, may require workers to perform certain green practices that are not essential to successfully producing the outputs for which the job was created. This is the case of an office worker contributing to a paperless office or a supermarket cashier offering paper bags instead of plastic bags. These types of green practices may require workers to have some environmental awareness or green-citizen skills.[9] However, such practices are not tasks since they are not essential to the production of the output for which the job was created. Thus, this paper[10] does not consider as green those jobs that involve only these types of practices; they do not involve green tasks. Second, there are jobs that are created due to the greening[11] of the economy, but whose task-content is not green. This is the case of a team assistant in a solar power factory. Third, and slightly similarly to the previous case, there are jobs that are performed at firms that have adopted green technologies, but the technology does not alter tasks. This could be the case of a driver of an electric car. These are usually referenced in the literature as *indirect green jobs* or *green increased-demand occupations,* but for this note's definition, these are not green jobs. These cases are still relevant for other policy purposes though, as further explained in the next subsection.

B. Measurement approaches and their suitability for skills policy

This section describes the four approaches introduced above, looking into what they measure, the challenges of each of them during data collection or the application of the methodology, especially in developing countries, and how each of them contributes to informing skills policy, which is the reason for developing this paper. It also presents international examples of how they have been applied, with more details for the task approach since it is found to be the most suitable for informing skills policy.

The output approach

The **output approach** estimates the number of workers employed in firms producing environmentally friendly goods and services. These firms are likely to operate in the environmental goods and services sectors (EGSS). The OECD and Eurostat have laid out the foundation for data collection and analysis of the EGSS.[12] Identifying green jobs or occupations through this approach could be quite straightforward: when the firm produces only green outputs in the EGSS, all employees are considered to be performing

[9] What the ILO (2021) understands as 'Basic skills necessary for adapting oneself to related environmental regulation and requirements to curb climate change.'
[10] For this paper, from section 3 onwards, green jobs will be those with green tasks.
[11] Greening of the economy means the production of greener outputs (products and services) and the use of greener technologies.
[12] See OECD and Eurostat (1999), and Eurostat (2009). The OECD and Eurostat have been pioneers and have developed a handbook to determine environmentally friendly goods and services. The handbook has guided the efforts of other institutions and the development of survey instruments like the Green Goods and Services Survey of the BLS.

green jobs. The most reliable and common data source to estimate the number of jobs is specific firm surveys.[13]

Despite its simplicity, the output approach comes with several important shortcomings. First, specialized data is needed to classify goods and services as green or environmentally friendly. There are several working definitions. Some researchers use estimates of CO2 emissions;[14] others, like the Bureau of Labor Statistics (BLS), collect specialized data for that purpose.[15] Once this is known, a second challenge arises as firms might produce both green and non-green goods and services. In these cases, if there is a rich firm survey with detailed input and output variables, assumptions can be made about the proportion of labor utilized for green outputs. For example, that proportion could be estimated by the percentage of working time or wages spent on the production of green outputs, or the share of revenues coming from green outputs.[16, 17] When output data is not available, then granular industry information about the main activity of the firm can be used to approximate it. This implies further assumptions to assign a category or a share of green outputs to each industry code.

Applying the output approach in developing countries can pose additional challenges. Usually, developing countries do not have detailed data to classify locally produced goods and services as environmentally friendly or not. Measurement of CO2 emissions is not widespread[18] and conducting specific surveys mapping industry to occupation, such as the BLS GGS, might be unaffordable and not exempt from its own challenges. Consequently, most analysts appeal to relying on classifications of EGS and EGSS from other countries and estimate emissions based on the industry and input-output data. In the first case, the analyst must assume that the technology of production of goods and services is similar in both countries and will need a detailed mapping from EGS to the industrial classifications, both in the country used as reference and in the country of its application. Such mappings are not usually available in all countries, which means that further assumptions are needed regarding the shares of green and non-green outputs for each industry code, and across country-specific industrial classifications.[19]

The output approach is useful for understanding the implications of structural transformation on sectoral employment, as well as the linkages between green industrial policy,[20] green stimulus packages, and employment growth. For example, Bontadini and Vona (2021) are interested in understanding the comparative advantage of green production as a way to reconcile economic growth with environmental preservation and the mitigation of climate change-related risks. The authors find that green production is highly concentrated in a set of high-tech industries producing capital goods, while polluting and green

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[13] Eurostat (2009).

[14] For example, the UK uses multiple data sources including satellite images. For more information consult the UK Office for National Statistics at https://www.ons.gov.uk/economy/environmentalaccounts/bulletins/ukenvironmentalaccounts/2023#measuring-the-data.

[15] BLS (2013a).

[16] Eurostat data collection handbook (2009) proposes various ways to adjust the estimate.

[17] Winkler et al. (2022) forthcoming.

[18] Countries report their emissions through what is known as a 'bottom up' approach, where national emissions are estimated by combining data on types of activity with the emissions typically produced by those activities.

[19] The implications of these assumptions are further explored for the task approach.

[20] Including policies related to trade on green outputs and services.

production occur in two separate sets of industries that are only related through intra-industry linkages such as the purchase of capital assets. These findings have implications for taxing polluting agencies and subsidizing green outputs.

However, the output approach is less useful for informing skills policy. On the one hand, it leaves out jobs in firms that produce non-green outputs but implement green technologies. For example, a leather manufacturing firm may implement technologies to clean wastewater and may employ workers in charge of this process. On the other hand, it includes all jobs regardless of whether they involve green tasks. For example, it would include the receptionist at a firm producing a filter to purify air. This issue cannot be solved by just restricting the count to production workers since not every worker involved in the production of a green output will perform green tasks or require green skills. For example, while an engineer designing an electric car may require energy efficiency knowledge, most assemblers of such cars may perform the same tasks as assemblers of gas-powered cars.

Moreover, to inform skills policy it is crucial to profile occupations, which reveals an additional limitation of the output approach for this policy objective. Most notably, surveys that are designed to measure green jobs based on their output (or the data that aligns well with this approach) do not collect or link occupational data. Occupational data is necessary to understand the task content and skills requirements of such jobs.[21] In the best-case scenario, analysts would need to work with multiple surveys or databases to adequately inform skills policy.

The U.S., Canada, and the E.U. have good applications of the output approach. In 2011, the U.S. Bureau of Labor Statistics conducted the Green Goods and Services (GGS) survey.[22] The GGS survey was a firm-level survey on a sample of 120,000 establishments in industries identified as potentially producing green outputs—333 industries out of 1,200 detailed at the six-digit American Industrial Classification System (NAICS). The selected industries represent 23 percent of all establishments and 20 percent of employment in the U.S. economy. Specifically, the GGS survey asks establishments for the percentage of revenues (or, for firms that do not generate revenue, the percentage of employment) deriving from green outputs according to the BLS definition. This self-reported percentage was then decoded into an establishment's green percentage. Most sampled establishments ended up not having revenues or employment associated with a green output (confirming limitations of relying solely on standard classifications), only around 2 percent of the U.S. workforce was estimated to do so.[23] Lastly, replicating a survey like the GGS in developing countries would represent a costly endeavor, not only in terms of sampling a substantial number of firms to have statistical power but also in explaining sophisticated questions to respondents.

The BLS could overcome the critical limitation mentioned above regarding occupational information by linking the GGS survey to the Occupational Employment Survey (OES), a well-established survey designed to produce employment and wage estimates for nearly 800 narrowly defined occupations

[21] To the best of our knowledge, the U.S. is only country that collects data on green outputs and links it to occupational data.
[22] BLS (2013a), BLS (2013b), and BLS (2012a).
[23] BLS (2013a).

using Standard Occupational Classifications (SOCs). For the creation of GGS-OCC estimates, the same sampling frame was used, and OES staffing patterns were matched to the firm's green percentage calculated with the GGS. The results of the GGS-OCC survey showed that 30.6 percent of 2011 employment was in establishments producing a green output and that occupations whose duties are expected to be directly linked to green activities are also employed in non-green establishments (e.g., environmental engineers, environmental scientists and specialists).

The process approach

The **process approach** estimates the number of workers involved in technologies used to reduce the environmental footprint of the firms in which they work, regardless of the outputs the firm produces. This approach is useful when analysts' main objective is to understand firms' labor needs to implement new technologies, but without a tight link to occupational and skills data this approach falls short of generating enough information to adequately design skills policy solutions.

The Bureau of Labor Statistics (BLS) of the U.S. developed this approach and designed a survey to apply it. The Green Technologies and Practices (GTP) survey is a firm-level survey that captures whether firms use certain environmentally friendly technologies and practices (or GTPs) that can reduce environmental impact.[24] The survey also collects information on whether workers are involved in these GTPs by researching, developing, maintaining, using, or installing GTPs, or training other employees on them. In cases where workers spend more than half of their time involved in the GTPs, the survey also collects the occupational job description, which is then used to code jobs into the 4-digit Standard Occupational Classification (SOC), along with wages for such jobs. The following are the GTPs surveyed:

1. Generate electricity, heat, or fuel from renewable sources primarily for use within the establishment
2. Improve energy efficiency within the establishment
3. Reduce greenhouse gas emissions (other than by 1 and 2)
4. Either reduce the creation or release of pollutants or toxic compounds produced, or to remove pollutants or hazardous waste from the environment
5. Reduce or eliminate the creation of waste materials
6. Conserve natural resources

In 2011, the BLS carried out the GTP survey. It sampled 35,000 firms stratified by region and 2-digit North American Industry Classification System (NAICS) sector. The survey results showed that 75 percent of firms used at least one GTP. Not surprisingly, the top GTP was improving energy efficiency, for which any firm using at least one Energy Star certified appliance would qualify, followed by reducing the creation of waste materials, for which any firm recycling waste—a widespread practice and mandatory in some cities in the U.S. The GTP is not exempt from the measurement challenges. First, while the survey provides examples of each GTP and includes the most salient types, it does not include an exhaustive list of GTPs, leaving room for respondents' subjective interpretation on whether they use or not a GTP. Second, the respondents of the survey are not the workers themselves, but employers or CEOs, which might lead to biased answers about the importance and applicability of GTPs by workers.

[24] BLS (2011) and BLS (2012b).

Although the process approach combines aspects of both the firm and worker levels, it has limitations. Firstly, this approach only includes green jobs that contribute to reducing the firm's environmental footprint, while overlooking other green jobs that generate green outputs to reduce consumers' footprint (see Appendix A for a description of pilot projects that combine both the output and process approaches). Even if the objective is to count green jobs, this limitation cannot be easily resolved by simply summing up jobs obtained from both the output and process approaches, as there will likely be significant overlaps that result in double counting issues.[25] Secondly, while the firm may be reducing its environmental impact by using the listed GTPs, it is not necessarily the case that the worker is the one making the difference by using these GTPs. In other words, even if workers use certain GTPs, their tasks may not necessarily reduce the firm's environmental impact.

This approach does not perfectly fit the objective of identifying jobs that contribute to lessening the impact on the environment and may need skills training. For example, a food manufacturing company using Energy Star certified refrigerators (an example under the GTP improving energy efficiency) will surely reduce energy consumption, but workers using the refrigerator or even installing it may do exactly the same tasks as a similar company using regular refrigerators. According to this measure, the BLS found that Heating, air conditioning, and refrigeration mechanics and installers were the second occupation with the highest GTP employment.[26] For a more recent example affecting a significant part of the global employment, due to the COVID-19 pandemic, many firms have implemented telework programs (an example under GTP reducing GHG emissions). Telework programs for sure reduce firms' environmental footprint but part of it is transferred to workers, and workers may be just doing the same sort of tasks as they were doing at the firm location. Besides this issue, it is not clear in the survey how workers should be counted when involved in GTPs (should all teleworkers or e-car drivers be counted as green workers?) or how to capture the intensity with which a worker may be performing green and non-green tasks.

Applying the BLS process approach to developing countries also brings its own challenges. Besides the challenges already noted, this approach falls short of capturing the informal sector and the agriculture sector, both usually large in the developing world. Moreover, it should be added that the cost associated with these surveys is high, especially as they may require large sample sizes. While a large percentage of firms have adopted GTPs, very few have workers who dedicate time to them. For example, in the U.S., the BLS GTP survey found that 75 percent of firms adopted a GTP and that 0.7 percent of workers use these more than half of their time.[27] Hence, for the occupational module to be relevant, the survey needs to have a large enough sample size to generate statistical power. As one could imagine, these proportions are even lower in developing countries, exacerbating the sample size requirements.[28] For example, we added a few questions similar to the BLS GTP survey in the Environmentally Friendly Industry Study (SIRL) survey conducted in 2021 in Indonesia. It was found that about half of firms have

[25] Stoevska & Hunter (2012) also raises this issue.
[26] BLS (2012b).
[27] BLS (2012b).
[28] Of course, the statistical power also depends on the standard deviation of the variables of interest, which even if small they contribute little to reduce the sample size.

at least one energy efficiency measure or technology[29] and that 60 percent of firms have dedicated energy teams or personnel.[30] However, only 0.7 percent of workers were involved in GTPs. Given the low percentage of workers directly involved in carrying out GPTs, it would require a very large survey to retrieve occupational information with statistical power, that can later on be used to link it to skills policy.

The task-content approach

The task-content approach is the most suitable one to inform skills policy. The approach looks into the nature of occupations, their task content, and can be later easily linked to the skills required to perform the job well if that information is available in the country. It allows understanding whether a job has specific tasks assigned to lessen consumers' and/or firms' environmental impact.

To our knowledge, there are two methods currently applied to classify tasks as green and non-green. The most prominent application of the task-content approach is the O*NET Green Economy Program (O*NET GEP).[31] The Occupational Information Network (O*NET) is the primary source of occupational information in the United States, which is worldwide recognized and used by researchers. The objective of the O*NET GEP was to identify the occupations that are to be impacted by the greening of the economy (i.e., by green economic activities and technologies).[32] The program comprised a desk review of about 60 publications related to the greening of the economy, which was then used by O*NET experts to produce the occupational and tasks classification.[33] The desk review covered 12 major green economic sectors tightly linked to the greening of the economy and selected the occupations commonly employed in these sectors, and hence likely to be subject to change (see appendix B for a list of the 10 steps followed by O*NET to classify occupations and tasks).[34] Using the same desk review, it then categorized the resulting occupations into the following groups:

[29] The surveyed measures included Heating and cooling the environment, Increased use of climate-friendly energy plants, Upgrade machinery and equipment, Energy management; Waste reduction, recycling, and waste management; Control of air pollution; Water management; Vehicle upgrades; Improved lighting system; Conservation of natural resources (excluding the use of recycled inputs); and other pollution control efforts. The technologies surveyed included: Equipment that has an Energy Star rating; LEED certified buildings; Energy-efficient lighting; Programmable thermostat; Cogeneration (combined heat and power); and Energy-efficient manufacturing equipment.

[30] Results from the SILR survey prepared for the Indonesia CCDR.

[31] This paper was prepared in 2020 and 2021, with decision review meeting in June 2022. In that month, O*Net released the paper proposing a linguistic approach for green topics (Lewis et al, 2022), which we understand is still in piloting stages, as it is the methodology proposed here.

[32] Dierdorff et al. (2009) and Dierdorff et al. (2011).

[33] The publications included those "in educational institutions, in academic journals, commissioned reports, industry white papers, and governmental technical reports. Additionally, numerous associated/relevant internet sources on the world of work were reviewed." Dierdorff et al. (2009). A list of the publications consulted can be found in O*NET (2013).

[34] The 12 green economic sectors include: Renewable energy generation, Transportation, Energy efficiency, Green construction, Energy trading, Energy and carbon capture, Research, design, and consulting services (indirect jobs), Environment protection, Agriculture and forestry, Manufacturing (of green technologies and energy efficient manufacturing processes), Recycling and waste reduction, Governmental and regulatory administration (Dierdorff et al., 2009).

- *Green increased demand occupations* are those that will be in demand due to the greening of the economy. Although the work context may be green or become greener, these occupations do not perform green tasks, and their work and work requirements are not expected to change. This group accounts for 64 occupations classified in the O*NET-SOC taxonomy.[35] For example, electrical power line installers in energy efficient and infrastructure upgrades. However, these jobs are not considered green jobs according to the proposed definition in this note. Some researchers refer to this category as indirect green jobs.

- *Green enhanced skills occupations* are those that the greening of the economy will change their work and work requirements –tasks, skills, knowledge, credentials, etc. This group accounts for 62 occupations classified in the O*NET-SOC taxonomy. For example, architects who may be required to have LEED (Leadership in Energy and Environmental Design) certification.

- *Green new and emerging occupations* are those that were not in the O*NET-SOC taxonomy but that O*NET created an O*NET-SOC for them given that they are appearing due to the greening of the economy. Occupations created have distinct work and work requirements and needed to show evidence of being relevant—having at least 5,000 workers, showing evidence of projected growth, having existing accredited education or training programs offering tailored credentials for the occupation, showing evidence of at least one national association serving workers in the occupation, and showing evidence of trade or professional journals for workers in the occupation. In total, the program created 78 new O*NET-SOC occupations. For example, solar system technicians.

In addition, the O*NET GEP also classified tasks. O*NET developed new green task statements for both the green enhanced skills occupations and the green new and emerging occupations.[36] The green enhanced skills occupations have 870 tasks in the database, of which 113 were identified as green. In addition, 196 tasks were generated for these occupations. The green new and emerging occupations, on the other hand, had no task in the database since all of these were new occupations to the O*NET-SOC taxonomy. In total, 626 task statements were generated for this group.

Two major advantages stand out from the O*NET GEP green classification. First and above all, O*NET is a highly reputable agency whose data is trusted and used by academics all over the world, as well as government agencies, training institutions, and the private sector in the U.S. Second, the O*NET green data constitutes an addition to the existing occupational database that contains detailed descriptions of almost 1,000 occupations in the O*NET-SOC taxonomy, including the importance and level of their tasks, skills, abilities, knowledge, and other work requirements. The O*NET task approach, as well as the O*NET green occupation classification, have been prominently used by academics to estimate the consequences of the greening of the U.S. economy.[37]

Despite its advantages, the green occupational database of O*NET has methodological limitations. First, O*NET GEP limited the analysis to occupations in 12 green sectors, excluding green jobs in the rest of the economy that contribute to the sustainability of the environment. Second, the methodology relies

[35] The O*NET-SOC is based on the U.S. SOC, by assigning the 6-digit SOC code plus an additional level.
[36] O*NET (2010).
[37] Consoli et al. (2016); Bowen et al. (2018); Vona et al. (2018); Vona et al. (2019); Rutzer, Niggli, and Weder (2020).

on a review of 60 publications of very diverse nature, dated back to 2009 and revised later in 2011. Although such qualitative work is important and should be an integral part of any data driven strategy, on its own it cannot be considered comprehensive or objective, and it is not easy to update. Progress in the adoption of green technologies during the last decade has been phenomenal, and this progress is being left out of the GEP.

The use of O*NET GEP outside the U.S. and in developing countries is also subject to important assumptions that cast doubts about its validity in these contexts. When O*NET data is used to study countries outside the U.S. the following assumptions are inevitably made: first, the production function (technology, capital, and labor—tasks and skills) is the same as that of the U.S. Internationally comparable firm data, like that from the World Bank Enterprise Surveys, show that the input mix and the returns of firms vary across countries. Country efforts to replicate O*NET in Indonesia and Uruguay show that there is variation in the task content and skills requirement of occupations across each of these countries and the U.S.[38] A second major problem is that most countries when collecting occupational data use the International Standard Classification of Occupations (ISCO) at the 4-digit level of aggregation or higher. This entails relying on a crosswalk to transform the 8-digit O*NET SOC to the 4-digit ISCO and making assumptions about the structure of employment within each 4-digit occupation. Although crosswalks are available[39] and commonly used by the research community, they have been found particularly problematic for capturing green jobs given the low levels of employment and the high measurement errors produced by the crosswalks.[40] For example, Elliot et al. (2021) applies the O*NET classification and Vona et al. (2019) methodology to study how eco-innovations impact employment in the Netherlands, finding that there is no impact on overall employment but that they increase green jobs. However, the share of green jobs is significantly higher than that in the U.S., bringing into question the quality of the crosswalk to measure green employment.[41] Section four of this paper reports the same issue when applying O*NET classification to estimate green employment in Indonesia.

A second modality of the task content approach consists of applying text analysis to occupational manuals with task descriptions. Janser (2019) applied text mining to the German occupational database to calculate the level of "greenness" of occupations. The dictionary included 153 green terms and was applied to a database with occupational requirements at the 8-digit level, containing 14,546 words, to identify green tasks for each occupation. Following Consoli et al. (2016), Janser created a greenness index, which is the share of green requirements (tasks) in the occupation. Janser shows that there was a greening of jobs between 2011 and 2016 in Germany, with slight wage increases, and that the greenness of occupations and employment growth are positively correlated.

This second modality also has some methodological limitations. First, the country of interest needs to have an occupational manual that includes task statements as part of the occupational description. The more narrowly defined the occupations are and the more precisely defined the task statements are, the

[38] Alatas, Granata and Posadas (2020), Apella & Rovner (2021) for Indonesia and Uruguay respectively. Granata and Moroz (2022) describe Viet Nam's efforts to replicate and adjust select modules of O*NET to Viet Nam, but do not attempt to compare it with the U.S.
[39] https://www.bls.gov/soc/isco_soc_crosswalk.
[40] Vona, F. (2021).
[41] Vona, F. (2021).

richer and more reliable the analysis will be. Second, the occupational manuals need to be regularly revised if the green index is to be updated. While Germany has a rich occupational manual developed at the 6-digit occupational classification, most developing countries simply adhere to ISCO (and at best, at the 4-digit occupational classification), missing the opportunity to profit from the richness of text analysis.

The skills requirements approach

One of the main limitations of the task approach, for both O*NET and text analysis methodologies, is that updating the green classification over time is not easy and time-consuming. The O*NET methodology would require regularly reviewing the literature to evaluate if there are new green tasks and/or new technologies. The text analysis methodology, however, is also subject to this problem since occupational manuals with task statements are usually updated every 10 years, a period that seems too long for the current pace of technological change. Countries with modern labor market information systems, usually with a more disaggregated occupational classification (6-digit ISCO or equivalent), may overcome this limitation by directly working with online vacancy data to identify green occupations.

The skills approach uses green skills required in job postings as a signal of the greening of the economy. LinkedIn, for example, is relying on this approach. Consistent with this note, LinkedIn defines green skills as those that enable the environmental sustainability of economic activities.[42] However, their definition is broader, as these skills are grouped into *core green skills* (such as recycling) which are most directly related to these sustainability-promoting activities; *ambivalent green skills* (such as fleet management) which may or may not be used for sustainability, and *adjacent green skills* (such as biology) which can support the acquisition of core and ambivalent green skills. To our knowledge, their methodology for coding the 38,000 unique skills terms into green and non-green is not publicly available.[43] For LinkedIn, green jobs are occupations that cannot be performed without extensive knowledge of green skills. Instead, Lightcast (formerly Burning Glass, BG) uses a combination of data sources, including O*NET classification, job titles, and job text searches.[44]

Like the others, this approach presents advantages and disadvantages for its implementation in advanced and developing countries. The most salient advantage is the granularity and frequency of the data. However, it is difficult to infer from vacancy data if the job to be filled will require the skills to carry out tasks, or if green skills are simply desired or used as a signal for some other job need. Developing countries face the additional challenge that the use of online matching platforms is not yet widespread, and hence the data is usually biased towards large metropolitan areas and the high-skilled segment of the market.[45] The next section illustrates these challenges applied to the Indonesian and U.S. cases in more detail.

[42] LinkedIn 2022 Green economy report 2022.
https://economicgraph.linkedin.com/content/dam/me/economicgraph/en-us/global-green-skills-report/global-green-skills-report-pdf/li-green-economy-report-2022-annex.pdf.
[43] This team has unsuccessfully attempted to connect with LinkedIn to learn about the methodology.
[44] Based on our communication with Lightcast.
[45] See Granata, Posadas, and Testaverde (2021) for a discussion of biases applied to the Indonesian labor market.

It should be noted that even if skills data from job vacancy postings is not best suited to identify green jobs, it brings valuable information to understand and design skills policy. Skills analysis from big data allows profiling of green jobs, including their skills requirements, and understanding other key features such as skills demand variation across industries and regions.

3. Using text analysis to develop an alternative methodology for the task-content approach

This section introduces the text analysis methodology that identifies green occupations based on a green dictionary developed by the authors. The methodology falls under the task-content approach, which is our preferred approach for skills policy. It applies the green dictionary to a task database that is used for data collection in many countries, called the international standard classification of occupations (ISCO-08). One advantage of the methodology is that the green dictionary can also be easily applied to any other task database or adjusted to other country settings. This section also discusses the extent to which the methodology can be trusted by conducting two reliability tests. The first test compares the outcome of applying the methodology to the O*NET task database against green occupations listed in the O*NET Green Economy Program. The second test assumes that green skills are necessary to perform green tasks and checks the correlation between a green task index and a green skills intensity measure, both constructed by applying the same methodology to different databases.

A. Applying text analysis to the International Standard Classification of Occupations (ISCO) to produce the green task intensity index

Classifying occupations according to their level of "greenness" consists of three steps: (1) creating a green dictionary, (2) applying it through text analysis techniques to an occupational database containing task statements, and (3) calculating the GTI index.

Step 1: Development of the green dictionary

The first step was the development of a green dictionary, a database of terms that were used as the basis for the text analysis. The terms in the dictionary are not tasks, but rather words, word roots, and expressions directly linked to environmentally friendly concepts. Our assumption was that a task statement containing any of these key terms would be related to environmentally friendly tasks. The selection of terms was the result of a careful desk review of diverse sources. Naturally, since terms are short and general, most of them are present in multiple sources. Thus, the creation of the dictionary should be understood as a systematic iterative process of adding and confirming the appropriateness of terms as they consistently came up in the consulted sources. As we continued reviewing sources, fewer new terms were included for consideration in the dictionary.

For the creation of the dictionary, the starting point was to examine the terms commonly mentioned in the diverse material from the methodological approaches described in section 2, including the O*NET green project description, and from the labor environmental economics literature. First, the dictionary included terms that appeared in the BLS GTP survey questionnaire, most common terms from machine-based text analysis of all O*NET green task statements, terms within the skills/competences from the ESCO taxonomy,[46] and terms in Eurostat manuals for data collection and analysis (1999 and 2009). Second, it also included commonly mentioned terms that frequently appeared in more than 72 papers and reports in the labor environmental economics literature. The green dictionary was then compared with dictionaries shared by Lightcast (formerly Burning Glass Technologies, BG), a list of 81 job titles within O*NET, and a list of 154 words or phrases from Janser (2019). These dictionaries were informative in the sense that they confirmed the appropriateness of many terms already selected. It should be noted that these dictionaries also included terms that may or may not be environmentally friendly depending on the context applied (e.g., energy engineers, thermograph, battery technology) which received different treatment as explained below or were not included. The desk review resulted in the evaluation of 451 terms, organized into 14 main green categories according to topic areas—categories that frequently appeared in the consulted sources (e.g., GTP survey questionnaire).[47] Appendix C contains a full list of all the consulted sources and table 3.1 provides some examples of terms present in the cited sources that were considered for inclusion.

Table 3.1. Examples of terms under consideration

Consulted sources	**Examples of terms present in cited sources**
BLS GTP survey	Renewable source, renewable energy, solar energy, wind energy, landfill gas, energy efficient, carbon offset, composting, remanufacturing, greenhouse gas, LEED
Most common environmental words in O*NET green tasks	Environmental, energy, solar, green, waste, wind, carbon, biofuels, recycling, hazardous, repair, landfill
ESCO taxonomy S3.3.2 complying with environmental protection laws and standards	environmental impact, erosion control, sea pollution, protect trees, protect wilderness areas, conserve natural resources
Eurostat manuals for data collection and analysis	Air pollution control, solid waste management, noise control, wastewater management, soil remediation, hazardous waste collection, waste recovery and recycling, resource-efficient, energy saving, eco-tourism, renewable energy
Commonly mentioned terms the in environmental economics literature	Climate change, global warming, environmental, sustainability, recycling, renewable energy
Emsi-Burning Glass Technologies dictionary	Clean energy, renewable energy, wind energy engineers, recycling coordinator, climate change policy analyst, conservation scientist
Janser (2019) dictionary	Lithium ions, smart grid technology, passive house, tree care, bicycles, lightweight construction

Once the first version of the dictionary was completed, it underwent several robustness checks. First, it was manually examined through more than 50 rounds of random tests to ensure that the dictionary correctly identified the task statements in the occupational database. As a result of this process, 104

[46] Those within S3.3.2 complying with environmental protection laws and standards.
[47] Topic areas were include Agriculture, forestry, and fish production, Clean energy, Climate change common terms, Energy efficiency, Environmental certifications, Environmental knowledge, Environmental regulations and compliance, Environmental software, Greenhouse gas reduction and pollution reduction & removal, Low-carbon mobility, Low-polluting construction, Natural resource conservation, Recycling and reuse of waste and materials, and Repair.

terms were removed from the dictionary as they were found to be capturing unrelated concepts. Additionally, 172 exemptions were established for the remaining terms to exclude words that contain the term but are not related to the topic. For instance, the terms 'hazardous material' and 'waste' were removed, while the term 'ecolog' has an exemption 'gynecolog', and the term 'environmental' has an exemption 'environmental sanitation'.

Second, the dictionary underwent a sensibility analysis, which consisted of classifying terms into two categories: green and green potential. While some terms strictly captured environmentally friendly tasks (green terms), others captured tasks that may or may not be environmentally friendly depending on the level of greening of the economy in a specific country's context. These latter terms are referred to as green potential terms since, even though the tasks may not be green at present, they have the potential to become green as countries become greener. For example, many terms related to agricultural activities, 'energy engineer,' or 'motor buses.' Green potential terms also include those that capture tasks whose outputs may be less polluting or more resource-efficient than the equivalent average output.[48] For example, 'repair' captures the task of repair activities, which may consume fewer resources or prevent the generation of waste compared to producing a new one. However, it should be noted that this term should be used with caution when repairing old goods leads to consuming more energy than their newer alternatives. The distinction between green and green potential terms provides a narrow and broad definition of greenness, or a lower bound of greenness—what we know for sure is green—and an upper bound—what may be considered green or could be green if greener technologies are adopted.

The dictionary contains a total of 308 terms categorized as *green* and 39 terms were categorized as *green potential.* Table 3.2 provides a summary of term selection and selected examples. For transparency and replicability purposes, the toolkit with the final green dictionary and do file is available to readers.[49] It contains the exact list of terms with their exemption rules and their categorization into green and green potential. It also includes the 104 removed terms marked as 'remove.' Users of the toolkit can adjust the dictionary to the country context and as technology and green jobs evolve.

Table 3.2. Green dictionary terms

(a) Selection of green terms

451	Considered terms	
-104	Not related terms	
347	Green and green potential terms	➔ Broad dictionary
- 39	Green potential terms	
308	Green terms	➔ Narrow dictionary

(b) Select examples of terms in the green dictionary

Green terms	Green Potential terms
carbon reduction	energy engineer
climate change	passenger train
deforestation	refuse collection
emission reduction	repair
clean technology	Fertiliz
energy efficien	timber construction

[48] This concept is similar to the definition of 'adapted goods' in Eurostat (2009).

[49] For World Bank staff, it is saved in the Operations Workplace Portal of this task, and colleagues from outside the institution can request it from the authors via email.

Source: author's green dictionary

Step 2: Application to the ISCO-08 task database

The green dictionary is then applied to a task database, created from the occupational manual of the International Standard Classification of Occupations 2008 (ISCO-08). ISCO is a hierarchically structured system that classifies and aggregates occupational information for all jobs in the world into 433 4-digit level occupations (referred to as occupations here on) to be used for the collection of occupational data in statistical census, surveys, and administrative databases (See appendix D for more details on ISCO).[50] For each occupation in ISCO-08 there is an occupational title, a job description that delimits the scope of the occupation, a list of up to 14 tasks performed,[51] and examples of job titles included within the occupation.[52] Hence, the created occupational database contains 433 occupations; 3,245 task statements; and 46,184 words (equivalent to 8,010 unique words). Since ISCO-08 has been widely adopted in several countries, the results of the analysis described here can be applied to any country that uses ISCO-08.

The green dictionary captured 78 unique terms and 329 tasks from the ISCO-08 occupational database. Out of the 347 unique terms in the green dictionary, 78 terms were also present in the occupational database (figure 3.1 panel a).[53] Many of the captured terms were related to greenhouse gas reduction, pollution reduction and removal, and natural resource conservation. Out of the 3,245 task statements, the green dictionary captured 329 green tasks (or 10 percent of the total tasks) (figure 3.1 panel b – examples in table 3.3), of which 83 are strictly green.[54] These tasks are related to natural resource conservation (16%), climate change (14%), recycling and reuse of waste and materials (13%), and 36 percent fall into multiple green categories.

The sensitivity analysis can also be thought of as providing an upper bound. While the broad dictionary only contains 39 additional terms (or 11 percent additional terms), these terms serve to capture 246 additional tasks (or 7.6 percent of the total number of tasks). These additional tasks will be referred to as having green potential, hereafter. The vast majority of green potential tasks relate to either agriculture, forestry, and fish production (50%) or repair activities (44%). Random quality checks confirmed that the matches were appropriate for the identification of green tasks.

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[50] ISCO-08 has a total of 436 4-digit occupations, but 3 are Armed forces occupations, which do not include a list of tasks performed.

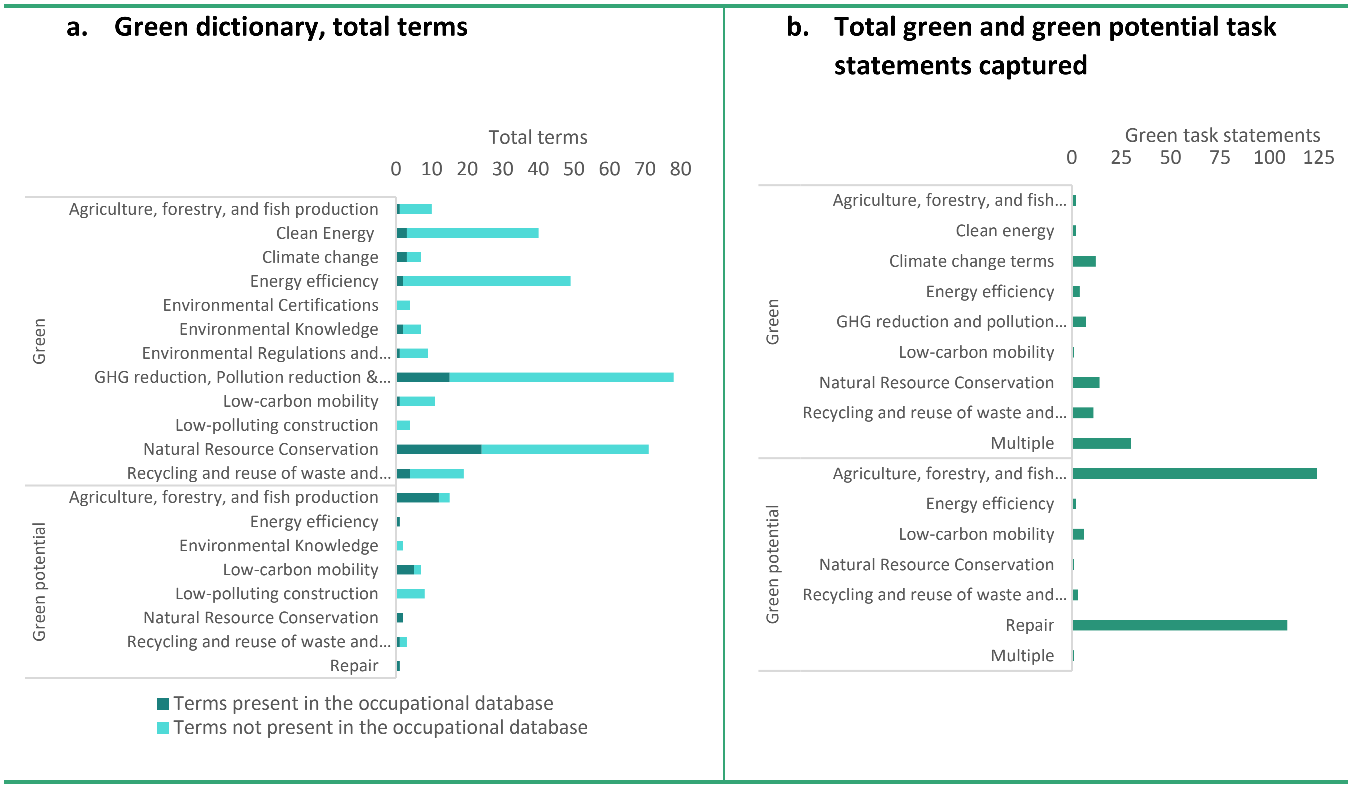
[51] Min=1, p25=6, p50=7, p75=9, max=14.

[52] The classification can be downloaded online from the ESCO European Commission website: https://esco.ec.europa.eu/en/use-esco/download.

[53] Of the 347 unique terms, 308 are strictly green and 39 are green potential. Of the 58 captured terms, 56 are strictly green and 22 are green potential.

[54] Strictly green refers to terms that match the narrow dictionary.

Figure 3.1 Green dictionary capturing green tasks



Source: authors

Table 3.3 Select examples of green and green potential task captured by the green dictionary

Task type	Task statement
Green tasks	providing environmental engineering assistance in network analysis, regulatory analysis, and planning or reviewing database development;
	assisting in the development of environmental pollution remediation devices under the direction of an engineer;
	analyzing workforce utilization, facility layout, operational data and production schedules and costs to determine optimum worker and equipment efficiencies;
Green potential task	advising on techniques for improving the production of crops, livestock and fish, and alternative production options;
	fitting, adjusting and repairing electrical parts in domestic appliances, industrial machines and other appliances;
	driving and tending street tramcars transporting passengers;

Source: authors

Step 3: Estimation of the green task intensity index

The Green Task Intensity (GTI) index measures the green task-content of occupations. It is the proportion of green tasks in an occupation o as described in the formula below. Similar to Vona et al. (2018) measure of the greenness of the occupation, it captures the extensive and intensive margin.

$$GTI_o = \frac{\#\, green\ tasks_o}{\#\, tasks_o}$$

While the GTI is a useful measure of greenness, it is not exempt from drawbacks. First, it assumes that each task is performed with the same frequency and has the same importance. In the U.S., Vona et al. (2019) compute weights according to the importance score attributed to each occupation-specific task based on the richness of the task module of O*NET data. Second, it should be noted that the GTI may underestimate the level of greenness of an occupation since the task statements listed under each occupation are not necessarily a fully exhaustive list, but rather a good description of what the occupation involves for the majority of jobs. Third, emerging occupations—many of which are associated with the greening of the economy—may now be under the residual occupation code ('not elsewhere classified occupations') and may not be captured since the task description of these residual occupations tends to be broad.

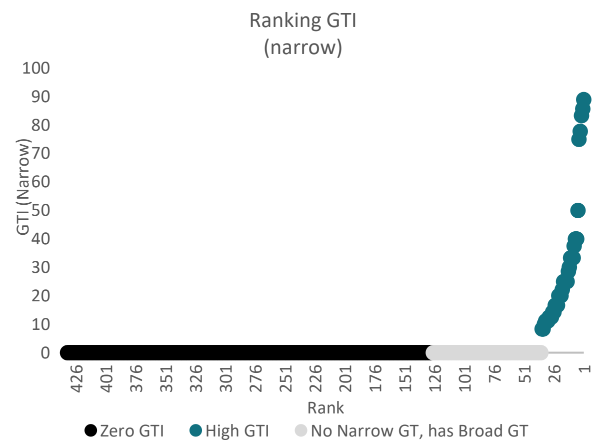
Next, we compute two indexes, one for each dictionary, and label them accordingly: GTI narrow and GTI broad (see appendix E for GTI at 4-digit occupational level). The extensive margin simply measures whether occupations have at least one green task or not. The GTI narrow classifies 36 out of 433 occupations as green (or 8% of all occupations) (figure 3.2 panel a). The intensive margin measures the level of greenness, with some occupations with close to 90 percent of their tasks being green as plotted in figure 3.2 panel b). Green occupations are found across all skill levels and independently of the main activity of the firm; however, larger percentages are found among high skilled occupations. Forty-one percent of the occupations are either professionals or technicians and associate professionals, but almost a quarter are craft and related trade workers, and 14 percent are skilled agricultural, forestry, and fishery workers (figure 3.3).

As mentioned above, the sensitivity analysis carried out with the broad dictionary led to classifying more green tasks and in turned 91 additional occupations as having green potential (or 21 percent of all 4-digit occupations). This leaves 306 occupations without any green task regardless of the tolerance of greenness applied. The broad dictionary captures relatively more low-skilled occupations, in the craft and related trade workers, and plant and machine operators and assemblers. Very few occupations within the managerial, service and sales representative, and clerical support workers major occupational groups have green task content. Not surprisingly, the intensive margin changes less when using the broad dictionary. As seen in the green shaded area of figure 3.2 panel (b), the vast majority of the occupations (31 out of the 36 green occupations) that were considered green, only have minor increases in the greenness level.[55] In sum, the expansion of the dictionary acts mostly on the extensive margin rather than on the intensive margin.

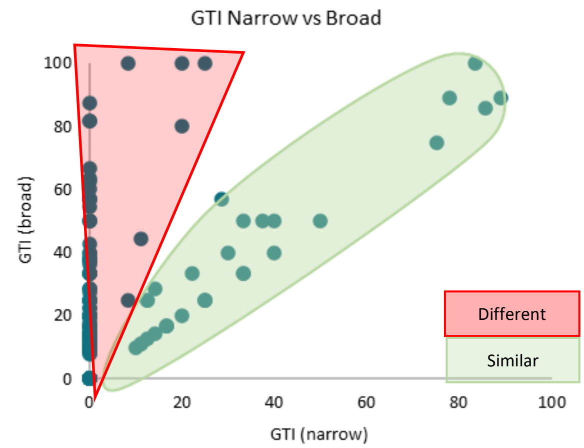
[55] The five occupations with notable changes are Environmental engineers, Environmental protection professionals, Refuse sorters, Meteorologists, and Garbage and recycling collectors.

Figure 3.2 Occupational GTI

a. Occupational GTI (narrow) and ranking

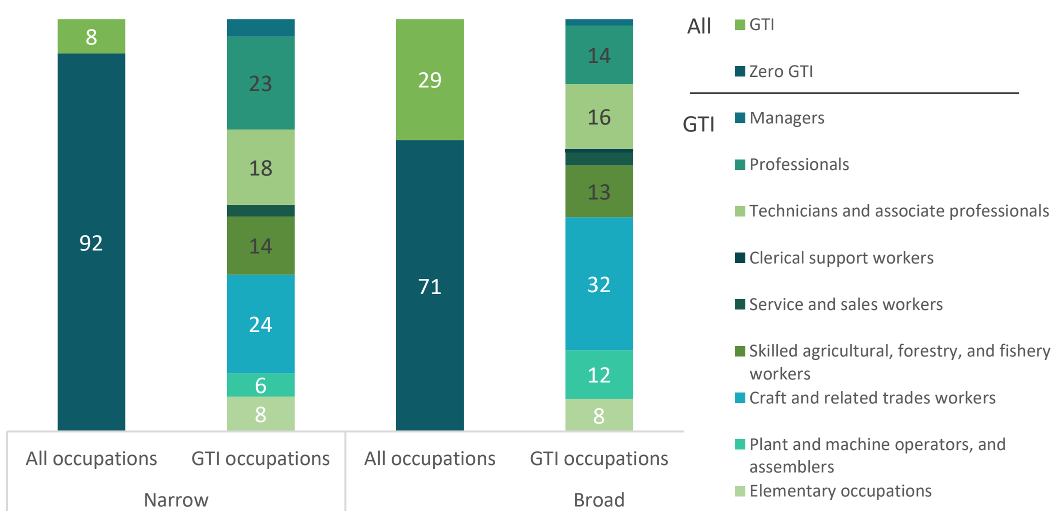


b. Comparison of GTI between Narrow and Broad



Source: authors

Figure 3.3 Share of occupations, all by GTI and green occupations by major occupational group



Source: authors

B. How much can the proposed methodology be trusted?

A natural question is whether the proposed methodology is reliable for identifying green jobs and whether it is preferred over other methodologies. To answer this, two reliability tests are performed. First, the cleanest exercise is to compare the results against another tasks approach methodology in one country. Since the only alternative methodology is the well-respected O*NET GEP run for the U.S., we first examine how well the text analysis works against this gold standard for U.S. occupations. We do this using the narrow dictionary, which only contains strictly green terms. Second, as an alternative exercise, we test the reliability of the identification strategy by applying the same dictionary to a skill database and observing how the GTI correlates with green skills intensity.

Reliability test #1: The proposed text analysis methodology applied to O*NET task taxonomy versus O*NET GEP

To carry out this test, we apply our dictionary and text analysis techniques to the O*NET task statements database (version 23.3, which uses O*NET SOC 2010 and contains green occupations and task statements). In total there are 19,636 unique task statements for 974 occupations. Our green narrow dictionary successfully captures 77 percent of O*NET GEP green tasks. At the same time, our green dictionary identifies 293 green tasks that the O*NET GEP missed. The differences may be due to the GEP focus being circumscribed to certain sectors and qualitative work. Table 3.4 shows the detailed comparison of the results of applying both methodologies. A thorough analysis of the task statements confirms the validity of our methodology. Tasks that are green to O*NET but are not green according to the text analysis are: *'coordinate with other marketing team members and workers such as graphic artists to develop and implement marketing programs'*, or *'prepare, maintain, or revise quality assurance documentation or procedures*,' or to '*monitor the flow of energy in response to changes in consumer demand*', or '*fill out defective equipment reports*.' Our dictionary also detects 300 green tasks within occupations that are non-green to O*NET. Examples are the tasks *'determine or recommend radioactive decontamination procedures, according to the size and nature of equipment and the degree of contamination*,' or *'conduct audits at hazardous waste sites or industrial sites or participate in hazardous waste site investigations*.' However, a few tasks that are green to O*NET GEP are misclassified and should even be considered brown. For example, Power plant operators, a green enhanced occupation, has as tasks to '*operate, control, or monitor gasifiers or related equipment, such as coolers, water quenches, water gas shifts reactors, or sulfur recovery units, to produce syngas or electricity from coal*.' The quality check performed found very few tasks that may have been classified as green, such as '*conduct well field site assessment*' or '*deposit recoverable materials into chutes or place materials on conveyor belts*'. Potentially, these could be fixed by adding terms to the dictionary.

Table 3.4 O*NET GEP tasks vs Text analysis methodology

	Text analysis based on narrow green dictionary		
O*NET GEP task classification	**Not green tasks**	**Green tasks**	**Total tasks**
Non-green task	17,957	293	18,250
Existing green tasks	113	169	282
New green tasks	204	900	1,104
Total tasks	18,274	1,362	19,636

Source: authors

As expected, misclassifying green task statements affects the extensive and intensive margins of the GTI. At the occupational level (extensive margin), Table 3.5 shows that our methodology categorizes 862 occupations (or 89 percent) in the same way as O*NET GEP. Specifically, 675 are not on O*NET GEP's list of green occupations; 47 are what O*NET GEP refers to as green increased demand occupations (occupations without green tasks); and most importantly, all green occupations according to O*NET GEP (62 green enhanced skills occupations and 78 green new and emerging occupations) are also green according to the text analysis. However, our methodology also classifies 112 additional occupations as green (meaning they have at least one green task) which are not green according to O*NET GEP (shaded cells in Table 3.5); 17 of these are green increased demand occupations (see Appendix F for the list of all occupations that are green to us but not to O*NET GEP).

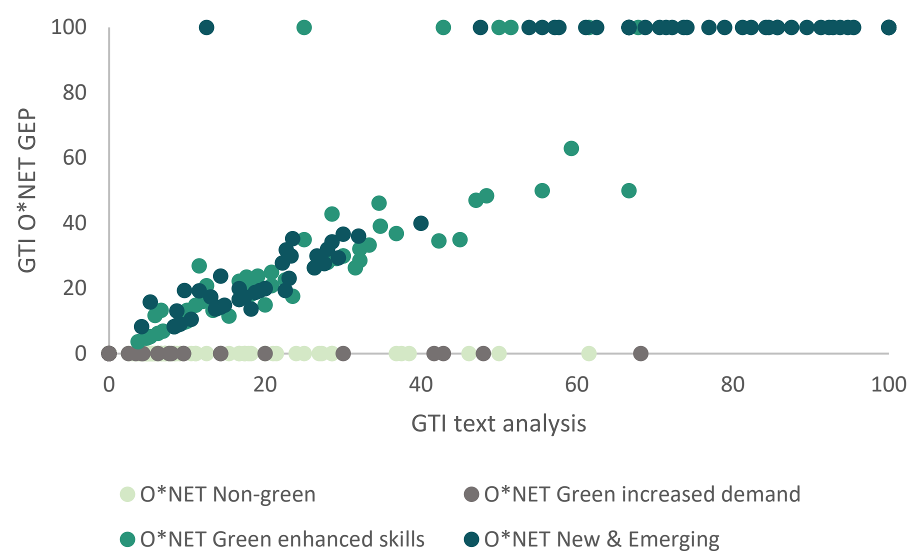
Table 3.5 O*NET GEP occupations vs Text analysis methodology

	Text analysis based on narrow green dictionary		
O*NET occupational classification	**Zero GTI**	**GTI task**	**Total occupations**
Non-green occupations	675	95	770
Green increased demand (GID)	47	17	64
Green enhanced skills		62	62
Green new & emerging		78	78
Total occupations	722	252	974

Source: authors

When comparing the results of the GTI under both methodologies, although highly correlated (0.9), the text analysis methodology proves to be better for understanding the greenness (or intensive margin) of occupations. Figure 3.4 plots the occupational GTI when calculated through the text analysis methodology versus when calculated based on O*NET GEP. The figure shows that there are many occupations that are either all green or all non-green according to O*NET GEP, while when applying text analysis, occupations have different levels of greenness.

Figure 3.4 Occupational GTI text analysis vs O*NET GEP



Source: authors

A detailed look into the task statements of green occupations detected through our dictionary and text analysis but not in the O*NET GEP confirms that these occupations have green task content, even those with the lowest GTI. For example, Home appliance repairers with a GTI of 3.2 have the task '*conserve, recover, and recycle refrigerants used in cooling systems*', or Real estate brokers with a GTI of 5.2 have tasks such as '*review property details to ensure that environmental regulations are met*", or Molecular and cellular biologists with a GTI of 4.7 have a task '*conduct applied research aimed at improvements in areas such as disease testing, crop quality, pharmaceuticals, and the harnessing of microbes to recycle waste*'.

Reliability test #2: Correlation between the GTI and green skills intensity

Since relying on occupational classifications can be rather static because they are not constantly updated, the second reliability test compares the GTI against a similarly constructed green skills intensity index (GSI) after applying the text analysis methodology to an occupational skills database in the same country. The assumption is that green skills are needed to perform green tasks, and therefore the two indexes should be positively correlated. Recall that the green dictionary is not a list of tasks but of green terms, so the dictionary should be able to pick up skills containing green words. For example, the term 'environmental' can pick up the task 'reporting on the environmental impact of existing and proposed construction' in the task database and also the skill 'environmental testing' in the skills database. It is important to note that merely applying the dictionary to the skills database will not capture all the skills needed to perform a green job since these will be more comprehensive than just skills with green words.

This reliability test is carried for two countries: the U.S.—a high-income country with rich data—and Indonesia—a middle-income country with some data. For the U.S., we use the BG skills database for 2017; for Indonesia we also use a database retrieved by BG for 2020. While both databases follow the same protocols, there are important differences related to the size of the online job intermediation market and the localization of the algorithm, mainly the exclusion of postings in Bahasa Indonesian.[56] One problem common to both databases is that they do not cover all occupations. For the U.S., 773 out of 840 SOC titles (version 2010) are observed in the BG database, and for Indonesia, 272 out of 465 occupations appear in the BG database. Given the number of vacancies per occupation in each database, the reliability test includes all occupations for the U.S. and only high-skilled occupations (159) for Indonesia.

Applying the (narrow) green dictionary to skills databases resulted in 343 green skills out of 10,798 unique skills for the U.S. and 193 green skills out of 6,263 unique skills for Indonesia. As we did for tasks, a green skills intensity (GSI) index can be defined as the percentage of green skills in an occupation o, as described in the following formula

$$GSI_o = \frac{\#\, green\ skills_o}{\#\, skills_o}$$

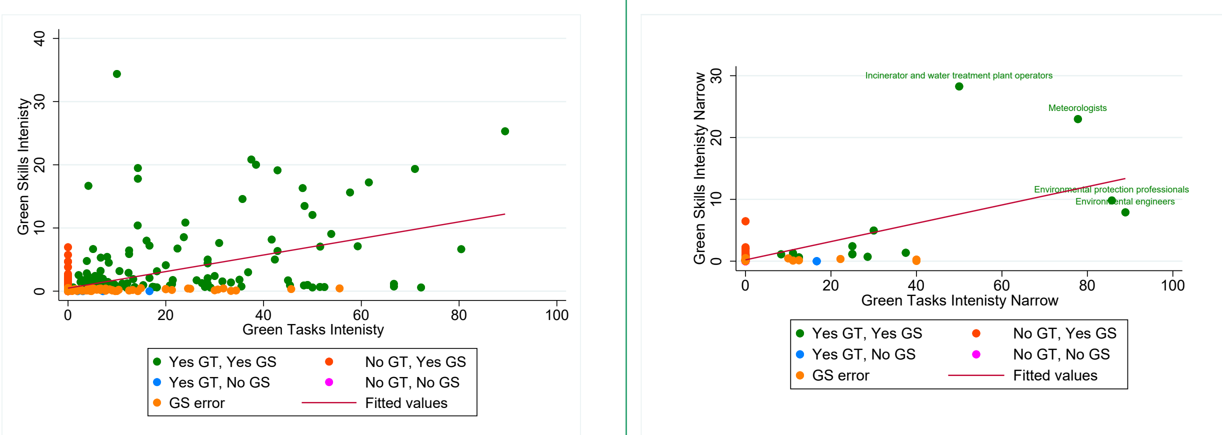
Two things can be concluded from the comparison between the GTI and GSI indexes. First, the applied text analysis methodology is appropriate to capture green tasks, and therefore green jobs, since both

[56] For more details on the data collection as well as potential biases see Granata, Posadas, and Testaverde (2021).

indexes are positively correlated (Figure 3.5). Second, the skills requirement approach alone is not enough to classify an occupation as green or non-green. While the correlation is high, there is no simple way to determine the level of skills intensity needed to categorize an occupation as green. Leaving aside concerns about biases from online job vacancy data, the extensive margin of the GSI index classifies many more occupations as green than the GTI index. One could argue that the zero cutoff for the extensive margin could be too low for two reasons. First, employers could be tempted to include green skills regardless of their importance for carrying out tasks, simply because they are important for the firm culture or as a signal of other desired skills. Second, the presence of just one vacancy requiring a green skill would result in a positive GSI. And there might be cases in which a green skill is important for a specific job in a particular firm, but may not necessarily be representative of the common skills demand for the occupation. This issue arises because most occupations have at least one vacancy requiring a green skill. Table 3.6 shows that 723 out of the 773 occupations studied in the U.S. and 106 out of the 159 occupations studied in Indonesia have at least one vacancy requiring one or more green skills. To understand where to place the cutoff, we examine how many occupations would be considered green if we raise the cutoff level and compare this with the results of the GTI index. We do this for both countries as described in Table 3.6 and Figure 3.5. It can quickly be inferred that the skills requirement approach leads to high levels of errors (assuming the task approach is correct). Increasing the threshold to be classified as a green job decreases the false positive (type 1 error) but increases the false negative (type 2 error). In other words, when we increase the threshold, fewer non-green jobs are identified as green (false positive), but more green jobs are incorrectly classified as non-green (false negative). This result holds true for both countries.

Figure 3.5. GTI vs GSI

a) U.S. **b) Indonesia**



Source: authors

Table 3.6. Number of green occupations for different cutoff levels of the GSI index and relative to the GTI index

	U.S.				Indonesia			
If GSI cutoff	# of	Of which	# of non-	Of which	# of	Of which	# of non-	Of which

	is…	green occupations	are green by GTI	green occupations	are non-green by GTI	green occupations	are green by GTI	green occupations	are non-green by GTI
GSI index	GSI = 0	723	178	50	46	106	19	53	51
	GSI < 0.1	512	167	261	246	89	17	70	66
	GSI < 0.25	396	148	377	343	61	16	98	93
	GSI < 0.5	284	124	489	431	42	13	117	109
	GSI < 0.75	207	101	566	485	31	11	128	118
	GSI < 1	155	84	618	520	24	11	135	125
	GSI > 1								

Although the skills database may not be the most appropriate tool for identifying green occupations, it can still be very useful in understanding the skills (both green and non-green) that are required in green jobs identified through the task database. This skills profile can then be used to inform training programs. This is discussed further in application #2 in the next section.

4. Application of Green Task Intensity to Indonesia

The GTI index at the 4-digit occupational level can then be applied to datasets from countries collecting occupational data with ISCO-8. As an example, this section uses the case of a developing country, Indonesia, to calculate levels of green employment. It shows how different the results are when using the proposed methodology or O*NET data, either the O*NET GEP or the GTI calculated with O*NET task statements. Differences arise from the level of data collection in the country (4-digit)—which is the usual level collected in developing countries—and from the assumptions made when using crosswalks between taxonomies. Next, it describes the skills in demand by green jobs. Lastly, it applies the GTI (binary and continuous) to explore other green employment characteristics: gender and wage premium.

Green employment can be measured using the GTI index and Indonesia's labor force survey (Sakernas). In 2016, Sakernas started collecting occupational data using the national standard occupational classification system, *Klasifikasi Baku Jenis Pekerjaan Indonesia* (KBJI) version 2014.[57] The KBJI 2014 corresponds to the adoption of ISCO-08 by Indonesia. However, two important warnings should be kept in mind. First, the illustration is done for Sakernas data for 2017, which is the latest year for which we have access to 4-digit occupational data.[58] Unfortunately, the shared micro data contains KBJI 2002 (based on ISCO-88) instead of KBJI 2014, for which the GTI was computed. Thus, the analysis needs to rely on a crosswalk for employment from KBJI 2002 to KBJI 2014. Such a crosswalk contains several many-to-many matches, which had to be split equally across matches. As a result, employment estimates could be inaccurate for these occupations. Nine out of the 35 green occupations are subject

[57] BPS (2014).

[58] The team is currently working with BPS to have more recent data including KBJI 2014 classification, and hopefully available by the time of the publication of this note.

to these biases. Second, we excluded workers in the agriculture sector and workers in the armed forces (major group 0).[59]

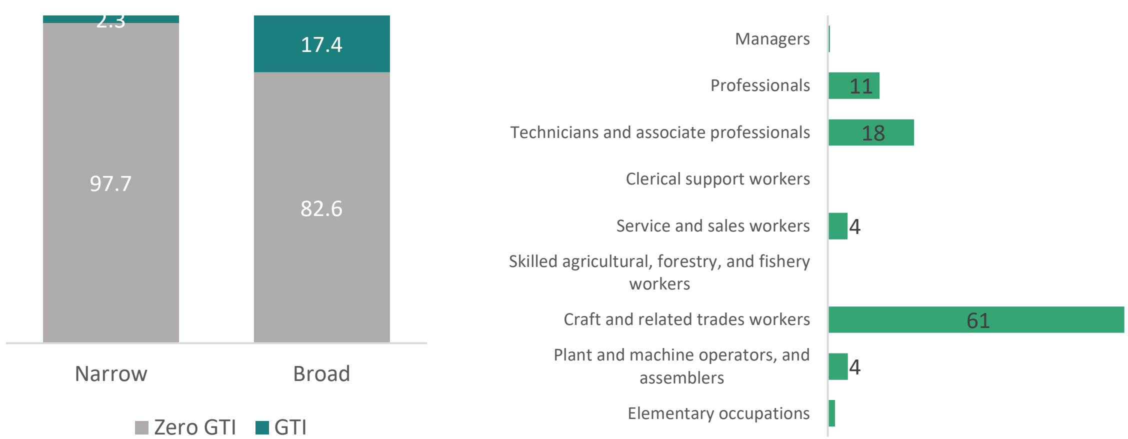
Application #1: Estimation of employment levels

If green employment is defined as working in an occupation that performs at least one green task (meaning a positive GTI), then about 2.3 percent of workers have a green job in Indonesia. When using the broad dictionary, the share of green employment rises to 15 percent, meaning that the greening of the economy could push these workers to perform green tasks if greener technologies were applied in Indonesia (Figure 4.1 panel a).[60] Restricting the analysis now to the narrow definition of green jobs, the majority of jobs are relatively skilled ones: almost two-thirds of green jobs are in occupational group 7:Craft and related trade workers; 29 percent of jobs are high-skilled, either professionals or technicians but not managerial occupations (occupational groups 2 and 3, respectively). Managers, clerical support workers, service and sales representatives (group 1), and elementary occupations (group 9) only represent 6 percent of green jobs.

Figure 4.1 Green employment, based on text analysis applied to ISCO-08 taxonomy

a) Employment, by GTI

b) Share of green employment (narrow definition), by occupation major group



Source: GTI and Sakernas 2017

Green employment is significantly larger when using the O*NET taxonomy due to the need to rely on crosswalks to transform occupations from O*NET SOC 8-digit to ISCO 4-digit. Given the lack of

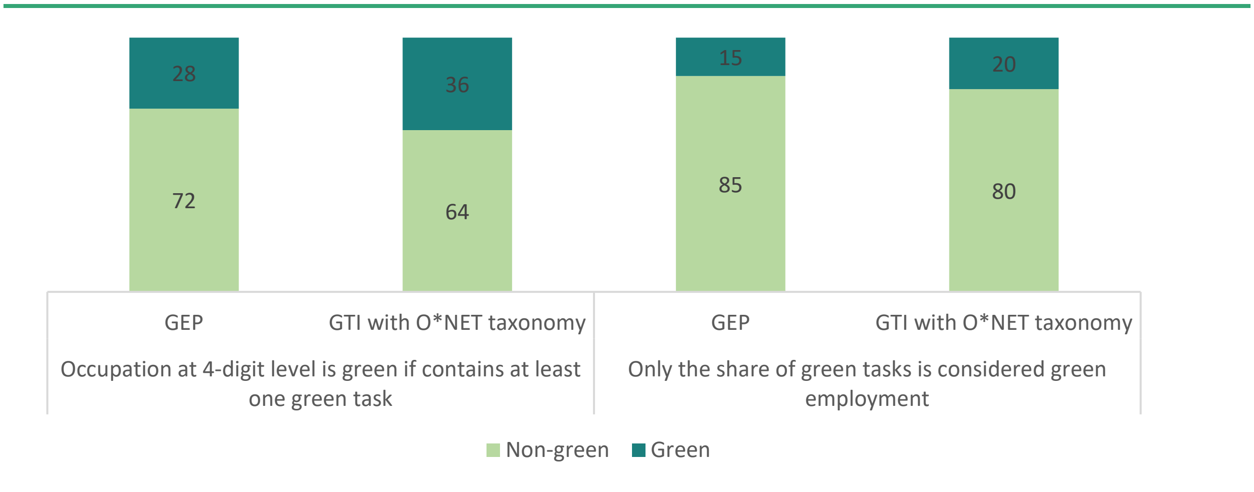
[59] Agriculture represents about a third of the employment in Indonesia, and hence it is an important sector to describe. However, the description of the green terms and the task statements were assessed not to be granular enough to produce a meaningful classification.

[60] Notice that an alternative way of computing green employment would be to use the GTI to weight employment. This way of computing employment would assume that workers split their time equally across tasks. Since this is a strong assumption, we prefer not to use this measure.

employment information at higher disaggregation levels, the common practice is to equally weight all occupations at 8-digits merged to the same 4-digit occupation. Once the crosswalk is done, there are two options to categorize employment into green and non-green: a) assume that the 4-digit occupation is green if it contains at least one green task, or b) assume that only the share of green tasks within the 4-digit occupation represents green employment. If we compute estimates using the O*NET GEP methodology (green enhanced occupations and green new and emerging occupations), then 104 4-digit occupations are green or partially green,[61] which represent between 28 and 15 percent of employment in Indonesia, depending on whether a) or b) is assumed (Figure 4.2). Similarly, when carrying out the text analysis method and applying the narrow green dictionary to the O*NET occupational database, 164 4-digit occupations are green, which represent between 36 and 20 percent of employment, respectively. The employment level is higher using this latter method since the text analysis captured more green tasks and occupations in the O*NET taxonomy than the O*NET GEP.

These results imply that, given the level of greening of the economy in Indonesia, the text analysis applied to the ISCO-08 taxonomy may better reflect Indonesia's level of greening of the economy.

Figure 4.2 Green employment using O*NET taxonomy, O*NET GEP and text analysis applied to O*NET taxonomy



Source: authors calculations based on O*NET database

Application #2: Skills demanded by online jobs add to high-skilled green occupations

Understanding the skills that are in demand for green jobs is essential for supporting the transition to a greener economy. This knowledge can then be used to shape skills policies, particularly in terms of adjusting education and training programs. It can also inform civil society about the specific skills that employers are seeking when hiring for green occupations. The BG online job vacancy data can be a valuable resource for exploring the skills that are demanded for green occupations. Green occupations

[61] Elliot et. Al (2021) find that in the Netherlands 106 out of 436 ISCO occupations have some level of greenness when using a crosswalk from O*NET-SOC to ISCO.

are identified using the GTI index, which is based on ISCO-08 task statements (described in section 3.A). For the purpose of this discussion, occupations are classified into three categories: Zero GTI (occupations without any green tasks), Low GTI (occupations with less than 30% of their tasks being green), and High GTI (occupations with 30% or more of their tasks being green). It is important to note that, due to the inherent biases of the OV data, only high-skilled occupations with at least 30 job posts in the database are considered for application #2.[62]

Project management skills are particularly crucial for high-skilled occupations that involve green tasks. On average, 60% of job advertisements for high GTI occupations require at least one project management skill, which is 10% higher compared to occupations without green tasks (Figure 4.3). Specifically, jobs in high GTI occupations typically require an average of 2.19 management skills. Examples of in-demand project management skills for these occupations include quality assurance and control, planning, people development, and compliance management (Table 4.1). There is a high demand for these skills in green occupations compared to non-green occupations. For instance, the skill of quality assurance appears 4.2 times more frequently in green jobs than in non-green jobs.

Similarly, jobs in high GTI occupations are more likely to require cognitive skills and specific field expertise. Table 4.1 illustrates the relative importance of these skills in high GTI occupations compared to occupations without green tasks (column 5). Skills such as fiber optics, research, occupational health and safety, and environmental management are particularly relevant to jobs that involve green tasks.

Figure 4.3. Average share of posts with at least one skill demanded in a skill group, by GTI index

Notes: analysis restricted to high-skilled occupations with at least 30 posts. For each occupation, we calculate the percentage of posts that required at least one skill in each of the skills groups. Then, we calculate the average of this percentage by the three categories: Zero GTI, Low GTI, and High GTI.

Table 4.1. Top 20 skills demanded in high GTI occupations

	Skill ranking	Skill	

[62] See Granata, Posadas, Testaverde (2021) for a discussion on the biases of Indonesia's online vacancy data.

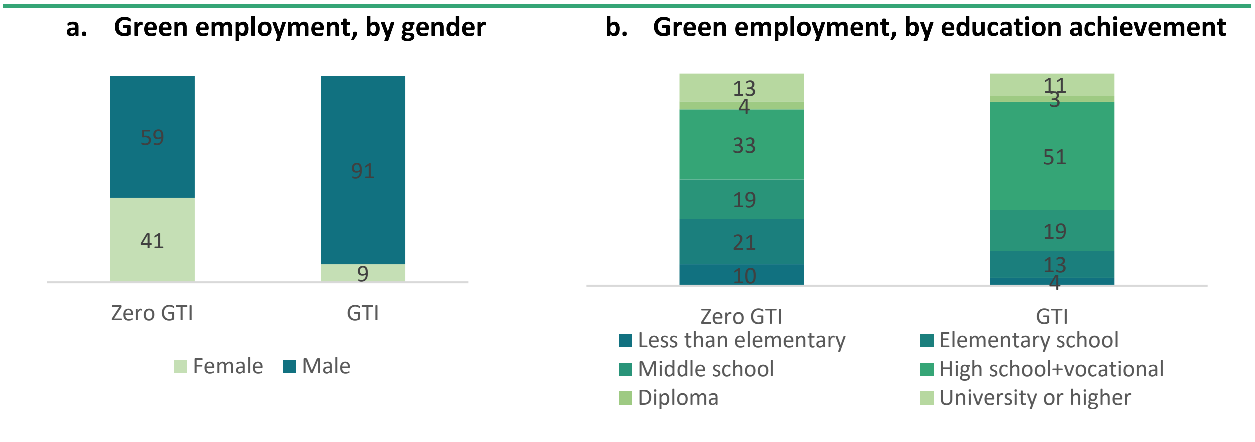
Skill	Zero GTI	Low GTI	High GTI	relative importance	Skills group
Communication Skills	2	4	1	1,03	Social
English	1	1	2	0,90	Foreign language
Quality Assurance and Control	40	7	3	4,26	Project management and business
Fiber Optics	1965	702	4	47,46	Field of study and industry knowledge
Research	14	5	5	2,01	Cognitive (analytical)
Planning	6	6	6	1,35	Project management and business
People Development	621	1156	7	13,85	Project management and business
Teamwork / Collaboration	5	11	8	0,93	Social
Microsoft Excel	7	15	9	1,12	Computer (basic)
Problem Solving	13	12	10	1,24	Cognitive (analytical)
Microsoft Office	10	8	11	0,95	Computer (basic)
Project Management	39	33	12	2,10	Project management and business
Occupational Health and Safety	498	227	13	8,03	People management
Environmental Management	963	369	14	12,06	Project management and business
Writing	15	18	15	1,07	Writing
Engineering	33	22	16	1,52	Cognitive (analytical)
Budgeting	18	37	17	1,06	Financial
Fundraising	935	478	18	9,77	Customer
Policy Research	3684		19	51,22	Cognitive (analytical)
Compliance Management	1244	267	20	11,26	Project management and business

Source: authors using OV data.

Application #3: Gender and education differences in employment

Access to green jobs is not even across groups of workers, with women being less likely to hold a green job independently of the definition applied. Females hold 9 percent of green jobs (Figure 4.4 panel a). This is significantly lower when compared to zero GTI (non-green) jobs, for which female represent 41 percent of workers. Furthermore, green jobs employ more educated workers (although not necessarily at the university level) (Figure 4.4 panel b). Two-thirds of green workers have at least a high-school or vocational degree as compared to half zero GTI workers. When using the narrow definition, our analysis also suggests that workers at green jobs are younger (43 percent of non-green workers are under the age of 35 while 54 percent of green workers are), which may be related to new jobs emerging thanks to the greening of the economy. Peters (2013) found similar results in the U.S.

Figure 4.4 Share of employment, by workers' characteristics based on text analysis applying green narrow dictionary to ISCO-08 taxonomy



Source: GTI and Sakernas 2017

Application #4: Green jobs wage premium

Green jobs are better paid jobs. This result that is found for the U.S. and other countries is corroborated for Indonesia. Comparing jobs within broad occupational groups which can be thought to require similar levels of effort and training and considering individual workers' and jobs' characteristics,[63] green jobs pay on average 6 percentage points more than a job that does not involve any green task (Table 4.2 column A). The higher the GTI, the better on average the job pays: when the GTI increases by 1 percentage point, the wage increases by 0.2 percentage points (column C). However, wage gains depend on the major occupational group: professionals; skilled agricultural, forestry, and fishery workers; and craft and related trades workers, who all represent 72 percent of green jobs, are paid better to those in the same occupational group but at non-green jobs. While managers, Technicians and associate professionals, Service and sales workers, and Plant and machine operators, and assemblers are paid less that those at the same non-green major occupational group.

Table 4.2 Green jobs wage premium based on text analysis applying green narrow dictionary to ISCO-08 taxonomy

	GTI (binary, green vs non-green)		GTI Index (continuous)	
	A ln (wage)	B ln (wage)	C ln (wage)	D ln (wage)
GTI	0.062***	0.100***	0.002***	0.007***
	(0.000)	(0.003)	(0.000)	(0.000)
Major occupational group (1-digit ISCO) *GTI				

[63] Based on a wage regression controlling for gender, education level, broad occupational groups (1-digit KBJI), province of residence, working hours, and sector of employment.

Managers * GTI		-0.449***		-0.049***
		(0.010)		(0.001)
Professionals * GTI		0.145***		-0.002***
		(0.003)		(0.000)
Technicians and associate professionals * GTI		-0.118***		-0.009***
		(0.003)		(0.000)
Clerical support workers * GTI, omitted		-		-
Service and sales workers * GTI		-0.137***		-0.008***
		(0.004)		(0.000)
Skilled agricultural, forestry, and fishery workers * GTI		0.585***		0.027***
		(0.034)		(0.002)
Craft and related trades workers * GTI		-0.028***		-0.004***
		(0.003)		(0.000)
Plant and machine operators, and assemblers * GTI		-0.147***		-0.010***
		(0.004)		(0.000)
Elementary workers * GTI, omitted				
CONTROLS				
Occupation major group (1-digit)	YES	YES	YES	YES
Education attainment	YES	YES	YES	YES
Sector of employment	YES	YES	YES	YES
Gender	YES	YES	YES	YES
Age	YES	YES	YES	YES
Province	YES	YES	YES	YES
Working hours	YES	YES	YES	YES
Constant	12.874***	12.876***	12.874***	12.875***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations weighted	53,022,977	53,022,977	53,022,977	53,022,977
Observations un-weighted	300,518	300,518	300,518	300,518
R-squared	0.515	0.515	0.515	0.515

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5. Conclusions

This paper provides a valuable methodology and toolkit for both analysts and policy makers engaged in the examination of skills policies, particularly those related to green jobs. For analysts, the adoption of the task approach for analysis is recommended, as it offers a more nuanced understanding on how to identify occupations that are core to the greening of the economy and the skills required by workers to perform green tasks. The methodology proposed in this paper, based on text analysis, is recommended due to its ability to mitigate biases that may arise from importing classifications from other countries; but it requires having access to a list of task statements, for example those found in an occupational manual. The methodological annex further equips practitioners with a toolkit for effective implementation.

Policy makers focusing on skills policy are urged to adopt a narrow definition of green jobs, emphasizing specific tasks aimed at reducing environmental impact. The paper recommends relying on the task approach and the proposed methodology to avoid assumptions inherent in classifications from other countries. Moreover, the utilization of online vacancy data with rich skills information is encouraged for profiling green occupations as well as understanding which skills may become in-demand in non-green occupations as the greening of the economy advances, offering a more dynamic and real-time understanding.

The overarching recommendation for policy makers involves the development of a robust labor market information system. This includes investments in detailed occupational classifications or job title taxonomies, updated more frequently than traditional classifications, and informed by ISCO-08, online job vacancy data, ONET-type data, and qualitative insights from labor market stakeholders. Additionally, the collection of skills and tasks data for narrowly defined occupations is emphasized, drawing lessons from established frameworks like ONET, ESCO, PIIAC, and STEP. Regular and comprehensive surveys are proposed to monitor changes in the labor market, inform skills policies, and enhance the understanding of green jobs and the skills they require.

It is crucial to recognize that green skills policy is just one facet of broader skills policies promoting the transition to a green economy. The paper underscores the importance of comprehensive policy instruments, such as advanced labor market information systems, to keep the population informed about in-demand jobs across various sectors. The integration of identified green jobs into competency standards, qualification frameworks, curricula, and certification programs is highlighted as an essential step for countries with well-established systems and a critical focus for those in the process of modernizing their educational, TVET, and employment systems. Accelerating this modernization is deemed vital to capitalize on the opportunities presented by the green transition.

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Appendices

Appendix A. Pilots combining the output approach and the process approach in developing countries

The ILO carried out two interesting pilot surveys to test the output and process approaches in developing countries. These pilots were deployed in Albania and Mongolia.[64] The instrument differed to those of the BLS in three ways. First, instead of a standalone survey the pilots were thought of as modules that could be attached to already established surveys. Second, while the U.S. examples are both enterprise surveys, the ILO piloted an enterprise module and a household module to be attached to already established surveys—the enterprise survey (ES) in Albania and the national labor force survey (LFS) in Mongolia. The reason for testing a household module was that in developing countries the informal sector, the self-employed, and the agriculture sector are a large part of the economy and are usually not captured in enterprise surveys. Third, the pilots included in both modules a combination of questions from both the GGS and the GTP surveys, with some adaptations to developing countries. For example, the instrument includes sustainable and organic agriculture in a separate category to the GTP conserving natural resources. Despite modules parallelism, results are not comparable due to differences in sampling frames and the underlying differences in each of the surveys. For example, the Albanian Enterprise Survey (ES) did not include the agriculture sector while the labor force survey (LFS) did, and the Mongolian ES did not include the banking and financial sector, private health sector, and government agencies while the LFS did.

Although the pilots have limitations natural to the approaches, they also present some advantages. First, by including in a single firm survey instrument questions on outputs and processes, jobs can be added up to get a single number of jobs (those involved in the production of an EGS and/or those involved in environmentally friendly processes), without the issue of double counting. Second, since the household module is attached to the LFS, it also provides useful information for occupational profiling of such jobs, including occupation titles, gender, age, educational achievements, and wages. The disadvantage of this combined approach is that it still might be including jobs which do not have any green tasks by counting all jobs at a firm producing a green output and all jobs using green technologies or carrying out green practices (but not necessarily green tasks).

[64] Stoevska, Elezi, & Muraku (2014) and Oyunbileg & Stoevska (2017).

Appendix B. O*NET GEP Steps for classifying green occupations

1	Locate and review existing literature. About 60 reports
2	Identify and compile job titles. Accumulating a list of all job titles that were mentioned in the reports
3	Review and sort collected job titles. Eliminate too molecular or too molar job titles (2%). Kept 467 job titles
4	Cluster job titles to identify occupations. Similar job titles were clustered
5	Identify occupational sectors. A 12 schema was used to group job titles
6	Determine overlap with ONET. Determine if the occupation was existent in ONET SOC or was a new occupation, and generate the 3 grouping: Green increased demand, green
7	Identify new and emerging. Group job titles into occupations
8	Research potential N&E occupations
9	Build consolidated evidence for final N&E determination
10	Compile and report N&E skills

Source : Authors based on Dierdorff et al. (2009), Dierdorff et al. (2011) and O*NET (2010).

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Appendix D. ISCO classification system[65]

The level of analysis is the occupation at the 4-digit KBJI level. Indonesia adopted the KBJI classification following the International Standard Classification of Occupations 2008 (ISCO-08), which is a hierarchically structured system classifying and aggregating occupational information of all jobs in the world into 436 unit groups to be used for statistical census and surveys as well as administrative databases. ISCO was designed as a tool for international comparisons and not as a replacement of national classification systems since adaptation to the local context is extremely important. However, countries with lack of capacity to develop their own classification systems find it convenient to adopt ISCO-08.

Each unit group (referred as occupation now on) is made up of several occupations with high degree of similarity in terms of skill level and skill specialization. Each occupation is defined with a 4-digit code, a title, a job description delimiting the scope of the group, the tasks performed, and examples of occupations included. The unit groups are arranged into minor groups (3-digit codes, 130 in total), which are arranged into sub-major group (2-digit codes, 43 in total), which are arranged into major groups (1-digit code, 10 in total). The major group depends on the occupation skill level: the complexity and variety of tasks to be performed in the occupation, measured mainly by the nature of work performed and also by formal and informal education required. And the occupation's minor

[65] Source: ILO (2012).

and sub-major group depends on the skill specialization: the field of knowledge required, tools and machinery used, materials worked on or with, and kinds of goods and services produced. See Tables D1 and D2 for details.

Table D1. ISCO mapping of major groups according to skill level.

ISCO-08 major groups	Skill level
1 Managers	3 + 4
2 Professionals	4
3 Technicians and Associate Professionals	3
4 Clerical Support Workers	2
5 Services and Sales Workers	
6 Skilled Agricultural, Forestry and Fishery Workers	
7 Craft and Related Trades Workers	
8 Plant and Machine Operators, and Assemblers	
9 Elementary Occupations	1
0 Armed Forces Occupations	1 + 2 + 4

Table D2. ISCO definition of each skill level

Skill level	Job usually involves the performance of	Type of skills that the job may require	Knowledge and skills usually obtained through
1	simple and routine physical or manual tasks.	Physical strength and/or endurance	primary education or the first stage of basic education. A short period of on-the-job training may be required.
2	tasks operating machinery and electronic equipment, driving vehicles, maintenance and repair of electrical and mechanical equipment, and manipulation, ordering and storage of information.	Relatively advanced literacy and numeracy skills and good interpersonal skills. Many occupations require high level of manual dexterity.	First stage of secondary education or higher, some may require vocation-specific training. In some cases, o-the-job training may substitute for formal education, while in other may require significant specialized vocational education and on-the-job training.
3	complex technical and practical tasks and require extensive body of factual, technical, and procedural knowledge in a specialized field	High level of literacy and numeracy skills and well-developed interpersonal communication skills.	A higher educational institution for a period of 1-3 years (first stage of tertiary education of short or medium duration, or higher)
4	task that requires complex problem solving, decision making, and creativity based on an extensive body of theoretical and factual knowledge in a specialized field.	High to very-high levels of literacy and numeracy skills and excellent interpersonal communication skills.	A higher educational institution for a period of 3-6 years (first stage of tertiary education of medium duration, or higher)

Source: ILO (2012)

Appendix E. GTI for ISCO-08 occupational classification system

ISCO-08	Occupation title	GTI Narrow	GTI Broad
2143	Environmental engineers	88.89	88.89
2133	Environmental protection professionals	85.71	85.71
9612	Refuse sorters	83.33	100.00
2112	Meteorologists	77.78	88.89
9611	Garbage and recycling collectors	75.00	75.00
3132	Incinerator and water treatment plant operators	50.00	50.00
3257	Environmental and occupational health inspectors and associates	40.00	50.00
3119	Physical and engineering science technicians not elsewhere classified	40.00	40.00
2131	Biologists, botanists, zoologists and related professionals	37.50	50.00
7234	Bicycle and related repairers	33.33	50.00
7124	Insulation workers	33.33	33.33
5411	Fire-fighters	33.33	33.33
2263	Environmental and occupational health and hygiene professionals	30.00	40.00
2142	Civil engineers	28.57	57.14
2132	Farming, forestry and fisheries advisers	25.00	100.00
7122	Floor layers and tile setters	25.00	25.00
2114	Geologists and geophysicists	25.00	25.00
2113	Chemists	25.00	25.00
3112	Civil engineering technicians	22.22	33.33
3143	Forestry technicians	20.00	100.00
6210	Forestry and related workers	20.00	80.00
5419	Protective services workers not elsewhere classified	20.00	20.00
8182	Steam engine and boiler operators	16.67	16.67
3131	Power production plant operators	16.67	16.67
3111	Chemical and physical science technicians	16.67	16.67
8142	Plastic products machine operators	14.29	28.57
9623	Meter readers and vending-machine collectors	14.29	14.29
7231	Motor vehicle mechanics and repairers	12.50	25.00
2164	Town and traffic planners	12.50	25.00
2162	Landscape architects	12.50	12.50
6221	Aquaculture workers	11.11	44.44
2163	Product and garment designers	11.11	11.11
2149	Engineering professionals not elsewhere classified	11.11	11.11
2141	Industrial and production engineers	10.00	10.00
1311	Agricultural and forestry production managers	8.33	100.00
7541	Underwater divers	8.33	25.00
9215	Forestry laborers	-	87.50
6112	Tree and shrub crop growers	-	81.82
6111	Field crop and vegetable growers	-	81.82
6123	Apiarists and sericulturists	-	66.67
6114	Mixed crop growers	-	63.64
8341	Mobile farm and forestry plant operators	-	62.50

7115	Carpenters and joiners	-	60.00
7422	Information and communications technology installers and servicers	-	57.14
7412	Electrical mechanics and fitters	-	57.14
7233	Agricultural and industrial machinery mechanics and repairers	-	57.14
6113	Gardeners, horticultural and nursery growers	-	54.55
9624	Water and firewood collectors	-	50.00
7215	Riggers and cable splicers	-	50.00
6130	Mixed crop and animal producers	-	50.00
7213	Sheet-metal workers	-	42.86
7232	Aircraft engine mechanics and repairers	-	40.00
3151	Ship's engineers	-	40.00
7536	Shoemakers and related workers	-	38.46
1312	Aquaculture and fisheries production managers	-	38.46
9211	Crop farm laborers	-	37.50
3142	Agricultural technicians	-	37.50
3118	Draughts persons	-	37.50
7222	Toolmakers and related workers	-	36.36
8332	Heavy truck and lorry drivers	-	33.33
7421	Electronics mechanics and servicers	-	33.33
7413	Electrical line installers and repairers	-	33.33
7112	Bricklayers and related workers	-	33.33
3113	Electrical engineering technicians	-	33.33
9622	Odd job persons	-	28.57
8331	Bus and tram drivers	-	28.57
6310	Subsistence crop farmers	-	28.57
9213	Mixed crop and livestock farm laborers	-	27.27
7411	Building and related electricians	-	25.00
7311	Precision-instrument makers and repairers	-	25.00
7127	Air conditioning and refrigeration mechanics	-	25.00
5153	Building caretakers	-	25.00
3155	Air traffic safety electronics technicians	-	25.00
9214	Garden and horticultural laborers	-	22.22
6330	Subsistence mixed crop and livestock farmers	-	22.22
8311	Locomotive engine drivers	-	20.00
7515	Food and beverage tasters and graders	-	20.00
7514	Fruit, vegetable and related preservers	-	20.00
7126	Plumbers and pipe fitters	-	20.00
7114	Concrete placers, concrete finishers and related workers	-	20.00
6224	Hunters and trappers	-	20.00
6222	Inland and coastal waters fishery workers	-	20.00
4223	Telephone switchboard operators	-	20.00
3522	Telecommunications engineering technicians	-	20.00
3116	Chemical engineering technicians	-	20.00
7531	Tailors, dressmakers, furriers and hatters	-	18.18

8141	Rubber products machine operators	-	16.67
7534	Upholsterers and related workers	-	16.67
7523	Woodworking-machine tool setters and operators	-	16.67
7522	Cabinet-makers and related workers	-	16.67
7214	Structural-metal preparers and erectors	-	16.67
6122	Poultry producers	-	16.67
3230	Traditional and complementary medicine associate professionals	-	16.67
6121	Livestock and dairy producers	-	15.38
7323	Print finishing and binding workers	-	14.29
7224	Metal polishers, wheel grinders and tool sharpeners	-	14.29
7221	Blacksmiths, hammersmiths and forging press workers	-	14.29
7211	Metal molders and coremakers	-	14.29
7113	Stonemasons, stone cutters, splitters and carvers	-	14.29
7111	House builders	-	14.29
3114	Electronics engineering technicians	-	14.29
2153	Telecommunications engineers	-	14.29
2144	Mechanical engineers	-	14.29
8322	Car, taxi and van drivers	-	12.50
7212	Welders and flame cutters	-	12.50
6340	Subsistence fishers, hunters, trappers and gatherers	-	12.50
6223	Deep-sea fishery workers	-	12.50
3152	Ships' deck officers and pilots	-	12.50
3117	Mining and metallurgical technicians	-	12.50
3115	Mechanical engineering technicians	-	12.50
2152	Electronics engineers	-	12.50
9332	Drivers of animal-drawn vehicles and machinery	-	11.11
8157	Laundry machine operators	-	11.11
8111	Miners and quarriers	-	11.11
7322	Printers	-	11.11
8114	Cement, stone and other mineral products machine operators	-	10.00
8113	Well drillers and borers and related workers	-	10.00
8112	Mineral and stone processing plant operators	-	10.00
5112	Transport conductors	-	10.00
3214	Medical and dental prosthetic technicians	-	10.00
8155	Fur and leather preparing machine operators	-	9.09
7542	Shotfirers and blasters	-	9.09
7313	Jeweler and precious-metal workers	-	9.09
7312	Musical instrument makers and tuners	-	9.09
7533	Sewing, embroidery and related workers	-	8.33
2261	Dentists	-	8.33
8152	Weaving and knitting machine operators	-	7.69

Notes: the occupations not listed in this table have zero GTI. the full list of 4-digit occupations with zero GTI is included in the toolkit

Appendix F. O*NET Occupations that are green according to our methodology but not to O*NET GEP

O*NET-SOC Code	Occupational title	Rank GTI Narrow	GTI Narrow	Total tasks	Narrow green tasks	O*NET GEP classification
19-2041.00	Environmental Scientists and Specialists, Including Health	27	68.18	22	15	GID
19-2043.00	Hydrologists	48	48.00	25	12	GID
19-1023.00	Zoologists and Wildlife Biologists	52	42.86	14	6	GID
33-3031.00	Fish and Game Wardens	55	41.67	24	10	GID
29-9011.00	Occupational Health and Safety Specialists	107	20.00	20	4	GID
45-4011.00	Forest and Conservation Workers	136	14.29	21	3	GID
19-4093.00	Forest and Conservation Technicians	135	14.29	21	3	GID
47-2131.00	Insulation Workers, Floor, Ceiling, and Wall	154	10.00	10	1	GID
17-2111.01	Industrial Safety and Health Engineers	158	9.52	21	2	GID
51-8021.00	Stationary Engineers and Boiler Operators	174	8.00	25	2	GID
17-2041.00	Chemical Engineers	175	7.69	13	1	GID
11-9121.00	Natural Sciences Managers	194	6.25	16	1	GID
49-9021.02	Refrigeration Mechanics and Installers	221	4.76	21	1	GID
49-9051.00	Electrical Power-Line Installers and Repairers	228	4.35	23	1	GID
45-1011.07	First-Line Supervisors of Agricultural Crop and Horticultural Workers	231	4.17	24	1	GID
47-2073.00	Operating Engineers and Other Construction Equipment Operators	244	3.45	29	1	GID
51-4121.06	Welders, Cutters, and Welder Fitters	251	2.50	40	1	GID
17-2111.02	Fire-Prevention and Protection Engineers	35	61.54	13	8	Non-green
19-1031.02	Range Managers	45	50.00	16	8	Non-green
13-1041.01	Environmental Compliance Inspectors	57	38.46	26	10	Non-green
47-2132.00	Insulation Workers, Mechanical	58	38.46	13	5	Non-green
51-8031.00	Water and Wastewater Treatment Plant and System Operators	59	37.50	8	3	Non-green
19-4051.02	Nuclear Monitoring Technicians	61	36.84	19	7	Non-green
17-2021.00	Agricultural Engineers	73	28.57	14	4	Non-green
33-2022.00	Forest Fire Inspectors and Prevention Specialists	75	28.57	14	4	Non-green
19-1020.01	Biologists	81	27.27	22	6	Non-green
33-1021.02	Forest Fire Fighting and Prevention Supervisors	82	26.92	26	7	Non-green
33-2021.01	Fire Inspectors	87	25.00	24	6	Non-green
19-1032.00	Foresters	89	24.00	25	6	Non-green
19-1022.00	Microbiologists	98	21.43	14	3	Non-green
11-9013.03	Aquacultural Managers	99	21.05	19	4	Non-green
29-1069.09	Preventive Medicine Physicians	106	20.00	15	3	Non-green
19-2012.00	Physicists	105	20.00	15	3	Non-green
51-2021.00	Coil Winders, Tapers, and Finishers	116	18.18	11	2	Non-green
33-1021.01	Municipal Fire Fighting and Prevention Supervisors	118	17.86	28	5	Non-green
17-2121.01	Marine Engineers	120	17.39	23	4	Non-green

33-2011.02	Forest Firefighters	122	17.39	23	4	Non-green
19-3092.00	Geographers	127	16.67	12	2	Non-green
17-2151.00	Mining and Geological Engineers, Including Mining Safety Engineers	124	16.67	18	3	Non-green
19-1012.00	Food Scientists and Technologists	129	15.38	13	2	Non-green
49-3091.00	Bicycle Repairers	142	12.50	16	2	Non-green
33-2011.01	Municipal Firefighters	150	11.11	27	3	Non-green
19-1011.00	Animal Scientists	149	11.11	9	1	Non-green
39-7011.00	Tour Guides and Escorts	152	10.53	19	2	Non-green
31-9099.01	Speech-Language Pathology Assistants	160	9.09	11	1	Non-green
43-5111.00	Weighers, Measurers, Checkers, and Samplers, Recordkeeping	163	9.09	22	2	Non-green
11-9161.00	Emergency Management Directors	164	8.70	23	2	Non-green
53-5021.01	Ship and Boat Captains	172	8.33	24	2	Non-green
19-3011.00	Economists	170	8.33	12	1	Non-green
31-1015.00	Orderlies	171	8.33	24	2	Non-green
49-9092.00	Commercial Divers	173	8.00	25	2	Non-green
49-9097.00	Signal and Track Switch Repairers	179	7.69	13	1	Non-green
25-4013.00	Museum Technicians and Conservators	178	7.69	26	2	Non-green
23-1021.00	Administrative Law Judges, Adjudicators, and Hearing Officers	177	7.69	13	1	Non-green
19-1042.00	Medical Scientists, Except Epidemiologists	176	7.69	13	1	Non-green
11-3011.00	Administrative Services Managers	180	7.14	14	1	Non-green
53-7072.00	Pump Operators, Except Wellhead Pumpers	186	7.14	14	1	Non-green
47-2151.00	Pipelayers	184	7.14	14	1	Non-green
33-2021.02	Fire Investigators	182	7.14	14	1	Non-green
33-3052.00	Transit and Railroad Police	183	7.14	14	1	Non-green
19-3091.01	Anthropologists	181	7.14	28	2	Non-green
47-5061.00	Roof Bolters, Mining	185	7.14	14	1	Non-green
47-5021.00	Earth Drillers, Except Oil and Gas	192	6.67	30	2	Non-green
27-1025.00	Interior Designers	190	6.67	15	1	Non-green
25-4012.00	Curators	189	6.67	15	1	Non-green
47-2161.00	Plasterers and Stucco Masons	191	6.67	15	1	Non-green
17-3011.02	Civil Drafters	188	6.67	15	1	Non-green
49-2095.00	Electrical and Electronics Repairers, Powerhouse, Substation, and Relay	196	6.25	16	1	Non-green
49-2098.00	Security and Fire Alarm Systems Installers	197	6.25	16	1	Non-green
51-4052.00	Pourers and Casters, Metal	198	6.25	16	1	Non-green
19-3091.02	Archeologists	195	6.25	16	1	Non-green
53-5031.00	Ship Engineers	202	5.88	17	1	Non-green
39-7012.00	Travel Guides	201	5.88	17	1	Non-green
19-1031.03	Park Naturalists	203	5.56	18	1	Non-green
29-1199.01	Acupuncturists	205	5.56	18	1	Non-green
19-4021.00	Biological Technicians	204	5.56	18	1	Non-green
17-2031.00	Biomedical Engineers	206	5.26	19	1	Non-green

41-9021.00	Real Estate Brokers	209	5.26	19	1	Non-green
29-2054.00	Respiratory Therapy Technicians	208	5.26	19	1	Non-green
47-2141.00	Painters, Construction and Maintenance	210	5.26	19	1	Non-green
49-2092.00	Electric Motor, Power Tool, and Related Repairers	212	5.13	39	2	Non-green
11-9013.01	Nursery and Greenhouse Managers	213	5.00	20	1	Non-green
49-3043.00	Rail Car Repairers	215	5.00	20	1	Non-green
49-9052.00	Telecommunications Line Installers and Repairers	216	5.00	20	1	Non-green
39-2021.00	Nonfarm Animal Caretakers	220	4.76	21	1	Non-green
19-1029.02	Molecular and Cellular Biologists	217	4.76	21	1	Non-green
39-1011.00	Gaming Supervisors	219	4.76	21	1	Non-green
19-3093.00	Historians	218	4.76	21	1	Non-green
29-1126.00	Respiratory Therapists	224	4.55	22	1	Non-green
23-1011.00	Lawyers	223	4.55	22	1	Non-green
45-2092.01	Nursery Workers	226	4.35	23	1	Non-green
45-3021.00	Hunters and Trappers	227	4.35	23	1	Non-green
17-2171.00	Petroleum Engineers	225	4.35	23	1	Non-green
47-3013.00	Helpers--Electricians	232	4.17	24	1	Non-green
25-1053.00	Environmental Science Teachers, Postsecondary	230	4.17	24	1	Non-green
53-2022.00	Airfield Operations Specialists	233	4.17	24	1	Non-green
51-9122.00	Painters, Transportation Equipment	235	4.00	25	1	Non-green
25-1064.00	Geography Teachers, Postsecondary	234	4.00	25	1	Non-green
37-3013.00	Tree Trimmers and Pruners	240	3.85	26	1	Non-green
29-1069.05	Nuclear Medicine Physicians	239	3.85	26	1	Non-green
25-1051.00	Atmospheric, Earth, Marine, and Space Sciences Teachers, Postsecondary	237	3.85	26	1	Non-green
19-4099.01	Quality Control Analysts	236	3.85	26	1	Non-green
47-2081.00	Drywall and Ceiling Tile Installers	241	3.85	26	1	Non-green
25-1052.00	Chemistry Teachers, Postsecondary	238	3.85	26	1	Non-green
11-9141.00	Property, Real Estate, and Community Association Managers	242	3.70	27	1	Non-green
29-2011.01	Cytogenetic Technologists	245	3.33	30	1	Non-green
45-3011.00	Fishers and Related Fishing Workers	246	3.33	30	1	Non-green
49-9031.00	Home Appliance Repairers	247	3.23	31	1	Non-green
51-4072.00	Molding, Coremaking, and Casting Machine Setters, Operators, and Tenders, Metal and Plastic	248	3.03	33	1	Non-green
25-9041.00	Teacher Assistants	249	2.94	34	1	Non-green
49-9012.00	Control and Valve Installers and Repairers, Except Mechanical Door	250	2.56	39	1	Non-green
51-9071.01	Jewelers	252	2.50	40	1	Non-green