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Abstract

This paper elaborates an empirical analysis of labour force characteristics associated to environmental sustainability. Using data on the United States we compare green and non-green occupations to detect differences in terms of skill content and of human capital. Our empirical profiling reveals that green jobs use high-level abstract skills significantly more than non-green jobs. Moreover, green occupations exhibit higher levels of education, work experience and on-the-job training. While preliminary, this exploratory exercise calls attention to an underdeveloped theme, namely the labour market implications associated with the transition towards green growth.

Keywords: Skills, Green Jobs, Task Model, Human Capital.

JEL: J21; J24; O31; O33; Q20; Q40

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1 Introduction

This paper elaborates an empirical analysis of green employment, and focuses on the salient labour force characteristics that emerge or change as a result of commitments towards environmental sustainability. The transition to greener forms of production, distribution and consumption is generally touted as a source of long-term benefits in the form of reduced environmental damage but, also, of new opportunities for economic development (Porter and van der Linde, 1995). While previous literature focuses on the effects of environmental regulation on employment, innovation and firm performance, no study has looked at the relationship between green technologies and the demand for skills. Yet this is an issue of primary importance to inform educational policy aimed at addressing issues such as skill shortages and skill mismatches.

Our belief is that understanding the labour market implications of green growth requires a careful articulation of how changes in the organization of production map onto the reconfiguration of work activities. This entails, first, acknowledging that the spectrum of actions for tackling environmental issues includes options as diverse as reducing greenhouse gas emission by developing renewable energy source; increasing the efficiency of energy usage in transport, building and industrial productions; recycling and reusing materials; et cetera. Such diversity implies that environmental sustainability can alter the organization of established industries but also stimulate the emergence of new ones (OECD, 2010). The implications for the workforce can be manifold and encompass the appearance of new occupations; the extinction of old ones; as well as significant changes in the job content or increased demand for continuing occupations (Dierdorff et al, 2009; Vona and Consoli, 2015). We argue that an articulation in these terms is important for locating, describing, and weighing the effect of green growth on employment.

The empirical analysis presented here focuses on the multifaceted nature of human labour, and considers complementary dimensions such as job task, formal education requirements as well as the professional pathways through which employees acquire and carry know-how, namely on-the-job training and work experience. While the latter are standard measures in human capital theory (Becker, 1962) the direct analysis of skills and tasks captures a different aspect, namely the relative importance of any work activity, and of the attendant know-how, within the mix of activities that characterise an occupation. Inspired after scholarly work on cognitive comparative advantage and artificial intelligence (Simon, 1969), empirical indicators based on the measurement of job skills and tasks allow a more nuanced understanding of how global economic forces stimulate the emergence of new abilities, the disappearance of old ones as well as the recombination of old and new skills (Autor et al, 2003; Levy and Murnane, 2004). This approach also calls attention to the trade-off between specialization and generality of labour skills across industries and occupations. The traditional human capital literature suggests that job displacement, a likely outcome of a technological transition like the greening of the economy, is more costly both for workers and society if skills are not easily transferable across contexts of use. But this raises the question of which types of know-how can either become or stay relevant in the transition towards sustainable economies. It will be argued here that the task-based approach complements standard human capital theory in that it facilitates the assessment of cross-occupational skill proximity (Poletaev and Robinson, 2008; Gathmann and Schoenberg, 2009).

Building on the above, the main goal of the paper is to profile the skill and educational content of green occupations in the United States (US). In so doing we seek to address the following questions:

1. Are occupation-specific levels of formal education, work experience and on-the-job training higher for green jobs compared to non-green ones?
2. Is the task profile of green jobs different from that of non-green ones?
3. To what extent are non-green skills transferable to green occupations?

Our analysis builds on cross-sectional data on 905 occupations based on the O*NET (Occupational Information Network) repository of occupation-specific information. The empirical strategy is articulated in two steps. First, using the O*NET taxonomy we identify one subset of green occupations and one of non-green occupations that share similarities in terms of occupational characteristics. Among the former we distinguish between existing occupations that undergo a transformation in both the task content and the attending skills (*Green Enhanced Skills*); and new occupations that emerge as a result of the green economy (*Green Emerging*). Secondly, we compare green and non-green occupations in relation to (i) standard measures of human capital (educational level, on-the-job training and work experience); (ii) the task content of occupations based on the taxonomy of Autor et al. (2003); and (iii) on occupational exposure to technology (including environmentally-oriented one) captured, among the others, by means of data on patents and R&D expenditure.

On the whole, our empirical exercise highlights important shortcomings of the binary logic of ‘green versus brown’ jobs that has dominated the scholarly and the policy debate so far. The empirical profiling reveals that in general green jobs use non-routine (resp. routine) cognitive skills significantly more (resp. less) than non-green jobs. At the same time, existing occupations that are expected to experience a change of skill content due to the greening of the economy exhibit higher levels of formal education, work experience and on-the-job training compared to non-green jobs. On the other hand, we find that on-the-job training is a distinctive feature of new occupations emerging in the context of the environmental transition. While preliminary, this exploratory analysis seeks to indicate a promising route for understanding the labour market implications of the transition towards green growth.

The remainder of the paper is organized as follows. Section 2 presents an overview of existing research on green employment and green skills. Section 3 outlines the data and the empirical methodology. Section 4 elaborates the empirical analysis. The last section concludes and summarises.

2 Green Employment vs. Green Skills

The achievement of environmentally sustainable growth is more than ever at the top of the global policy agenda. Ad-hoc interventions such as Europe’s 2020 strategy (European Commission, 2010) or the Green Jobs Act in the US are instances of governments’ commitment to provide a new impulse to smart, sustainable and inclusive economic growth. Parallel to the public debate, academic research strives to understand whether and to what extent the transition towards sustainable production yields job creation or destruction. This section provides an overview of the literature concerned with these issues organized in two blocks. First, we focus on studies that provide quantitative estimations of net employment effects due to environmental regulation and innovation. It will be argued that the neglect of the skill requirements of green jobs is a key conceptual shortcoming of this research considering that the costs of compliance and the opportunities afforded by environmental policies depend on the availability of appropriate human capital.

2.1 Government intervention, technology and employment

While there is broad consensus on whether government should be actively involved in promoting and supporting environmental sustainability, how such an involvement should be designed and implemented remains controversial. The spectrum of possible actions is wide and encompasses options such as carbon prices, R&D subsidies and regulation, as well as many other routes for implementation (Aghion et al., 2009; Mowery et al, 2010). In practice, several instruments are embedded within a policy mix that seeks a balance among multiple, at times contrasting, issues while at the same time preserving flexibility and adaptability (OECD, 2007). Unsurprisingly assessing the effectiveness of government intervention in support of green growth is at the core of a fierce debate (see reviews by Jaffe et al, 1995, and Bowen, 2012).

The empirical evidence on the employment effects of environmental policies and regulation is mixed. Some studies are openly critical towards environmental policy on the grounds that it is either cost-ineffective (Michaels and Murphy, 2009; Hughes, 2011) or conducive to job destruction (Álvarez, 2009; Morriss et al., 2009). This stands in contrast with positive forecasts on the expansion of the markets for environmental goods and services which are normally labour intensive (e.g. Engel and Kammen, 2004; Selwyn and Leverett, 2006; UNEP, 2008). More nuanced evidence comes from studies on direct interventions, such as regulation that establishes emission criteria. In the United States the latter is enforced by government organizations in charge of mandating plant-specific interventions such as the installation of state-of-the-art technology.[1] Again, the evidence is mixed. Some scholars evaluate the employment effects of environmental regulation in relation to industry specificities (e.g. Morgenstern et al, 2002), plant characteristics (e.g. Becker, 2005; Becker et al, 2013) or type of pollutant (e.g. Greenstone, 2004). Accordingly, some works report job losses (e.g. Henderson, 1996; Khan, 1997; Greenstone, 2002), others find no significant impact (e.g. Berman and Bui, 2001; Morgenstern et al, 2002; Cole and Elliott, 2007) while others conclude that environmental regulation triggers job creation (Bezdek et al, 2008). Very recent estimates reinforce the notion that ER has a negative effect on employment (Walker,

[1] In the US a national organization, the Environmental Protection Agency, and individual states have a prominent role in enforcing compliance with emission standards. For instance, state regulation programs must undergo EPA approval in order to ensure balance in regulatory intensity across states. If a county is not in attainment, the state must submit local intervention plans or fine non-compliers. In turn, non-compliance on the part of a state entails loss of federal funding (Becker and Henderson, 2000).

2013).[2] Consistent with these findings, studies by Mulatu and Wossink (2014) on European countries and Kahn and Mansur (2014) on US states find that energy-intensive and polluting industries tend to relocate and, hence, to destroy jobs as a consequence to ER.

Another strand of research gauges the effects of environmental technological change on employment (see Yi, 2014 for a review). From a theoretical point of view product innovations are expected to have a positive, demand-related, effect (Harrison et al., 2014) while process innovations to a negative effect because of increased labour productivity (Licht and Peters, 2013, 2014; Pfeiffer and Rennings, 2001). Conversely, empirical studies contemplate multiple scenarios ranging from negative labour market outcomes (e.g. Cainelli et al., 2011) to weakly positive employment effects. In addition, cleaner production methods have been found to have a positive employment effect while end-of-pipe solutions have a negative effect (Pfeiffer and Rennings, 2001; Rennings et al., 2004). Other studies highlight contrasting employment effects of innovation in materials and energy savings, which increase competitiveness and stimulate job creation, compared to innovation in air and water processes, wherein end-of-pipe solutions and labour demand is expected to decrease (Horbach and Rennings, 2013). Scholars also distinguish labour market outcomes depending on whether innovation is specifically environmental or has a more general character, but the evidence is not conclusive. In particular, Horbach (2010) and Gagliardi et al. (2014) find positive and stronger effects for environmental innovations only, while Licht and Peters (2013, 2014) find positive but not significant differences between environmental and non-environmental product innovations.

We argue that the almost exclusive focus on quantitative employment effects in the literature reviewed above overlooks the role of qualitative changes in the organization and the content of labour. The emergence of a new technological paradigm is likely to stimulate the appearance of new occupations, new skills and novel combinations of existing know-how (Vona and Consoli, 2015) which the extant literature neglects. We address this gap by shifting perspectives and using jobs, rather than sectors or firms, as unit of analysis with a view to capture changes in the knowledge content of occupations.

[2] In particular, using US worker-level data, he finds negative employment and wage effects due to job displacement following the 1990 Amendments of the CAA.

To do that, however, we first need to clarify some important aspects of the type of employment that is usually associated to green growth.

2.2 Green jobs and Green Skills

In spite of growing recurrence in the policy discourse there is no standard definition for what a green job is, and such a gap can be a serious shortcoming vis-à-vis the goal of evaluating and informing policy (Strietska-Ilina et al. 2011). To date, there have been four approaches for identifying green jobs. The first consists in selecting occupations involved in industrial *green processes* – such as active waste management, treatment, recycling, et cetera. The shortcoming of this approach is that it relies on information that is often firm-specific and thus unsuitable for the coherent classification of green jobs. A second method for capturing green employment relies on the association between *products and services* that are known to contribute to environmental and conservation objectives and the workforce involved in their production or delivery (see e.g. US Department of Commerce, 2010). The identification of those products and services follows the descriptions contained in federal procurement programs, and encompasses usual suspects such as hybrid or electric automobiles, insulation products or energy monitoring systems. While referring to tangible and easily recognizable items is no doubt a virtue, this approach relies on ad-hoc definitions that may well yield many false negatives, namely by overlooking green activities that are not directly associated with the production of a particular product or service, for example energy conservation within a firm. Yet another approach to the identification of green employment relies on selecting *industries* that have a high fraction of firms actively engaging environmental and conservation objectives such as, for example, the manufacturing of energy-efficient appliances, filters or wind turbines. Similar to the first approach reviewed above, such an approach carries the advantage of capturing employment at the industry level, and therefore of being amenable to comparative analysis. At the same time industrial classification schemes are not detailed enough so as to distinguish green products and services from similar, non-green products and services. This in practice means that the green jobs count may easily include 'false positives' (Peters et al, 2011).

The three approaches reviewed so far define green jobs only indirectly, either by using an aggregate level to define what is green (industry) or by univocal association between the greenness of process or product and the nature of the job. The 'Green

Economy' program developed by the Occupational Information Network (O*NET) under the auspices of the US Department of Labor offers a more direct approach. O*NET is a database of occupation-specific information encompassing multiple aspects such as work tasks, education and experience requirements as well as characteristics of the work context. The Green Economy program of O*NET identifies green jobs in three broad groups[3]:

(i) Existing occupations that are expected to experience significant employment growth due to the greening of the economy (*Green Demand)*;

(ii) Existing occupations that are expected to undergo significant changes in terms of task content (*Green Enhanced Skills*); and

(iii) New occupations that emerge as a response to specific needs of the green economy (*Green Emerging*).

The strength of this approach is that it focuses on occupations, which is the natural unit of analysis for the study of employment. Yet another virtue of the O*NET method is that it uses large-scale surveys at establishment-level to retrieve detailed information on green jobs.[4] In the remainder of the paper we use this information to profile the skill content of green jobs, in particular of *Green Enhanced Skills* and *Green Emerging* occupations. The *Green Demand* group captures employment effects, and indeed a look at their job content and task description confirms that these can be considered only indirectly 'green'.[5]

The goal of elaborating an empirical analysis based on the direct observation of job characteristics is better interpreted through the lenses of the human capital literature. As anticipated in the introduction, there are two main approaches to human capital in economics: the standard approach and the task-based approach. The former has contributed significantly to the field of labour economics by shedding light on the different forms of training that contribute to increase workers' know-how (Becker,

[3] The three typologies of green occupations are identified with the multi-step methodological approach detailed in Dierdorff et al. (2009). In short, this involves reviewing the existing literature to assist the compilation of job titles, clustering titles to identify occupations, assigning occupations to sectors and to O*NET occupational categories.

[4] This approach is not free from criticism: some argue that it still underestimates occupations that bring to bear on green production activities indirectly (Peters et al, 2011; Pollack, 2012).

[5] The *Green Demand* group is excluded because it includes only pre-existing occupations that do not undergo any significant change in terms of the labour force characteristics under analysis, changes that are the main focus of the present paper. Clearly, the identification of non-green matches (see Section 3.1) would have been hardly meaningful for this particular group.

1962; Mincer, 1962). Accordingly, formal education is expected to deliver a general type of learning while on-the-job training programmes are tailored around firm specific needs and are arguably more responsive to emerging skill-gaps. This supply-side approach focuses on the accumulation of knowledge by workers at school or in the workplace through learning by doing (experience) or specific training. For the purpose of our analysis we extend this conceptual framework by drawing on the approach of Autor, Levy and Murnane (2003) (ALM henceforth) based on the study of the skill content of occupations. Though the paradigmatic case that inspired this approach was the diffusion of Information and Communication Technologies (ICTs) in the US, the attendant logic can be usefully translated to other empirical contexts. In the seminal paper by ALM occupations are partitioned depending on the connection between task content and the associated cognitive endowment. Accordingly, jobs that are more intensive in "non-routine" tasks use relatively more adaptive problem solving either for interpreting information (*non-routine cognitive*), communicating with others (*non-routine interactive*) or dealing with circumstances that require physical adaptability (*non-routine manual*). Conversely, occupations intensive in "routine tasks" entail repeated cognitive activities (*routine cognitive*), such as book-keeping or monitoring, or standardized *routine manual* activities like sorting and assembling. Routine tasks are prevalent in contexts where the organization of work is consolidated and the attendant cognitive attributes are aimed at processing, rather than generating, information (see e.g. Simon, 1969).

The task-based approach is appealing for the analysis of human capital for a number of reasons. From a conceptual viewpoint it allows for flexible interpretations of the relation between labour and capital, which is especially suited when technology plays a dual role, partly complementing and partly substituting human work (Autor, 2013). Secondly, it resonates with evidence on non-neutral labour market outcomes and changes in the organization of production associated to the diffusion of new General Purpose Technologies (GPTs) for which the traditional capital-skill complementarity hypothesis (i.e. Krusell et al. 2000) does not suffice. Beyond the renowned case of ICTs, this framework provides a reasonable account for cross-country empirical evidence (Goos et al, 2009), for another major technological transitions, electrification in the XIX century, (Gray, 2013), and for more recent analyses of changes in the structure of employment due to globalization (Autor et al, 2013; Consoli et al, 2014). Last but not least, the task-based approach is a promising avenue to address key questions concerning the employment effects of green growth, namely: is the task content of green jobs proximate to that of existing occupations? And, where will the necessary know-how come from?

Allied to these questions is another issue, namely the transferability of know-how. As the standard human capital literature has it, job displacement and unemployment entail higher costs for both workers and the economy if human capital is not easily transferable across jobs. Poletaev and Robinson (2008) add to this by drawing attention to skill portfolios, that is, combinations of skills within an occupation. This work shows that the largest human capital losses are not due to switching across industry or occupation per se but, rather, to job-to-job transitions that entail significant changes in the tasks content. This leads also to expect that staying in the same occupation and having experience with various occupation-specific tasks can trigger “inter-task learning” and the build-up of a broader or deeper human capital stock. On the whole greater understanding of the composition of know-how of occupations, as per the task-based approach provides useful insights into this debate beyond the standard arguments of the human capital literature (see Gathmann and Schoenberg, 2009).

To the best of our knowledge the academic literature has so far neglected the labour market consequences of the transition towards green economies. We argue that this issue is central to the policy debate considering that adaptability and transferability of workers’ competences are crucial for reorganizing the economy towards a low-carbon regime (Strietska-Ilina et al., 2011; OECD/Cedefop, 2014). The next section will present the data, the empirical strategy and the analysis.

3 Skill Measures, Methodology and Data

3.1 Methodology

The main goal of this paper is to provide a descriptive analysis of the extent to which the skill content of green occupations differs from that of non-green occupations. The focus on occupations resonates with literature emphasising that employment is a pathway for the translation of human know-how into productive activities (Holland, 1997; Levy and Murnarne, 2004). This is especially relevant for innovation studies because it draws attention to the mechanisms by which forms of know-how acquire or lose relevance, and to the role of technology (Consoli and Rentocchini, 2015; Consoli et al, 2015).

To operationalize matters, we estimate the following equation:

$$Skill_i = \beta^1 Green\_en\text{h}\_skill_i^{0,1} + \beta^2 Green\_emerg_i^{0,1} + SOC\_3digit_i^{0,1} + \varepsilon_i \qquad (1)$$

where $Skill_i$ is a set of skill measures for occupation *i*; $Green\_en\text{h}\_skill_i^{0,1}$ and $Green\_emerg_i^{0,1}$ are dummy variables that are equal to 1 for 8-digit occupations that have been identified respectively as *Green enhanced skill* and *Green emerging* (see section 2.2), and zero otherwise; $SOC\_3digit_i^{0,1}$ is a full set of 3-digit SOC (Standard Occupational Classification) dummy variables; ε_i is the residual.

As will be discussed in section 4, green occupations are mostly concentrated within few macro-occupational groups. Failing to account for this peculiarity when comparing the skill content of green and non-green occupations might yield results that are driven by heterogeneity in the average skill content of macro-occupations rather than true specificities of green occupations. Accordingly, we look beyond mere differences across macro-occupations by implementing a rough 'matching' approach.

The inclusion of the 3-digit SOC dummies allows us to control for macro differences related, for example, to job complexity and thus drawing comparisons among narrow occupations within the same macro-occupational group. Moreover we focus on 3-digit macro-occupational groups wherein at least a green occupation (either *Green enhanced skills* or *Green emerging*) exists. An example will illustrate: 'Environmental engineers' (SOC 17-2081.00) falls in the *Green enhanced skills* group within the 3-digit occupation (SOC 17-2) 'Engineers'. Rather than comparing 'Environmental engineers' with all non-green occupations (e.g. SOC 35-3011.00 'Bartenders'), we select from the same group peers that share similar characteristics in terms of occupational tasks complexity and educational background.

Equation 1 is estimated by an OLS with occupations weighted by employment share and standard errors clustered by 3-digit SOC occupation. Data on occupational employment are only available at 6-digit SOC level, for a total of about 700 occupations[6], while skill measures are at 8-digit SOC level for a total of 905 occupations. While for the majority of occupations (i.e. 665) there is just one 8-digit item for each 6-digit occupational group, 51 6-digit occupations have two 8-digit items (102 8-digit occupations) and for the remaining 31 6-digit occupations there are, on average, 4.45 8-digit occupations for each 6-digit occupation. In the absence of employment data for 8-digit occupations within 6-digit groups, we assign the same weight to each 8-digit occupation belonging to a certain 6-digit group. This allows maintaining detailed information on skills for narrow occupations but entails the risk of systematically overestimating or underestimating the relevance of some occupations. This risk is however limited because for the majority of occupations we can establish a perfect one-to-one matching between the 8-digit and the 6-digit SOC level.

The estimated coefficients β^1 and β^2 of equation (1) provide an aggregate indication of the differences between Green and non-Green occupations but are not informative on whether such differences depend on occupational quality. This limits their use for the purpose of policy, particularly to target educational and training programs to specific occupational categories. The ideal solution would be using quantile regressions but the small sample size available – 465 occupations – prevents us from conditioning the estimated β^1 and β^2 to occupational quality. We therefore opt for a descriptive approach based on computing for each 3-digit SOC group a skill distance between the two green jobs categories on the one hand and the 'control' non-Green group on the other. Gathmann and Schonberg (2010) employ a similar method to measure the loss of occupation-specific human capital due to job-to-job transitions. Their analysis builds on the uncentered correlation between skill vectors of two occupations, basically a distance metric similar to those for measuring technological distance (see e.g. Jaffe, 1986; Nesta and Saviotti, 2005; Neffke et al, 2011). However, this kind of measure exhibits reasonable level of variability only when very different occupational types are compared, in our case green and non-green jobs within narrow and rather similar 3-digit SOC groups. To address this shortcoming, we propose a simpler metric based on the sum of the module of the difference between task items:

[6] Following the literature reviewed in section 2.1, we select employees in the private non-agricultural sector. We exclude NAICS codes 11 (Agriculture, Forestry, Fishing and Hunting) and 92 (Public Administration).

$$Skill\ Distance_{g,ng} = \frac{\sum_{j}^{6}|task_{j,g} - task_{j,ng}|}{6} \quad (2)$$

where *g* and *ng* denote, respectively, green and non-green jobs; *tasks* denotes the key items *j* of ALM's (2003) task constructs, e.g. "Routine" and "Non-Routine" (see Table 1).[7] Since each of these constructs includes six task items and each item varies between 0 and 1, the theoretical maximum for the sum of the distance between task items equals six.[8] Notice that we compare Non-Green, Green enhanced skills and Green emerging occupations and that for each 3-digit group more than one occupation can belong to each group. To simplify, we compare the average skill measure for each of the three groups weighted for the employment shares of the individual occupation within that group. Overall, the index allows us to gather policy-relevant insights on whether skill differences between green and non-green jobs are concentrated in top or bottom occupational groups.

The final step of our analysis consists in re-estimating equation (1) with the inclusion of various indicators of occupational exposure to technology (see Section 3.2 for further details on the construction of these indicators). The idea is that differences in skill content between green and non-green occupations may be driven by differential exposure to technology – that i.e. may require particular types of skills – rather than by other factors affecting the skill profile of green occupations, such as organizational factors. Going back to the earlier example, exposure to 'environmental patents' for 'Environmental engineers' is about 1.88 patents per 1,000 employees while exposure to 'environmental patents' of the non-green occupation 'Agricultural engineers' (17-2021.00) is about ten times smaller (0.186). Thereby differences in the skill profiles of 'Agricultural engineers' and of 'Environmental engineers' may be due to exposure to technology that affects the demand for some types of skills (see section 2.2) rather to than actual specificities of the green occupation relative to the non-green one. Accounting for this type of occupational exposure allows us to capture skill specificities (or absence thereof) beyond simple effects due to complementarity or substitutability between skills and technology. As the following section will illustrate, our measures of

[7] This approach cannot be meaningfully extended to our measures of human capital (i.e. experience, training and education) as each of them is unidimensional. For these measures, the heterogeneity across occupations would only reflect into one-dimensional measures of distance.

[8] To illustrate, a value of 0.15 indicates that the skill distance between two occupations is 15% of the highest possible distance.

technology exposure include general measures that have been used in the literature reviewed earlier (capital investment and investment in ICTs) as well as measures strictly relevant to the green economy.

3.2 Measures and Data

A relevant problem in the quantitative research on green occupations and related skills is the limited availability of data (ILO, 2011b). To overcome this limitation we rely on cross-sectional data on 905 occupations (8-digit SOC) in the United States (US). In particular, we combine occupation-specific information (detailed skill measures, required levels of education, training and experience, employment by occupation-industry) with industry-level measures of technology exposure. The skill content of US occupations is calculated using the O*NET database of the U.S. Department of Labor (release 17.0, July 2012). O*NET represents a suitable option in the absence of reliable statistical information on green occupations and their skills (ILO, 2011a). This database gathers information on job characteristics for more than 900 occupations and allows for an expanded range of empirical inquiries into the multifaceted nature of human capital and of labour.[9] At the core of the repository is the Content Model, a framework that encompasses cognitive and physical features of job characteristics divided in six major domains: worker characteristics, worker requirements, experience requirements, occupational requirements, labour market characteristics, and occupation-specific information. Trained evaluators and incumbents assign importance scores (on a likert scale 1-5) to each individual descriptor on the basis of informed assessments and questionnaire data. O*NET content is revised and expanded periodically by means of surveys (e.g., Smith and Campbell 2006). As already remarked, O*NET data refer only to occupational categories and have no inherent connection with industry data which are available from a different source, namely the employment data of the Bureau of Labor Services (BLS). The two sources can be matched because the respective information, on job characteristics and on employment levels, is organized by a common code, the Standard Occupational Classification (SOC) code. Table 1 shows a summary of O*NET items that are relevant for the present paper.

[9] From the initial set of 974 occupations we end up with 905 occupations as a consequence of the exclusion of employment in the non-business industries.

[Table 1 about here]

We use nine O*NET descriptors to assess differences in the skill content of green jobs compared to non-green ones. The first three items relate to standard human capital measures such as minimum years of education required for the job (a proxy of general skills), required training (a proxy of specific skills) and required experience (a proxy of learning on the job). The second group of measures is based on the work on routinization of ALM (2003) and Acemoglu and Autor (2011).[10] In particular, we consider six task-based measures of skills: non-routine abstract tasks (including cognitive and interactive tasks), routine cognitive tasks, routine manual tasks and non-routine manual tasks and a synthetic index that measures the prevalence of routine tasks vis-à-vis non-routine task, called Routine Intensity Index (RTI henceforth, see Table 1 for details). The first four measures are computed as the raw average of items' scores, normalized to vary between 0 and 1.

For each occupation we evaluate the extent to which workers are exposed to technology. This is useful to account for additional conditioning factors in the skill profiling of green occupations. Our indicator of exposure is:

$$Tec\_Exposure_{occ} = \sum_{ind} \left(\frac{Technology_{ind}}{Employment_{ind}} \times Employment_{occ,ind} \right) \quad (3)$$

This should be interpreted as intensity of investment (or patents) per employee invested, on average, for each employee in an occupation independent of the industry. We build indicators for various forms of technology, namely investment in fixed assets, investment in ICT technologies, total R&D and environment-related R&D expenditure and total and environment-related patent stock. Details on data sources and construction of the variables are reported in Appendix 1.

Employment data are organized by 8-digit SOC occupation and 4-digit NAICS industry for the years 2011-2012 and have been retrieved from the BLS Occupational Employment Statistics.[11] BLS collects information on employment in each 6-digit SOC occupation and its distribution across 4-digit NAICS industries. This is true also when

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[10] Our task and skill measures are exactly those used by Acemoglu and Autor (2011).

[11] http://www.bls.gov/oes/tables.htm

we compute measures of technology exposure that can be only computed at the SOC 6-digit level, thus assuming that it is constant across SOC 8-digit occupations within the same SOC 6-digit occupation.

4 Results

The present section operationalizes the empirical strategy laid out in Section 3.1, and is organized in three steps. After having presented aggregate evidence on green employment in the US, the first subsection includes a comparison between green and non-green jobs within similar 3-digit SOC classes, and pinpoints the occupations that exhibit the greatest differences. Subsequently, we put the skill distance measure between green and non-green occupation by macro-occupational group to the test in section 4.2 and, finally, test the robustness of our skill profiling by means of various proxies of technology.

4.1 Skill profiling of green occupations

Table 2 shows the count of 8-digit SOC occupations, split by macro-occupation (2-digit SOC) and green and non-green occupations. *Green enhanced skills* and *Green emerging* jobs concentrate in occupations that are intensive in abstract skills (e.g. problem-solving, management and coordination): specifically, out of 111 green occupations, 76 belong to macro-groups such as Management (SOC 2-digit: 11), Business and Financial Operations (SOC 2-digit: 13) or Architecture and Engineering (SOC 2-digit: 17). The remaining are in mid-skill occupational groups such as Construction and Extraction (SOC 2-digit: 47) or Production workers (SOC 2-digit: 53).

[Table 2 and Table 3 about here]

To gauge the scale of green employment we report employment shares by macro-occupation in Table 3. As discussed in section 3.1, we cannot observe employment figures at the 8-digit level but only at the 6-digit level. Accordingly we assume that employment is distributed uniformly across 8-digit occupations within the same 6-digit occupation. If 8-digit green occupations were systematically smaller (bigger) in terms of employment that non-green occupations within the same 6-digit occupation, the aggregate employment of green occupations would be overestimated (underestimated). On the basis of our lower bound estimates (assuming that, in presence of both green and non-green occupations within the same 6-digit occupations, green occupations have no employees), green occupations account for about 9.8 percent of total private sector non-agricultural employment in the US. Conversely, when employing the approximate SOC 8-digit weights, this figure increases to 11 percent and to a further 12.3 percent when the 'green occupation' status is attributed to all occupations within the 6-digit group with at least one green occupation. This appears at variance with estimates of US green employment coming from sources such as BLS and OECD that usually range between 2 and 4 percent (see also Deschens 2013).[12] However, as anticipated in section 2.2, these approaches focus on employees of the Green Goods and Services sector defined at industry or establishment level. To illustrate, occupations that are labelled as green therein include jobs that are not necessarily associated to environmental issues such as Financial Analysis or Metal Sheet Workers. Our estimate of the size of green jobs is therefore an upper bound of the actual work engagement in green activities.

Looking at the distribution of employment in green occupations in Table 3 we observe that, similar to the number of occupations, they are concentrated in few macro-occupational groups, particularly occupations intensive of abstract tasks or routine-manual occupations. Among 2-digit SOC high-skill abstract occupations, Management (SOC 2-digit: 11) and Architects and Engineers (SOC 2-digit: 17) have the largest share of green employment shares both in absolute terms and relative to the 2-digit total. Computer and Mathematical jobs (SOC 2-digit: 15), especially relevant in relation to ICTs, have a negligible share of green employment. For what concerns low-skilled 2-digit SOC, green employment is mostly concentrated among Construction and Extraction (SOC 2-digit: 47), Transportation (SOC 2-digit: 53) and Installation, Maintenance and Repair (SOC 2-digit: 49). These figures are in line with policy reports stressing the importance of manual and technical occupations in the transition to sustainable growth (UNEP, 2008; UKCES, 2010; OECD/Cedefop, 2014).

[Table 4, Table 5 and

Table 6 about here]

[12] See e.g. http://www.bls.gov/news.release/pdf/ggqcew.pdf (BLS News Release 2013, last accessed 10/02/2015), or http://www.oecd.org/els/emp/50506901.pdf (OECD´s Employment Outlook 2012, last accessed 10/02/2015).

Results based on the task measures of ALM (2003) are reported in Table 5, while Table 4 contains descriptive statistics on our skill measures for the 465 occupations of interest. Here we observe clear-cut significant differences between green occupations and similar non-green occupations that are concentrated in cognitive skills. In particular, non-routine cognitive skills are higher for *Green enhanced skills* and to a lesser extent *Green emerging* occupations relative to similar non-green occupations, while both *Green enhanced skills* and *Green emerging* occupations are relatively less intensive in routine cognitive tasks than their peer occupations. Not surprisingly, the synthetic indicator of prevalence of routine skills over non-routine skills (*RTI index*) highlights a significant negative difference between green occupations, although such a difference is only near significant for *Green emerging occupations*, and matching non-green occupations. The lower statistical significance of the coefficients for *Green emerging* occupations, whose magnitude is generally in line with that of *Green enhanced skills* occupations, may be due to greater measurement errors in O*NET scores for new occupations. Indeed, the assessment of the importance of general tasks and skills in O*NET is prone to greater measurement errors for new and emerging occupations compared to the revision of scores for existing occupations, for which a consolidated profile exists already and only requires an update.[13]

To gauge the magnitude of these differences, we quantify the estimated effects in terms of interquartile ranges (IQRs). Since our skill measures are intrinsically qualitative, an ‘absolute’ quantification based on standard deviation differences would be not appropriate. For the sake of space, we only comment on differences in skill measures that are statistically significant. Starting with Green enhanced skills, the differences are modest but not negligible: the importance of NRC skills occupations is 0.13 IQRs higher than that of non-green occupations, while the importance of RC skills is 0.2 IQRs lower. The overall difference is somehow diluted up to 0.086 IQRs when using the RTI indicator that also contains NRI and RM skills. In *Green emerging* occupations, the only significant difference is the lower importance of RC skills that is however quite large in since these are about 0.32 IQRs less important compared to non-

[13] The periodical updates to importance scores of skills and tasks in the O*NET database is exactly aimed at consolidating the profile of occupations and to update these profiles to account for changes in the skill and task content of occupations.

green occupations, while the coefficient for RTI is only near significant (p-value 0.147), with a difference with respect to non-green occupations of about 0.1 IQRs.

To reiterate, according to the standard literature (e.g. Autor et al, 2003; Levy and Murnane, 2004) non-routine tasks entail cognitive or interpersonal know-how to deal with non-fully predictable work environments, while routine skills are intensive in occupations based on the execution of explicit instructions (e.g. book-keeping, clerical work, automated productions). In general our results suggest that the task environment of green occupations (both green emerging and green enhanced) is less routinized than that of their peer non-green jobs, and therefore that green work activities are in the process of definition. This seems to hold particularly true for cognitive tasks and resonates with the observation that green technology is still at early stages and, thus, that it requires scientific and technical creativity to be mastered and operationalised by the workforce (Vona and Consoli, 2015).

Moving to other dimensions of human capital, education, experience and on-the-job training, the differences between green occupations and similar non-green occupations are more substantial. This is especially the case for *Green enhanced skills* occupations which require 1.9 percent more years of education than comparable non-green occupations, about 13 weeks when evaluated at the overall sample mean. The relative difference increases substantially for *Green enhanced skills* when considering additional years of experience (43 percent, corresponding to about ten months when evaluated at the overall sample mean) and years of training (41 percent, corresponding to about 15 weeks when evaluated at the overall sample mean). Finally, for *Green emerging* occupations, no difference relative to non-green occupations is found in terms of years of education and years of experience while they require 18 percent more years of training than non-green occupations, corresponding to slightly less than seven weeks when evaluated at the overall sample mean. These results therefore point to interesting differences also between the two types of green occupations under analysis, and in particular to the prominence of on-the-job training programmes as opposed to formal education for new *Green emerging occupations*, which resonates with the basic tenet of human capital theory (e.g. Becker, 1962).

4.2 Skill distances across occupations

The results of section 4.1 identify average skill differences between green and non-green jobs but say nothing on which 3-digit SOC occupational groups exhibit the greatest gaps. This is essential to understand where skill transferability from non-green to green activities may be smoother within the occupational spectrum. To fill this gap we compute for each 3-digit SOC group a skill distance between the two categories of green jobs, on the one hand, and the non-green job, on the other (see Equation 2). The distance measure is computed separately for Routine and Non-Routine skills, and here reported only for Non-routine for the sake of space. Table 7 reports the skill distances, with the 5 biggest distances in bold and the 5 smallest distances in italic. Since our indicator captures large differences in basic items that offset each other, but says nothing about the direction of the difference, we report also the synthetic index of Routine Task Intensity by group (last three columns).

[Table 7 about here]

To be sure, such an exercise highlights the remarkable difficulty of identifying coherent clusters of occupations with respectively large and small skill distance. To illustrate, consider the example of Construction workers (low distance) and other construction workers (high distance) (Table 7). As concerns *Green enhanced skills*, high differences resonate with the results outlined above and indicate an association with significantly lower Routine intensity (around one standard deviation lower) for Architects, Other construction workers and Lawyers. Green social scientists are an exception and appear considerably more routine intensive than their non-green counterpart. As expected, green enhanced jobs with low skill distance display also a negligible difference in the RTI index. Looking at the *Green emerging group*, comparisons are limited by the fact that these occupations are only in few 3-digit groups disproportionately concentrated among top occupations. It is therefore quite surprising that the largest skill differences are concentrated in few middle- and low-skill occupations such as residual production jobs, sales representative and construction trade workers. Conversely, engineering, scientists and operation managers display the lowest skill distance.[14]

[14] Interestingly, construction and design occupations emerge as prominent jobs from policy reports on green jobs (e.g. Cedefop, 2011). We believe that this is an issue for future research.

4.3 Green skills and exposure to technology

As anticipated earlier (section 3.2) differences in skills within narrow comparison groups may be driven by differences in the exposure to technology (and consequently by the link between technology and skills) rather than actual specificities in the skill profile of green occupations. For this reason we check whether green occupations differ from similar occupations (within the same 3-digit SOC occupational group) in terms of exposure to our measures of technology. Results are reported in Table 8.

[Table 8, Table 9, Table 10, Table 11 and Table 12 about here]

Green enhanced skills are significantly more exposed to all measures of technology except ICT, for which no difference is found with respect to similar non-green occupations. As regards *Green emerging* occupations we find higher exposure to investment in fixed assets as well as to general R&D and patents relative to similar non-green occupations. Interestingly, no differences emerge between *Green emerging* occupations and similar occupations in terms of green technologies. While this does not point to lack of exposure to green technologies, it suggests that activities involved in new green occupations do not specifically involve use and operation of codified green-specific technologies (like *Green enhanced skills* occupations), but possibly adaptation of “general” knowledge to emergent environmental needs. The magnitude of these differences, especially if we consider that we are looking at the variation within 3-digit occupational groups, is large. This is especially so when considering general patents (about 0.6 log points for *Green enhanced skills* occupations and 0.5 log points for *Green emerging* occupations) and general R&D (about 0.3 log points for both *Green emerging skills* and *Green enhanced skills* occupations). On the other hand, differences in exposure to green-specific technologies (environmental patents and environmental R&D) are only significant for *Green enhanced skills* though the magnitude of the relative differences is smaller for green-specific technologies than for general technologies. For what concerns investments in fixed capital and in ICT capital, the difference in exposure between green occupations and other occupations is bigger and statistically significant for *Green emerging* occupations than for *Green enhanced skills* occupations, with *Green emerging* occupations showing an exposure to investments in fixed capital (resp. ICT capital) about 0.19 (resp. 0.13) log points greater than similar non-green occupations.

To appreciate whether skill differences between green and non-green occupations are driven by differences in the exposure to technology and not by other specificities of green occupations, we enrich the baseline specification of equation 1 with a series of variables that capture exposure of occupations to technology (see Section 3.1). In line with the literature reviewed in Section 2, we include log investment in equipment (*inv_tot*) and in ICT capital (*ICT*) and, in addition, exposure to less mature technologies (i.e. not yet embodied in physical capital) measured, alternatively, by R&D (total and green R&D – Table 9 and Table 10) and patents (total and green patents – Table 11 and Table 12). It is important to stress that the cross-sectional nature of our data does not allow controlling for unobserved heterogeneity across occupations, and the goal of our exercise is primarily illustrative.

Generally, the inclusion of measures of exposure to technology does not influence the estimated differences in the skill and human capital content of green occupations with respect to non-green occupations. Statistical significance is unaffected both when including exposure to R&D and exposure to patents: the only notable difference is that now no significant difference is found in terms of years of training between *Green emerging* occupations and non-green occupations. For what concerns differences in the skill content of green and non-green occupations, these tend to be slightly smaller in absolute terms when controlling for exposure to technology, with the exception of RC skills for which the difference in absolute terms is slightly higher. It should be noted, however, that even after considering exposure to technology the results for the *Green emerging* and *Green enhanced skills* are not statistically different from those reported above (Table 5 and

Table 6).

In sum, with the exception of on-the-job training for *Green emerging* occupations, differences between green and non-green occupations do not depend on differences (though significant) in their exposure to technologies but, rather, on other characteristics of green activities vis-à-vis non-green ones that affect the workforce profile, e.g. organisational changes. The obligatory caveat at this point is that our study is a preliminary go at an arguably complex issue, and hopefully future research will propose more suitable measures of green technology adoption than those based on patent counts or environmental R&D expenditure.

5 Concluding remarks and the way ahead

This paper has proposed an empirical analysis of the skill content of green occupations, a theme that will no doubt attract considerable interest in the near future, especially among scholars of innovation and science and technology policy. The main motivation of our study is that labour is the pathway through which new forms of know-how or criteria of operation are channelled into the productive system, and that understanding the workforce implications of green growth requires a careful articulation of how changes in the organization of production map onto the reconfiguration of work. We propose to do this by using traditional measures of human capital as well as task-based skill indicators recently used to study the relationship between technology and employment.

The main result is that green occupations exhibit significant differences from non-green occupations. In particular, green jobs are characterized by higher levels of non-routine cognitive skills and higher dependence on formal education, work experience and on-the-job training. The empirical evidence also indicates that the greening of the economy is in progress, and that work activities are not characterized by a high degree of routinization. This resonates with the remark that environmental technologies are still at early stages of the life cycle wherein cognitive skills such as design and problem solving are essential in guiding future developments. Our results show that formal education, work experience and on-the-job training are more prominent among existing occupations that are undergoing qualitative change due to the greening of the economy compared to similar non-green jobs. Parallel to this, on-the-job training emerges as very important among new green occupations. The main implication is that educational policy per se may not be sufficient to support green human capital formation, and that learning by doing should be kept in strong consideration when formulating policies that favour the adaptation of workforce skills to the demands of a changing production paradigm. Likewise, we envisage actors such as industry and sector *consortia* and inter-firm associations to be well positioned for mitigating the risk of free-riding and favouring positive externalities in the creation of green human capital.

The limitations of the present study suggest interesting directions for future research. First, given the paucity of academic research on green employment we relied on established measures of skills and human capital. Future work will hopefully take further steps at identifying the skills that are crucial in the transition to environmental sustainability. Second, we could not analyse complementarities among different types of skills and different forms of learning based on formal education, on-the-job training and experience. Third, our analysis is silent on the timing of entry in the job market, and results may be sensitive to the age of workers, so that the relative advantage of formal education versus on-the-job training and experience may change depending on the proportion of entrants over tenured workers. One might expect that when many young cohorts enter the job market, university education is more important and, on the contrary, re-skilling is more relevant during stagnant phases. It is hoped that future research will explore these and other relevant issues in this promising line of work.

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Appendix 1 – Sources and other information concerning the measures of exposure to technology

We retrieve information on investment (total investments and investments in ICTs) by NAICS industry for years 2009-2010 from US Census data. Investments in ICT at the 3-digit or 4-digit NAICS level (depending on the industry) are obtained from the *2010 Information and Communication Technology Survey, Table 2a* while total investment at 3- or 4-digit NAICS level (depending on the industry) are retrieved from the *2010 Annual Capital Expenditures Survey, Table 4a and Table 4b*.

Data on R&D expenditure (2008-2010) are made available by the National Science Foundation (NSF). We further split total R&D into the amount of R&D related to environmental protection and energy applications. This is particularly relevant as a measure of the 'green' orientation of industries since it captures the extent to which future technological developments account for environmental concerns.

Finally, we retrieved information on patent fillings at the USPTO (from the Patstat database) by NAICS sector, further split between environmentally-related and other patents. We built patent stocks in the 1975-2009 time window using the perpetual inventory method with annual depreciation rate of 15%. Patent stocks are assigned to NAICS industries by using the IPC-NAICS concordance matrix developed by Lybbert and Zolas (2014).[15] Environmental patents are identified using a list of environmentally-relevant IPC classes compiled by the OECD (OECD-ENVTECH). These patents identified pertain to the following technology fields: renewable energy generation technologies, emission abatement and fuel efficiency in transportation, general environmental management, energy efficiency in buildings and lighting. Relevant IPC classes are reported in Table A1.

[15] This concordance links each IPC class at 4-digit to one or more NAICS industries (11- Agriculture, Forestry, Fishing and Hunting; 21 - Mining, Quarrying, and Oil and Gas Extraction; 22 – Utilities; 23 – Construction; 31-33 – Manufacturing.) at 6-digit for which patents in that class are relevant, with industry-specific weights. The link is constructed by means of an algorithm that exploits the description of both IPC classes and industries. The peculiarity of this approach based on co-occurrence of words in the descriptions of technology classes and industries, is that it measures the relevant knowledge of each industry regardless of whether inventions occurred within the industry or in other industries. Moreover, and different from other approaches (e.g. Schmock et al.,2003), it acknowledges that each specific (IPC 4-digit) technology may be relevant for a plurality of industries, thus resulting in multiple assignment of IPCs and industry-specific weights.

Tables and figures

Table 1 – Skill measures

	Indicator	Task Items in O*NET	Description of task items in O*NET
Non-Routine	Non-routine analytical (NRA)	4.A.2.a.4 (IM)	Analyzing data or information
		4.A.2.b.2 (IM)	Thinking creatively
		4.A.4.a.1 (IM)	Interpreting the meaning of information for others
	Non-routine interactive (NRI)	4.A.4.a.4 (IM)	Establishing and maintaining interpersonal relationships
		4.A.4.b.4 (IM)	Guiding, directing, and motivating subordinates
		4.A.4.b.5 (IM)	Coaching and developing others
Routine	Routine cognitive (RC)	4.C.3.b.4 (CX)	Importance of being exact or accurate
		4.C.3.b.7 (CX)	Importance of repeating same tasks
		4.C.3.b.8 (CX, reverse)	Structured versus unstructured work
	Routine manual (RM)	4.A.3.a.3 (IM)	Controlling machines and processes
		4.C.2.d.1.i (CX)	Spend time making repetitive motions
		4.C.3.d.3 (CX)	Pace determined by speed of equipment
	Non-routine manual (NRM)	4.A.3.a.4 (IM)	Operating vehicles, mechanized devices, or equipment
		4.C.2.d.1.g (CX)	Spend time using hands to handle, control or feel objects, tools or controls
		1.A.2.a.2 (IM)	Manual dexterity
		1.A1.f.1 (IM)	Spatial orientation
	Routine index (RTI index)	Autor and Dorn (2013)	log(1+4.5*RC+4.5*RM) – log(1+4.5*NRA+4.5*NRI)
Standard Skill Measures	Years of education	2.D.1 (weighted average)	Required level of education
	Years of experience	3.A.1 (weighted average)	Related work experience
	Years of training	3.A.3 (weighted average)	On-the-job training

Table 2 - Distribution of occupations (8-digit SOC) across macro-occupations and category of green occupation

SOC 2-digit	Tot N of occupations	Green emerging	Green enhanced skills
11 - Management	46	9	6
13 - Business and Financial Operations	45	6	4
15 - Computer and Mathematical	27	2	-
17 - Architecture and Engineering	61	19	13
19 - Life, Physical, and Social Science	58	7	10
21 - Community and Social Service	14	0	0
23 - Legal	6	0	1
25 - Education, Training, and Library	58	0	0
27 - Arts, Design, Entertainment, Sports, and Media	43	0	2
29 - Healthcare Practitioners and Technical	83	0	1
31 - Healthcare Support	17	0	0
33 - Protective Service	25	0	0
35 - Food Preparation and Serving Related	16	0	0
37 - Building and Grounds Cleaning and Maintenance	8	0	0
39 - Personal Care and Service	32	0	0
41 - Sales and Related	22	1	1
43 - Office and Administrative Support	58	0	1
45 - Farming, Fishing, and Forestry	16	0	0
47 - Construction and Extraction	59	2	9
49 - Installation, Maintenance, and Repair	54	2	4
51 - Production	107	2	6
53 - Transportation and Material Moving	50	0	3
Total	905	50	61

Table 3 - Distribution of employment across macro-occupations

SOC 2-digit	Total	Green occupations ('Green enhanced skills' and 'green emerging')		
		Lower bound	Upper bound	Homog. distr. within 6-digit
11 - Management	5.09%	2.11%	2.70%	2.43%
13 - Business and Financial Operations	4.52%	0.62%	1.51%	0.98%
15 - Computer and Mathematical	2.40%	-	0.05%	0.01%
17 - Architecture and Engineering	1.77%	0.94%	1.10%	1.03%
19 - Life, Physical, and Social Science	0.68%	0.10%	0.21%	0.17%
21 - Community and Social Service	1.14%	-	-	-
23 - Legal	0.65%	-	-	-
25 - Education, Training, and Library	6.13%	-	-	-
27 - Arts, Design, Entertainment, Sports, and Media	1.41%	0.21%	0.21%	0.21%
29 - Healthcare Practitioners and Technical	5.05%	0.01%	0.01%	0.01%
31 - Healthcare Support	2.67%	-	-	-
33 - Protective Service	1.06%	-	-	-
35 - Food Preparation and Serving Related	10.05%	-	-	-
37 - Building and Grounds Cleaning and Maintenance	3.55%	-	-	-
39 - Personal Care and Service	2.96%	-	-	-
41 - Sales and Related	11.54%	0.33%	0.33%	0.33%
43 - Office and Administrative Support	16.83%	0.61%	0.61%	0.61%
45 - Farming, Fishing, and Forestry	0.34%	-	-	-
47 - Construction and Extraction	3.97%	1.31%	1.31%	1.31%
49 - Installation, Maintenance, and Repair	4.06%	1.21%	1.92%	1.57%
51 - Production	6.87%	0.93%	0.93%	0.93%
53 - Transportation and Material Moving	7.28%	1.42%	1.43%	1.43%
Total	100.00%	9.80%	12.30%	11.01%

Table 4 – Descriptive statistics (weighted by employment share; 465 occupations)

Variable	Mean	SD	Min	Q1	Median	Q3	Max	Q3-Q1
Years of educ	13.50	2.04	9.70	11.77	12.88	15.45	20.94	3.68
Years of exp	2.79	1.88	0.06	1.10	2.62	3.93	9.16	2.83
Years of train	0.98	0.76	0.10	0.44	0.77	1.22	4.61	0.78
NR cognitive	0.54	0.15	0.23	0.44	0.52	0.66	0.91	0.23
NR interactive	0.51	0.12	0.22	0.43	0.48	0.59	0.90	0.15
R cognitive	0.44	0.08	0.21	0.40	0.44	0.50	0.71	0.10
R manual	0.41	0.19	0.07	0.24	0.41	0.54	0.93	0.30
NR manual	0.42	0.22	0.03	0.20	0.46	0.60	0.80	0.40
RTI index	-0.17	0.38	-1.18	-0.54	-0.10	0.14	0.72	0.68

Table 5 – Profiling of green occupations: skill measures

	(1) NR cognitive	(2) NR interactive	(3) R cognitive	(4) R manual	(5) NR manual	(6) RTI index
Green emerging	0.0293	-0.00737	-0.0320*	-0.0152	-0.00291	-0.0692
	(0.0187)	(0.0205)	(0.0192)	(0.0149)	(0.0364)	(0.0476)
Green enhanced skills	0.0297**	0.00404	-0.0198*	-0.00508	0.0152	-0.0583**
	(0.0130)	(0.0145)	(0.0108)	(0.0155)	(0.0162)	(0.0269)
Joint sign. green occ dummies (F)	3.309**	0.120	2.489*	0.519	0.456	2.996*
N	465	465	465	465	465	465

OLS estimates weighted by employment share. Robust standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. SOC 3-digit dummies included. Occupations in SOC 3-digit categories with no green occupation have been excluded.

Table 6 – Profiling of green occupations: education, experience and training

	(1) log(years of educ)	(2) log(years of exp)	(3) log(years of train)
Green emerging	0.0205	-0.0515	0.168*
	(0.0221)	(0.124)	(0.0998)
Green enhanced skills	0.0191**	0.357***	0.341***
	(0.00861)	(0.113)	(0.129)
Joint sign. green occ dummies (F)	2.609*	5.982***	3.815**
N	465	465	465

OLS estimates weighted by employment share. Robust standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. SOC 3-digit dummies included. Occupations in SOC 3-digit categories with no green occupation have been excluded.

Table 7 – Distance in routine and non-routine task (by 3-digit SOC occupation)

SOC 3-digit	Description	Distance				Average RTI index		
		Non-routine		Routine				
		Green enhanced skills	Green emerging	Green enhanced skills	Green emerging	Non-green	Green enhanced skills	Green emerging
11-1	Top Executives	**0.1308**		0.1154		-0.8914	-1.2680	-0.8330
11-2	Advertising, Marketing, Promotions, Public Relations, and Sales Managers	0.0758		*0.0353*		-1.0237		-1.1010
11-3	Operations Specialties Managers	0.0590	*0.0535*	0.0793	0.0687	-0.7646	-0.6295	-0.7256
11-9	Other Management Occupations	0.0866	0.0730	*0.0360*	*0.0508*	-0.9056	-0.8423	-0.8598
13-1	Business Operations Specialists	0.1086	0.0674	*0.0378*	**0.0984**	-0.6974	-0.8320	-0.8322
13-2	Financial Specialists	0.0924	0.0643	0.0688	**0.0966**	-0.5091	-0.9108	-0.7608
15-1	Computer Occupations		*0.0560*		0.0594	-0.4156	-0.3948	
17-1	Architects, Surveyors, and Cartographers	**0.1314**		**0.1577**		-0.3054		-0.7156
17-2	Engineers	*0.0334*	*0.0331*	*0.0385*	*0.0436*	-0.7051	-0.6934	-0.5384
17-3	Drafters, Engineering Technicians, and Mapping Technicians	0.0577	**0.0784**	**0.1294**	**0.1602**	-0.1332	-0.2548	-0.3144
19-1	Life Scientists	*0.0186*		0.0592		-0.6565		-0.7462
19-2	Physical Scientists	0.0766	*0.0506*	0.1170	**0.1306**	-0.4376	-0.8787	-0.7525
19-3	Social Scientists and Related Workers	**0.1516**	**0.0814**	0.0923	*0.0449*	-1.1799	-1.0646	-0.8338
19-4	Life, Physical, and Social Science Technicians	*0.0308*	0.0782	0.0721	*0.0592*	-0.1432	-0.3096	-0.1023
23-1	Lawyers, Judges, and Related Workers	0.0990		**0.1282**		-0.8146		-1.1870
27-3	Media and Communication Workers	0.0498		**0.1558**		-0.3988		-0.8135
29-9	Other Healthcare Practitioners and Technical Occupations	0.0588		0.0740		-0.8721		-0.5132
41-4	Sales Representatives, Wholesale and Manufacturing	0.0821	**0.0954**	0.0648	*0.0535*	-0.7232	-0.5700	-0.8309
43-5	Material Recording, Scheduling, Dispatching, and Distributing Workers	0.0385		0.0583		0.1164		0.0500
47-2	Construction Trades Workers	*0.0267*	**0.0942**	*0.0517*	0.0960	0.0334	-0.2241	0.0538
47-4	Other Construction and Related Workers	**0.1317**	0.0764	0.0901	0.0637	-0.0140	-0.2162	-0.4288
47-5	Extraction Workers	0.0553		0.0758		0.2876		0.3160
49-3	Vehicle and Mobile Equipment Mechanics, Installers, and Repairers	*0.0165*		0.0575		0.0252		-0.0239
49-9	Other Installation, Maintenance, and Repair Occupations	0.0360	0.0592	0.0717	0.0747	-0.0040	-0.0659	-0.1597
51-2	Assemblers and Fabricators	0.0652		**0.2000**		0.2444		0.2586
51-4	Metal Workers and Plastic Workers	0.0375		0.0772		0.3531		0.2582
51-8	Plant and System Operators	0.1063	*0.0470*	0.0928	0.0940	0.0146	0.0000	-0.0352
51-9	Other Production Occupations	0.0513	**0.1180**	0.0922	**0.1222**	0.3223	0.2414	0.1549
53-3	Motor Vehicle Operators	0.0771		0.0704		0.2302		0.0997
53-6	Other Transportation Workers	**0.1344**		0.1056		0.2198		0.0666
53-7	Material Moving Workers	0.0764		0.1181		0.2646		0.5264

Table 8 – Exposure of green occupations to green technology

	(1) log(R&D tot/L)	(2) log(R&D env/L)	(3) log(pat tot/L)	(4) log(pat env/L)	(5) log(investments/L)	(6) log(ICT/L)
Green emerging	0.331**	0.0566	0.477*	0.0798	0.192**	0.129*
	(0.142)	(0.0499)	(0.248)	(0.0727)	(0.0962)	(0.0668)
Green enhanced skills	0.277***	0.0861***	0.597***	0.161***	0.123*	0.0555
	(0.0915)	(0.0285)	(0.206)	(0.0550)	(0.0635)	(0.0410)
Joint sign. green occ dummies (F)	6.717***	5.209***	5.039***	4.490**	3.348**	2.634*
N	465	465	465	465	465	465

OLS estimates weighted by employment share. Robust standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. SOC 3-digit dummies included. Occupations in SOC 3-digit categories with no green occupation have been excluded.

Table 9 – Profiling of green occupations: skill measures (conditional on investments and R&D)

	(1) NR cognitiive	(2) NR interactive	(3) R cognitive	(4) R manual	(5) NR manual	(6) RTI index
Green emerging	0.0155	-0.0139	-0.0338*	-0.0196	-0.00516	-0.0573
	(0.0196)	(0.0218)	(0.0184)	(0.0157)	(0.0362)	(0.0500)
Green enhanced skills	0.0252**	0.00224	-0.0201**	-0.00479	0.0174	-0.0528*
	(0.0122)	(0.0142)	(0.0101)	(0.0154)	(0.0151)	(0.0278)
log(R&D non-env/L)	0.0379**	0.0202	0.0118	0.0357*	0.0242	-0.00533
	(0.0166)	(0.0201)	(0.0139)	(0.0211)	(0.0164)	(0.0417)
log(R&D env/L)	-0.0648	-0.0464	-0.0155	-0.0905	-0.0996**	-0.00294
	(0.0447)	(0.0518)	(0.0374)	(0.0570)	(0.0455)	(0.106)
log(ICT/L)	0.0583***	0.000224	0.0333**	-0.0121	-0.0231	-0.0213
	(0.0202)	(0.0221)	(0.0165)	(0.0204)	(0.0241)	(0.0481)
log(investments)	-0.00100	0.0140	-0.0210**	0.000442	0.0137	-0.0364
	(0.0119)	(0.0135)	(0.00987)	(0.0148)	(0.0135)	(0.0275)
Joint sign. green occ dummies (F)	2.220	0.234	2.997**	0.781	0.704	2.134
N	465	465	465	465	465	465

OLS estimates weighted by employment share. Robust standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. SOC 3-digit dummies included. Occupations in SOC 3-digit categories with no green occupation have been excluded.

Table 10 – Profiling of green occupations: education, experience and training (conditional on investments and R&D)

	(1) log(years of educ)	(2) log(years of exp)	(3) log(years of train)
Green emerging	0.0102	-0.124	0.138
	(0.0230)	(0.133)	(0.110)
Green enhanced skills	0.0137*	0.291***	0.301**
	(0.00778)	(0.107)	(0.128)
log(R&D non-env/L)	0.0294***	0.00216	-0.124
	(0.0111)	(0.0984)	(0.118)
log(R&D env/L)	-0.0118	0.641**	0.653**
	(0.0261)	(0.256)	(0.269)
log(ICT/L)	0.0241*	-0.108	-0.125
	(0.0139)	(0.0991)	(0.127)
log(investments)	-0.00131	0.227***	0.210**
	(0.00971)	(0.0796)	(0.0894)
Joint sign. green occ dummies (F)	1.557	5.188***	2.869*
N	465	465	465

OLS estimates weighted by employment share. Robust standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. SOC 3-digit dummies included. Occupations in SOC 3-digit categories with no green occupation have been excluded.

Table 11 – Profiling of green occupations: skill measures (conditional on investments and patents)

	(1) NR cognitiive	(2) NR interactive	(3) R cognitive	(4) R manual	(5) NR manual	(6) RTI index
Green emerging	0.0202	-0.0105	-0.0307*	-0.0154	-0.00141	-0.0576
	(0.0193)	(0.0214)	(0.0186)	(0.0142)	(0.0360)	(0.0487)
Green enhanced skills	0.0251**	0.00198	-0.0212**	-0.0105	0.0147	-0.0582**
	(0.0122)	(0.0147)	(0.0100)	(0.0150)	(0.0159)	(0.0282)
log(patent non-env/L)	0.00437	-0.000993	-0.000940	0.00593	-0.00374	0.00154
	(0.00635)	(0.00744)	(0.00511)	(0.00755)	(0.00598)	(0.0155)
log(patent env/L)	0.00182	0.00911	0.0267**	0.0363*	0.0172	0.0433
	(0.0155)	(0.0170)	(0.0135)	(0.0211)	(0.0205)	(0.0377)
log(ICT/L)	0.0690***	0.00567	0.0433***	-0.00115	-0.0239	-0.0165
	(0.0214)	(0.0225)	(0.0159)	(0.0214)	(0.0258)	(0.0479)
log(investments/L)	-0.00244	0.0115	-0.0326***	-0.0198	0.00872	-0.0595*
	(0.0138)	(0.0156)	(0.0121)	(0.0173)	(0.0158)	(0.0336)
Joint sign. green occ dummies (F)	2.361*	0.141	2.951*	0.663	0.436	2.484*
N	465	465	465	465	465	465

OLS estimates weighted by employment share. Robust standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. SOC 3-digit dummies included. Occupations in SOC 3-digit categories with no green occupation have been excluded.

Table 12 – Profiling of green occupations: education, experience and training (conditional on investments and patents)

	(1) log(years of educ)	(2) log(years of exp)	(3) log(years of train)
Green emerging	0.0139	-0.110	0.154
	(0.0226)	(0.127)	(0.104)
Green enhanced skills	0.0142*	0.307***	0.316**
	(0.00818)	(0.106)	(0.124)
log(patent non-env/L)	0.00739	0.0321	-0.0498
	(0.00454)	(0.0332)	(0.0384)
log(patent env/L)	0.00460	0.144	0.301***
	(0.0110)	(0.114)	(0.109)
log(ICT/L)	0.0404***	0.0495	-0.00230
	(0.0150)	(0.125)	(0.127)
log(investments/L)	-0.00636	0.142	0.0960
	(0.0124)	(0.104)	(0.108)
Joint sign. green occ dummies (F)	1.569	5.633***	3.424**
N	465	465	465

OLS estimates weighted by employment share. Robust standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. SOC 3-digit dummies included. Occupations in SOC 3-digit categories with no green occupation have been excluded.

Table A1 – Environmental patent classes (source: ENV-TECH Indicator, OECD, 2013)

Macro-category	Sub-category	IPC (CPC) classes
General environmental management	Air pollution abatement	BO1D46, B01D47, B01D49, B01D50, B01D51, B01D53/34-72, B03C3, C10L10/02, C10L10/06, C21B7/22, C21C5/38, F01N3, F01N5, F01N7, F01N9, F23B80, F23C9, F23G7/06, F23J15, F27B1/18
	Water pollution abatement	B63J4, C02F, C05F7, C09K3/32, E02B15/04-06, E02B15/10, E03B3, E03C1/12, E03F
	Solid waste collection	E01H15, B65F
	Material recovery, recycling and re-use	A23K1806-10, A43B1/12, A43B21/14, B03B9/06, B22F8, B29B7/66, B29B17, B30B9/32, B62D67, B65H73, B65D65/46, C03B1/02, C03C6/02, C03C6/08, C04B7/24-30, C04B11/26, C04B18/04-10, C04B33/132, C08J11, C09K11/01, C10M175, C22B7, C22B19/28-30, C22B25/06, D01G11, D21B1/08-10, D21B1/32, D21C5/02, D21H17/01, H01B15/00, H01J9/52, H01M6/52, H01M10/54
	Fertilizers from waste	C05F1, C05F5, C05F7, C05F9, C05F17
	Incineration and energy recovery	C10L5/46-48, F23G5, F23G7
	Waste management n.e.c.	B09B, C10G1/10, A61L11
	Soil remediation	B09C
	Environmental monitoring	F01N11, G08B21/12-14
Energy generation from renewable and non-fossil sources	Wind energy	Y02E10/7 (CPC)
	Solar thermal energy	Y02E10/4 (CPC)
	Solar photovoltaic (PV) energy	Y02E10/5 (CPC)
	Solar thermal-PV hybrids	Y02E10/6 (CPC)
	Geothermal energy	Y02E10/1 (CPC)
	Marine energy	Y02E10/3 (CPC)
	Hydro energy	Y02E10/2 (CPC)
	Biofuels	Y02E50/1 (CPC)
	Fuel from waste	Y02E50/3 (CPC)
Combustion technologies with mitigation potential	Technologies for improved output efficiency (combined combustion)	Y02E20/1 (CPC)
	Technologies for improved input efficiency	Y02E20/03 (CPC)
Climate change mitigation	CO2 capture or storage	Y02C10 (CPC)
	Capture or disposal of greenhouse gases other than CO2	Y02C20 (CPC)
Potential or indirect contribution to emissions mitigation	Energy storage	Y02E60/1 (CPC)
	Hydrogen technology	Y02E60/3 (CPC)
	Fuel cells	Y02E60/5 (CPC)
Emissions abatement and fuel efficiency in transportation	Integrated emissions control	F02B47/06, F02M3/02-055, F02M23, F02M25, F02M67, F01N9, F02D41, F02D43, F02D45, F01N11, G01M15/10, F02M39-71, F02P5, F02M27, F02M31/02-18
	Post-combustion emissions control	F01M13/02-04, F01N5, F02B47/08-10, F02D21/06-10, F02M25/07, F01N11, G01M15/10, F01N3/26, B01D53/92, B01D53/94, B01D53/96, B01J23/38-46, F01N3/08-34, B01D41, B01D46, F01N3/01, F01N3/02-035, B60, B62D
	Technologies specific to propulsion usin electric motor	B60K1, B60L7/10-20, B60L11, B60L15, B60R16/033, B60R16/04, B60S5/06, B60W10/08, B60W10/26, B60W10/28, B60K16, B60L8
	Technologies specific to hybrid propulsion	B60K6, B60W20
	Fuel efficiency-improving vehicle design	B62D35/00, B62D37/02, B60C23/00, B60T1/10, B60G13/14, B60K31/00, B60W30/10-20
Energy efficiency in buildings and lighting	Insulation	E04B1/62, 04B1/74-78, 04B1/88, E06B3/66-677, E06B3/24
	Heating	F24D3/08, F24D3/18, F24D5/12, F24D11/02, F24D15/04, F24D17/02, F24F12, F25B29, F25B30
	Lighting	H01J61, H05B33