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The skill-content of green jobs

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Keywords: Green skills, Innovation, Human Capital

JEL: J24, Q55, J62

***** PRELIMINARY DRAFT: PLEASE DO NOT QUOTE WITHOUT THE AUTHORS' EXPLICIT PERMISSION *****

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. In general, the transition to greener forms of production, distribution and consumption is 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. This is of crucial importance to inform educational policy aimed at absorbing shortages of know-how and skill mismatches associated to environmental sustainability.

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 is ample and 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, in turn, implies that environmental sustainability can both alter the organization of established industries as well as stimulating the emergence of new ones (OECD, 2010). As a result, the implications for the workforce can be manifold and encompass the appearance of new occupations; the extinction of old ones; and significant changes in the job content or increased demand for continuing occupations (Dierdoff et al, 2009). We argue that such an articulation is important for locating, describing, and weighing the effect of green growth on employment.

The empirical framework proposed in this paper focuses on the multifaceted nature of human labour by considering complementary dimensions of occupations such as job task, the skill base of the workforce and the pathways through which employees acquire and perfect knowledge. Under the perspective adopted here the intensity of use of a task within an occupation is a direct measure of the skills that are necessary for performing work activities (Autor et al, 2003; Levy and Murnane, 2004). Thereby changes in the scope or in the organization of industry challenge the relevance of both the existing know-how as well as the mechanisms for its diffusion such as formal education, on-the-job training or work experience. This, in turn, calls attention to the trade-off between specialization and generality of labour skills across industries or occupations. The 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. This raises the question of which types of know-how can either become or stay relevant under as commitments towards environmental sustainability give way to action.

We add to this debate by profiling the skill content of green occupations in the United States (US). In particular, 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 skill profile of green jobs different from that of non-green ones?

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 twofold. 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. Secondly, we compare the matching subsets 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 captured by means of data on patents and R&D expenditure. The idea is that differences in skill content between green and non-green occupations may be driven by differential exposure to a technology that may require particular types of skills, rather than by genuine skill specificity of green occupations.

Our empirical exercise offers an arguably nuanced interpretation of the differences between green and non-green jobs while, at the same time, elucidating on the interpenetration between forms of know-how and technology. Moreover, our empirical exercise highlights important shortcomings of the binary logic of ‘green versus brown’ occupations that has dominated the scholarly and the policy debate so far.

The remainder of the paper is structured as follows. Section 2 will present 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 summarizes.

2 Literature review

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 (EC, 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. In line with the context in which these strategies have been conceived, economic and environmental pressures coalesce in shaping the attendant strategies of intervention (Borghesi et al., 2013). Parallel to the public debate on the viability of eco-efficiency based on lowering natural resource depletion and increasing human labour (e.g. the motto “Make kilowatt-hours unemployed, not people”) (Pfeiffer and Rennings, 2001), academic research debates whether and to what extent the transition towards sustainable production can affects job creation and destruction. This section provides an overview of the existing literature organized in two blocks. First, we focus on studies that attempt a quantitative estimation of net employment effects due to environmental regulation and innovation. After having identified conceptual shortcomings in this literature we draw attention to important qualitative aspects of green employment, and propose an alternative framework for the analysis of the skill content of these occupations.

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 rather controversial. The spectrum of possible actions is rather wide and encompasses options such as carbon prices, R&D subsidies and regulation, as well as a variety of routes for implementation (Aghion et al 2009). In practice, several instruments are often embedded within a policy mix that seeks a balance among multiple, at times contrasting, issues at stake while at the same time allowing for flexibility and adaptability (OECD, 2007). In turn, there is growing interest towards assessing the effectiveness of government intervention in support of green growth, and the debate is characterized by sharp differences between opposing views (see reviews by Jaffe et al, 1995 and Bowen, 2012).

The empirical evidence concerning employment effects 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 the positive forecasts concerning the expansion of the markets for environmental goods and services, which are rather labour intensive (e.g. Kammen et al, 2004; Selwyn and Leverett, 2006; UNEP, 2008; Renner, 2009). Under this perspective also capital intensive activities – i.e.: carbon capture and storage – are expected to see higher demand for high-skill workers such as scientists and managers who are needed for the successful completion of ongoing pilot projects (IEA, 2009; OECD, 2010). Further empirical evidence comes from studies on more direct forms of intervention such as regulation, that is, the establishment of emission criteria which in the United States, for example, is enforced by government organizations that mandate the development of plant-specific interventions such as the installation of state-of-the-art technology.[1] Again, the empirical evidence is rather mixed. Some 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 find that environmental regulation triggers job creation (Bezdek et al, 2008). A number of scholars draw attention to important specificities of industry (e.g. Morgenstern et al, 2002), plant characteristics (e.g. Becker, 2005; Becker et al, 2013) or type of pollutant (e.g. Greenstein, 2004) when evaluating the employment effects of environmental regulation. Still others ascribe negative outcomes to workers´ displacement across industries rather than to job destruction (Arrow et al, 1996; Henderson, 1996; Greenstone, 2002).[2] A study by Greenstone (2004) on the effects of the 1977 Amendments to the Clean Air Act (CAA) at plant level concludes that nonattainment status has a modest negative impact on employment, and that these results tend to be pollutant-specific.[3] Walker (2011) finds that a significant portion of employment adjustments are due to increases in job destruction, and that this effect is stronger among newly regulated plants. A more recent paper by Walker (2013) uses US worker-level data and finds negative employment and wage effects due to job displacement following the 1990 Amendments of the CAA.

A strand of empirical studies focuses on the effects of environmental technological change on employment (see Yi, 2014 for a review). From a theoretical point of view it is expected that product innovations have a positive, demand-related, effect, though the net impact depends on whether innovation substitutes for or complements existing products (Harrison et al., 2014), while process innovations have a negative effect via increased labour productivity, though this may be compensated by lower production costs that would lead to lower prices and eventually to higher demand (Licht and Peters,

[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).

[2] Previous studies using plant-level and worker-level data found a strong link between plant-level job destruction and involuntary job loss (Davis et al, 2006) with subsequent growth of non-employment and of earnings losses (von Wachter et al, 2007).

[3] The effects of nonattainment with Tropospheric Ozone and Sulfur Dioxide are not significant. Greenstone (2004) remarks that the tightening of ozone and particulates standards in 1997 may be at root of a significant increase in the number of nonattainment counties for these pollutants.

2013, 2014; Pfeiffer and Rennings, 2001). From an empirical point of view the existing studies contemplate multiple scenarios ranging from negative labour market outcomes (e.g. Cainelli et al., 2011) to weakly positive employment effects. In particular, Pfeiffer and Rennings (2001) find a limited effect of cleaner production technologies; Rennings and Zwick (2002) and Rennings et al. (2004) report small effects of eco-innovations, with a higher impact of product and service innovation, while end-of-pipe solutions have a negative effect on employment. Yet other empirical studies highlight the 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 have also attempted to distinguish labour market outcomes depending on whether innovation is specifically environmental or has a more general character, but the evidence is not conclusive. Horbach (2010) and Gagliardi et al. (2014) find positive and stronger effects for environmental innovations while Licht and Peters (2013, 2014) find positive but not significantly different effects between environmental and non-environmental product innovations as well as a limited impact of process innovations on employment.

The bias towards the quantitative assessment of employment in the literature reviewed so far entails important oversights on qualitative changes in the organization and the content of labour. The emergence of a new technological paradigm is likely to be characterised by the appearance of new occupations, new skills and novel combinations of existing forms of know-how. However, as the mixed results commented above suggest, many green technologies are still at early stage and labour market outcomes following adoption are not clear as yet. Moreover the extant literature has elucidated industry-level effects but neglected changes in the way individuals work and by, the same token, of the consequences in terms of skill demand. The present paper seeks to fill this gap by focusing on changes in the knowledge content of work. 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: in search of a working definition

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 difficult to assemble for creating a coherent classification of green jobs. A second method is based on the identification of green products and services that are known to contribute to environmental and conservation objectives, and subsequently estimating the number of jobs involved in the production or delivery (see e.g. US Department of Commerce, 2010). The initial classification 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 the identification of tangible and easily recognizable items is no doubt a virtue, this approach relies on ad-hoc definitions and thus likely yields many false negatives, that is, it overlooks 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 method relies on selecting green 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. Employees in these industries are therefore identified as the green workforce. 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 turn 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:

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

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

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

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 build on this approach to green job identification and focus on the latter two of the aforementioned groups.[5]

In the absence of established and 'green-specific' skill taxonomies, we operationalize insights from the O*NET approach building on the framework proposed by Autor, Levy and Murnane (2003) (ALM henceforth) for the analysis of changes in skill content of occupations. Therein occupations are regarded as vectors of job-specific characteristics such as work tasks, required levels of formal education, on-the-job training and work experience. Though the paradigmatic case that inspired this approach was the diffusion of Information and Communication Technologies (ICTs) in the US, the characteristics that define occupations can be translated to the context of environmental sustainability. Thereby occupations more intensive in "non-routine" tasks relate to a broad class of adaptive problem solving, be it applied to interpreting information (non-routine cognitive), communicating with others (non-routine interactive) or dealing with circumstances that require situational adaptability (non-routine manual). Conversely, occupations more 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. Closer to the context at hand green occupations

[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).

[55] A cursory look at the increased demand occupational group suggests that these occupations are only relevant due to an employment effect, and thus can be considered indirectly 'green' at best. However their occupation characteristics bear no specific relation to sustainable economies, which is instead the main focus of our analysis.

encompass various skill-typologies (see e.g. Strietska-Ilina et al. 2011). To illustrate Non-routine cognitive tasks are typically associated with occupations such as engineers (chemical, renewable energy, civil, environmental), architects and designers as well as analysts, consultants and researchers (dealing both with environmental and hard sciences or business, economic, legal disciplines). Non-routine interactive tasks are particularly relevant for managerial specialists ranging from executives to experts in regulation, sustainability and plant production managers but also trainers, teachers and professors. Non-routine manual tasks are most common among drivers, installers and plumbers, mechanics, and construction workers. On the other hand, routine cognitive tasks are most prominent among activities of laboratory, production, maintenance, quality control technicians, while routine manual tasks are the competence of occupations like recycling and machine operators.

The foregoing approach is attractive on many counts. From a conceptual viewpoint it allows for flexible interpretations of the relation between labour and capital that 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 suitable to address recurrent questions at the core of studies on the employment effects of green growth, namely: is the skill content of green jobs proximate to that of existing occupations? And, where will the necessary know-how come from?

Answers these questions, firstly bear on the issue of the transferability of human capital. As the standard 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 industry or occupation code per se but, rather, to job displacement that entails either loss of know-how specificity or the underutilization of skills. This leads to expect, first, that occupational tenure reduces human capital loss. Moreover, incremental adaptation to changing job content is positively correlated with higher wages and productivity. In other words staying in the same occupation and having experience with various occupation-specific tasks can trigger “inter-task learning” and lead to the build-up or a broader, viz. multi-purpose, human capital stock. On the basis of the above, the outcomes of either job displacement or changes in job content will ultimately depend on length of tenure and complementarity across different tasks.[6] On the whole greater understanding of the composition of know-how of occupations, as per the task-based approach, is expected to provide useful insights for this debate. A second issue to be taken into account is the diverse nature of the processes upon which related knowledge and human capital are created. Since long, the economic literature has considered this aspect. Not only have scholars focused on experiential forms of knowledge creation and accumulation, where

[6] Clearly this calls into question the responsiveness and flexibility of the institutions for the supply of skills (Vona and Consoli, 2015).

learning by doing processes can be considered the 'by-product' consequence of the engagement in production (e.g. Arrow, 1962). The development of the human capital theory in the field of labour economics has also shed light on the different forms of training that affect the workers' knowledge (e.g. Becker, 1962; Mincer, 1962). Accordingly, while formal education is expected to deliver a general type of learning, on-the-job training programmes are generally more focused on firms specific needs and more responsive to the emerging skill-gaps.

To the best of our knowledge the academic literature has so far neglected the connection between the transition towards green economies and changes in the skill content of occupations. Yet this is a central theme in the policy debate. Adaptability and transferability of workers' competences are considered as crucial to meet and adjust to the requirements of the transition toward a low-carbon economy and deemed to build upon core and horizontal skills (e.g. literacy, numeracy, teamwork and problem solving) acquired in particular through formal education and initial training. Adaptability to green reconstructing is also expected to be supported by hands-on experience, as well as tailor-made and continuous workplace training, with these latter being capable to enhance upskilling and the formation of new competences in the most effective and yet flexible mode (Strietska-Ilina et al., 2011; OECD and 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 aim of this paper is descriptive and exploratory, in particular it seeks to assess the extent to which the skill content of green occupations differ that of non-green occupations. The focus on occupations resonates with the literature that emphasises that employment is a pathway for the translation of human know-how into productive activities (Holland, 1997; Levy and Murnarne, 2005; Consoli et al, 2014). From this it follows that understanding what mechanisms shape changes in the structure and the content of labour is the key to identify which forms of know-how are relevant as well as the role that technology plays in modifying this know-how.

To operationalize matters, we estimate the following equation:

$$Skill_{occ} = \beta^1 Green\_skill_{occ}^{0,1} + \beta^2 Green\_emerg_{occ}^{0,1} + SOC\_4digit_{occ}^{0,1} + \varepsilon_{occ} \quad (1)$$

where $Skill_{occ}$ is our set of skill measures for occupation occ; $Green\_skill_{occ}^{0,1}$ and $Green\_emerg_{occ}^{0,1}$ are dummy variables that are equal to 1 for 8-digit occupations that have been identified respectively as Green skill and Green emerging (see section 2.2), and zero otherwise; $SOC\_4digit_{occ}^{0,1}$ is a full set of 4-digit SOC (Standard Occupational Classification) dummy variables; ε_{occ} is the residual.

As will be discussed in section 4, green occupations tend to be concentrated in few macro-occupational groups. Failing to account for this peculiarity when comparing the skill content of green and non-green occupations would be misleading for results would be driven by heterogeneity in the average skill content of macro-occupations rather than true specificities of green occupations. Accordingly, we identify specificities beyond mere differences across macro-occupations by implementing a 'matching' approach. We include 4-digit SOC dummies to control for macro-occupational differences related, for example, to complexity and educational background that is common to narrow occupations within the same macro-occupational group. Moreover, again to single out specificities of green occupations, we just focus on 4-digit macro-occupational groups wherein at least a green occupation (either Green skills or Green emerging) exists.[7] An example will illustrate: 'Environmental engineers' (SOC 17-2081.00) falls in the Green skills group within the 4-digit occupation (SOC 17-20) '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.

We estimate equation 1 with OLS with occupations weighted by employment share. Data on occupational employment is available only at 6-digit SOC level, for a total of about 700 occupations[8], while skill measures are at 8-digit SOC level for a total of 905 occupations. While for 690 occupations (85.7 percent of employment and 52 8-digit green occupations) there is just one 8-digit occupation for each 6-digit occupations, for 51 occupations there are two 8-digit occupations for each 6-digit occupations (9.3 percent of employment and 20 8-digit occupations) and for the remaining 41 6-digit occupations (5 percent of employment and 39 green occupations) there are, on average, 3.4 8-digit occupations for each 6-digit occupation. Lacking a proxy for the relative importance of 8-digit occupations within 6-digit occupations, we weighted each 8-digit occupation within the same 6-digit occupation equally. This allows maintaining detailed information on skills for narrow occupations but, at the same time, entails the risk of systematically overestimating or underestimating the relevance of some occupations.

The second step of our analysis consists in re-estimating equation 1 with the inclusion of a series of indicators of occupational exposure to technology (see Section 3.2 for details 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 genuine skill specificity of green occupations. Going back to the earlier example, exposure to 'environmental patents' (see section 3.2 for details on the measures of exposure) 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 which affects substantially the demand for some types of skills (see section 2.2) rather than actual specificities of the green occupation relative to the non-green one. On the whole, accounting for this type of occupational exposure allows us to capture skill specificities (or absence thereof) beyond simple effects due to technology. As the following section will illustrate, our measures of 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 linked to the green economy.

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[7] It should be noted, however, that, differently from matching estimators widely used in policy evaluation exercises (Heckman et al, 1998), we are not claiming causal links between the green occupation status and the skill content.

[8] 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).

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 a particularly suitable dataset.

Specifically, our analysis is based on cross-sectional data for the US at the 8-digit SOC occupation level for 905 occupational titles. We combine occupation-level information (detailed skill measures, required levels of education, training and experience, employment by occupation-industry) with industry-level measures of technology exposure. We measure the skill content of US occupations using the O*NET (Occupational Information Network) database of the U.S. Department of Labor (DOL). O*NET represents a notable exception to the lack of good statistical information on green occupations and related skills (ILO, 2011a). It collects 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. At the core of the database 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, labor market characteristics, and occupation-specific information. These are further separated in specific categories and detailed hierarchies of descriptors. Trained evaluators assign quantitative ratings to each individual descriptor on the basis of informed assessments and questionnaire data. Scores are based on three dimensions: importance, level, and frequency along a standardized 0-100 scale. O*NET content is revised and expanded periodically by means of surveys (e.g., Peterson et al. 2001; Hadden, Kravets, and Muntaner 2004; 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.

[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 taxonomy of ALM (2003) and Acemoglu and Autor (2011)[9] and includes six measures of occupational task intensity: 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 (as in Acemoglu and Autor, 2011).[10] Measures are computed as the raw average of items' scores, normalized to vary between 0 and 1.

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

[10] For a definition of these skill groups, see Section 2.2.

For each occupation we measure 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 computed as follows:

$$Exposure_{occ} = \sum_{ind} \left(\frac{Technology_{ind}}{Employment_{ind}} \times Emp\_share_{occ,ind} \right) \quad (2)$$

This measure should be interpreted as the intensity of investment (or patents) per employee invested, on average, for each employee of the occupation, independently on the industry in which the employee is employed. We build indicators of exposure to various instantiations 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 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

Before turning to the profiling of green occupation we discuss aggregate evidence on green occupations. In the first place, we want to quantify the relevance of green occupations in the workforce employed in private sector, non-agricultural industries. Table 2 shows the count of 8-digit SOC occupations, split by macro-occupation (2-digit SOC) and green and non-green occupations. Green occupations, either Green skills or Green emerging polarize into occupations intensive in abstract skills (e.g. problem-solving, management and coordination): out of 111 green occupations, 76 green occupations are in the first five macro-occupations (11 to 19) and some other in routine manual occupations (47 to 53, 28 occupations).

[Table 2 and 3 about here]

To gauge the scale of green employment we report employment shares by macro-occupation and green and non-green occupations 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. Our preferred choice therefore is to assume that employment is distributed uniformly across 8-digit occupations within the same 6-digit occupation. If 8-digit green occupations were systematically smaller or bigger in terms of employment that non-green occupations within the same 6-digit occupation, we would overestimate or underestimate the aggregate employment of green occupations. According to 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

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

employment in the US, while when employing the approximate SOC 8-digit weights this number increases to 11 percent and it further raises to 12.3 percent when attributing the 'green occupation' status to all occupations within the 6-digit occupation with at least one green occupation. This aggregate figure seems to clash with the estimated size of green jobs in the US workforce provided by other sources such as BLS and OECD that instead ranges between 2 and 4 percent.[12] But as discussed in section 2.2, these approaches focus on workers, in any occupational group, employed in the Green Goods and Services sector defined at industry or establishment level. Looking at the distribution of employment in green occupations we observe that, similar to the number of occupations, they are concentrated in few macro-occupational group, either abstract occupations or routine-manual occupations.

[Figure 1 and 2 about here]

The uneven distribution of green occupations and of their corresponding employment share is confirmed when comparing the distribution of skill intensity of green and non-green occupations, weighted by employment shares (Figure 1 and 2). From the first three graphs of Figure 1 we observe that both Green emerging and Green skills occupations require higher amounts of experience and training, with their distribution being shift to the right with respect to the distribution of non-green occupations. When looking at formal education, however, only Green emerging occupations require substantially higher amount of schooling while Green skills occupations require more or less the same amount of formal education as non-green occupations. When looking at our six measures of skill, Green emerging occupations are quite apart from the remaining two in that they employ relatively more abstract skills, especially Non Routine Cognitive, and less of both Routine and Manual skills.

[Table 4, 5 and 6 about here]

Digging deeper into the skill specificity of green occupations we seek to single out differences across macro occupational groups. The profiling of green occupations based on the comparison of green occupations to similar non-green occupations in the same 4-digit SOC class, as described in Section 3.1, aims exactly at eliciting these specificities. Baseline estimates are reported in Tables 5 and 6 while some descriptive statistics for skill measures are reported in Table 4. As concerns the set of skill measures proposed by ALM (2003) and Autor and Acemoglu (2011), reported in Table 5, we observe only few significant differences between green occupations and similar non-green occupations. In particular non-routine cognitive skills are higher for Green skills occupations relative to similar occupations, while both Green skills and Green emerging occupations are relatively less intensive in routine cognitive tasks than their peer occupations. Finally, the synthetic indicator of prevalence of routine skills over non-routine skills (R index) evidences a significant negative difference between Green skills and similar non-green occupations while no significant difference is found for Green emerging. The other measures (non-routine interactive skills, routine manual skills and non-routine manual skills) show no significant difference between green and non-green occupations. Since these are measures of relative importance, an 'absolute'

[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).

quantification of the difference is not straightforward. We opt for an interpretation in terms of standard deviations between the two groups of occupations. Thereby for what concerns Green skills occupations, the importance of non-routine cognitive skills is 0.19 standard deviation higher than that of non-green occupations; the score of routine cognitive skills is 0.24 standard deviation lower; and the relative importance of routine to non-routine skills is 0.17 standard deviations smaller for green occupations compared to their non-green peers. As regards Green emerging occupations, the only significant difference is the lower importance of routine skills that are about 0.32 standard deviations less important than for non-green occupations. To reiterate, according to the standard literature (e.g. Autor et al, 2003; Levy and Murnane, 2004; Acemoglu and Autor, 2011) non-routine tasks require situational adaptability and, therefore, entail complex cognitive or interpersonal know-how to deal with a non-fully predictable work environment. Conversely, routine skills are involved in work activities based on the execution of explicit instructions such as e.g. book-keeping, clerical work, production and monitoring. 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). Our results suggest that, in general, the task environment of green occupations is not as routinized as that of their peer non green jobs, and therefore that work activities are in the process of definition. This finding resonates with the fact that technology in this remit is still at early stages. Moreover the latter is consistent also with the other finding that Green emerging occupations, jobs whose task content is expected to undergo significant changes due to the green transition, exhibit higher cognitive and interpersonal skills.

Moving to the other dimensions, education, experience and on-the-job training, the differences between green occupations and similar non-green occupations are more substantial. This is especially true for Green skills occupations which require 1.8 percent more years of education than similar non-green occupations, about three months when evaluated at the overall sample mean. The relative difference increases substantially for Green skills when considering additional years of experience (42 percent, corresponding to ten months when evaluated at the overall sample mean) and years of training (37 percent, corresponding to three months 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 we estimate that they require 22 percent more years of training than non-green occupations, corresponding to slightly less than two months when evaluated at the overall sample mean.

[Table 7 about here]

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 look at whether green occupations differ from similar occupations (within the same 4-digit SOC occupational group) in terms of exposure to our measures of technology. Results are reported in Table 7.

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

Green 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. On the contrary, the only significant (and positive) difference between Green emerging and non-green occupations is found for the exposure to investments in fixed assets. The magnitude of these differences, especially if we consider that we are looking at the variation within 4-digit occupational groups, is quite remarkable.

To understand whether differences in the exposure to technology rather than skills specificity of green occupations drive the differences between green and non-green occupations, we enrich the baseline specification of equation 1 with a series of variables that capture exposure of occupations to technology. 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 technology measured, alternatively, by R&D (total and green R&D – Tables 8 and 9) and patents (total and green patents – Table 10 and 11). Due to the cross-sectional nature of our data that does not allow controlling for the unobserved heterogeneity across occupations, we are not particularly interested in the role played in the regressions by our set of variables of exposure to technology. The inclusion of variables that measure the exposure of occupations to technology does not influence the estimated differences in the skill content of green occupations with respect to non-green occupations. The direction and significance of the estimated differences remain basically unaffected. If anything, we just observe a small (but not significant) reduction in the magnitude of differences.

5 Preliminary conclusions and the way ahead

Our results point to two main implications for policy. Especially for radically new occupations (i.e. green emerging), formal education does not seem to play a role among workers in green jobs. This suggests the necessity to update university curricula to the emerging requirements of green jobs, and to invest in skill monitoring and forecasting. At the same time our findings suggest that educational policy is not the only type of intervention required to assist the formation of a green and skilled workforce. Specific support has to be granted to on-the-job training programmes as these latter appear to adapt better and faster to the emerging requirements of the transition toward greener production paradigms. In this respect, industry and sector consortia and associations emerge as important actors, as they can mitigate the risk of free riding and spread externalities in the creation of green human capital among participating firms.

The present study opens up interesting directions for future research. Firstly, due to our research objective and setting, we could not analyse the possible complementarities that may exist among different types of skills and different forms of learning based on formal education, on-the-job training and experience. Second, we could not relate our analysis to the dynamics of the entry in the job market. Our results may indeed be sensitive to the “age” of workers: depending on the proportion of entrants over tenured workers, the relevance of formal education vis-a-vis on-the-job training and experience may change. Indeed, one may expect that with many young workers entering the job market, university education would be more important, and, on the contrary, during stagnant phases, green capabilities have to be developed by re-skilling existing workers.

References

TBA

Tables and figures

Table 1 – Skill and task measures

Indicator	Items in O*NET	Description of items in O*NET
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 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 (R index)	-	log(RC+RM) – log(NRA+NRI)
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 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 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; 905 occupations)

Variable	Mean	SD	Min	Q1	Median	Q3	Max	Q3-Q1
Years of educ	13.18	2.06	9.42	11.73	12.74	14.52	20.94	2.79
Years of exp	2.04	1.63	0.03	0.82	1.38	2.98	9.16	2.17
Years of train	0.70	0.62	0.05	0.29	0.51	0.89	5.58	0.60
NR cognitive	0.50	0.15	0.16	0.39	0.50	0.62	0.91	0.23
NR interactive	0.52	0.12	0.20	0.43	0.49	0.60	0.90	0.17
R cognitive	0.45	0.09	0.13	0.40	0.45	0.51	0.79	0.12
R manual	0.38	0.16	0.07	0.26	0.35	0.49	0.93	0.23
NR manual	0.34	0.17	0.03	0.21	0.31	0.44	0.85	0.23
R index	-0.22	0.44	-1.59	-0.53	-0.15	0.10	0.92	0.63

Table 5 – Profiling of green occupations: skill measures

	(1) NR cognitiive	(2) NR interactive	(3) R cognitive	(4) R manual	(5) NR manual	(6) R index
Green emerging	0.0233	-0.0107	-0.0292*	-0.0127	-0.00218	-0.0768
	(0.0201)	(0.0222)	(0.0168)	(0.0137)	(0.0361)	(0.0620)
Green skills	0.0291**	0.00290	-0.0215*	-0.00586	0.0165	-0.0753**
	(0.0133)	(0.0145)	(0.0110)	(0.0144)	(0.0151)	(0.0321)
N	451	451	451	451	451	451

OLS estimates weighted by employment share. Robust standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. SOC 4-digit dummies included. Occupations in SOC 4-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	0.0196	-0.0393	0.199**
	(0.0229)	(0.118)	(0.0850)
Green skills	0.0179**	0.354***	0.318***
	(0.00863)	(0.109)	(0.120)
N	451	451	451

OLS estimates weighted by employment share. Robust standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. SOC 4-digit dummies included. Occupations in SOC 4-digit categories with no green occupation have been excluded.

Table 7 – Exposure of green occupations to green technology

	(1) log(R&D tot)	(2) log(R&D env)	(3) log(pat tot)	(4) log(pat env)	(5) log(investments)	(6) log(ICT)
Green emerging	0.232	0.0520	0.355	0.0859	0.171**	0.0789
	(0.154)	(0.0537)	(0.261)	(0.0645)	(0.0832)	(0.0684)
Green skills	0.279***	0.0857***	0.591***	0.185***	0.146**	0.0561
	(0.0890)	(0.0271)	(0.211)	(0.0558)	(0.0640)	(0.0400)
N	451	451	451	451	451	451

OLS estimates weighted by employment share. Robust standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. SOC 4-digit dummies included. Occupations in SOC 4-digit categories with no green occupation have been excluded.

Table 8 – Profiling of green occupations: skill measures (conditional on investments and R&D)

	(1) NR cognitiive	(2) NR interactive	(3) R cognitive	(4) R manual	(3) NR manual	(4) R index
Green emerging	0.0141	-0.0150	-0.0312**	-0.0186	-0.00497	-0.0708
	(0.0207)	(0.0230)	(0.0157)	(0.0140)	(0.0364)	(0.0640)
Green skills	0.0251**	0.000905	-0.0210**	-0.00646	0.0175	-0.0686**
	(0.0127)	(0.0145)	(0.00986)	(0.0142)	(0.0144)	(0.0328)
log(R&D non-env)	0.0280*	0.0124	0.0241*	0.0546***	0.0326**	0.0490
	(0.0157)	(0.0193)	(0.0137)	(0.0173)	(0.0158)	(0.0429)
log(R&D env)	-0.0379	-0.0264	-0.0519	-0.132***	-0.116***	-0.144
	(0.0413)	(0.0480)	(0.0375)	(0.0455)	(0.0411)	(0.105)
log(ICT)	0.0562***	-0.00374	0.0355**	-0.00903	-0.0207	-0.0120
	(0.0205)	(0.0234)	(0.0139)	(0.0193)	(0.0232)	(0.0559)
log(investments)	-0.00162	0.0153	-0.0205**	0.00199	0.0159	-0.0461
	(0.0120)	(0.0141)	(0.00968)	(0.0136)	(0.0131)	(0.0335)
N	451	451	451	451	451	451

OLS estimates weighted by employment share. Robust standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. SOC 4-digit dummies included. Occupations in SOC 4-digit categories with no green occupation have been excluded.

Table 9 – 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	0.0118	-0.107	0.166*
	(0.0237)	(0.128)	(0.0904)
Green skills	0.0133*	0.292***	0.281**
	(0.00800)	(0.103)	(0.116)
log(R&D non-env)	0.0237**	-0.0416	-0.161
	(0.0107)	(0.0965)	(0.107)
log(R&D env)	-0.000667	0.695***	0.642**
	(0.0247)	(0.263)	(0.267)
log(ICT)	0.0231*	-0.111	-0.134
	(0.0139)	(0.102)	(0.120)
log(investments)	-0.00148	0.225***	0.232***
	(0.0100)	(0.0810)	(0.0863)
N	451	451	451

OLS estimates weighted by employment share. Robust standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. SOC 4-digit dummies included. Occupations in SOC 4-digit categories with no green occupation have been excluded.

Table 10 – Profiling of green occupations: skill measures (conditional on investments and patents)

	(1) NR cognitiive	(2) NR interactive	(3) R cognitive	(4) R manual	(3) NR manual	(4) R index
Green emerging	0.0176	-0.0128	-0.0287*	-0.0151	-0.00244	-0.0700
	(0.0205)	(0.0227)	(0.0165)	(0.0134)	(0.0359)	(0.0636)
Green skills	0.0251**	0.000609	-0.0227**	-0.0119	0.0148	-0.0755**
	(0.0124)	(0.0148)	(0.00995)	(0.0133)	(0.0148)	(0.0331)
log(patent non-env)	0.00154	-0.00317	0.000452	0.00650	-0.00397	0.00994
	(0.00598)	(0.00707)	(0.00475)	(0.00702)	(0.00557)	(0.0164)
log(patent env)	0.0140	0.0190	0.0220	0.0340*	0.0227	0.0199
	(0.0149)	(0.0163)	(0.0135)	(0.0186)	(0.0193)	(0.0404)
log(ICT)	0.0683***	0.00225	0.0435***	0.00259	-0.0202	-0.00968
	(0.0217)	(0.0231)	(0.0140)	(0.0201)	(0.0250)	(0.0557)
log(investments)	-0.00767	0.00907	-0.0301**	-0.0162	0.00896	-0.0605
	(0.0137)	(0.0157)	(0.0117)	(0.0150)	(0.0146)	(0.0388)
N	451	451	451	451	451	451

OLS estimates weighted by employment share. Robust standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. SOC 4-digit dummies included. Occupations in SOC 4-digit categories with no green occupation have been excluded.

Table 11 – 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	0.0145	-0.0941	0.174**
	(0.0235)	(0.122)	(0.0851)
Green skills	0.0136*	0.301***	0.287**
	(0.00812)	(0.100)	(0.113)
log(patent non-env)	0.00738*	0.0347	-0.0427
	(0.00425)	(0.0325)	(0.0373)
log(patent env)	0.00345	0.141	0.270***
	(0.0107)	(0.117)	(0.103)
log(ICT)	0.0377**	0.0311	-0.0478
	(0.0151)	(0.126)	(0.123)
log(investments)	-0.00646	0.139	0.129
	(0.0123)	(0.103)	(0.100)
N	451	451	451

OLS estimates weighted by occupational employment. Robust standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. SOC 4-digit dummies included. Occupations in SOC 4-digit categories with no green occupation have been excluded.

Figure 1 – Distribution of education, experience, training and skill measures for green and non-green occupations (weighted by employment share)

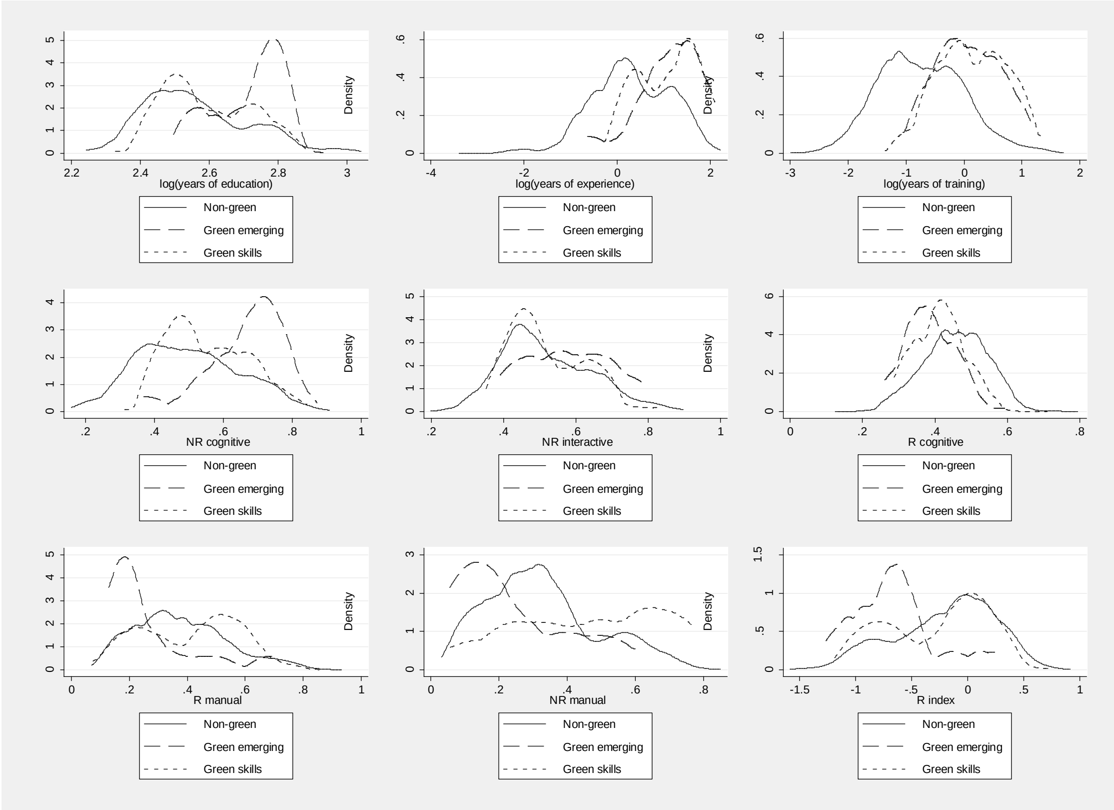

Table A1 – Environmental patent classes (source: ENV-TECH Indicator, OECD, 2013)

Macro-category	Sub-category	IPC 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
	Solar thermal energy	Y02E10/4
	Solar photovoltaic (PV) energy	Y02E10/5
	Solar thermal-PV hybrids	Y02E10/6
	Geothermal energy	Y02E10/1
	Marine energy	Y02E10/3
	Hydro energy	Y02E10/2
	Biofuels	Y02E50/1
	Fuel from waste	Y02E50/3
Combustion technologies with mitigation potential	Technologies for improved output efficiency (combined combustion)	Y02E20/1
	Technologies for improved input efficiency	Y02E20/03
Climate change mitigation	CO2 capture or storage	Y02C10
	Capture or disposal of greenhouse gases other than CO2	Y02C20
Potential or indirect contribution to emissions mitigation	Energy storage	Y02E60/1
	Hydrogen technology	Y02E60/3
	Fuel cells	Y02E60/5
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