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Do green jobs differ from non-green jobs in terms of skills and human capital?

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This paper elaborates an empirical analysis of labour force characteristics that emerge as a response to the growing importance of 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 more intensively high-level cognitive and interpersonal skills compared to non-green jobs. Green occupations also exhibit higher levels of standard dimensions of human capital such as formal education, work experience and on-the-job training. While preliminary, our exploratory exercise seeks to call attention to an underdeveloped theme, namely the labour market implications associated with the transition towards green growth.

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# Introduction

This paper elaborates an empirical analysis of green employ- ment, and focuses on the salient labour force characteristics that emerge, or change, as a result of commitment towards environmen- tal sustainability. The transition to greener forms of production, distribution and consumption is commonly touted as a source of long-term beneﬁts in the form of reduced environmental damage but, also, of new opportunities for economic development ([Porter](#_bookmark112) [and](#_bookmark112) [van](#_bookmark112) [der](#_bookmark112) [Linde,](#_bookmark112) [1995).](#_bookmark112) Previous literature has explored the effects of environmental regulation on a variety of dimensions such as innovation, ﬁrm performance and net employment effects but has neglected other issues, such as what kind of occupations make up ‘green jobs’, and whether and how these differ from non-green

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jobs. The present paper ﬁlls this gap by providing empirical evi- dence on these important aspects of structural change that several economies are already experiencing, or are about to, as they adapt to new criteria of environmental sustainability.

Our belief is that grasping the labour market implications of green growth requires a clear understanding of the qualitative transformations in the organisation and the content of work activ- ities. To put matters in context, the spectrum of actions for tackling environmental issues includes alternatives as diverse as reducing greenhouse gas emission by developing renewable energy source; or increasing the efﬁciency of energy usage in transport, building and industrial productions; or recycling and reusing materials; etc. Such a variety of options implies that environmental sustainability has the potential to modify the status quo of established industries but, also, to stimulate the emergence of new ones ([OECD,](#_bookmark101) [2010;](#_bookmark101) [Cedefop,](#_bookmark101) [2010;](#_bookmark101) [Cambridge](#_bookmark101) [Econometrics,](#_bookmark101) [2011).](#_bookmark101) Either way, the implications for the workforce are manifold, and encompass the appearance of new professional categories, the disappearance of old occupations, or simply changes in the job content for continuing ones ([Dierdorff et al., 2009; Vona and Consoli, 2015).](#_bookmark99)

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Following on this, the present paper identiﬁes and analyzes the deﬁning characteristics of green jobs. We opt for a broad approach that encompasses complementary dimensions of human labour such as job task, formal education requirements and the pro- fessional pathways through which employees acquire and carry know-how – namely on-the-job training and work experience. While the latter are rather standard items in human capital the- ory (see, e.g. [Becker,](#_bookmark79) [1962;](#_bookmark79) [Mincer,](#_bookmark79) [1962),](#_bookmark79) the direct analysis of skills and tasks is a recent addition to the battery of existing indi- cators on how workers’ know-how matches job tasks ([Autor et al.,](#_bookmark73) [2003; Levy and Murnane, 2004).](#_bookmark73) Against this backdrop, the main goal of the paper is to proﬁle the key occupational characteristics of green jobs in the United States (US). In so doing we address two questions:

* 1. Are occupation-speciﬁc levels of formal education, work experi- ence 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?

Our analysis builds on cross-sectional data on 905 occupations based on the O\*NET (Occupational Information Network) repos- itory of occupation-speciﬁc information. The empirical strategy consists of two steps. First, using the O\*NET taxonomy we iden- tify two subsets, one of green occupations and one of non-green occupations, that exhibit similar occupational characteristics. Sub- sequently, we compare these in relation to (i) standard measures of human capital (educational level, on-the-job training and work experience); (ii) the task content of jobs based on the taxonomy of [Autor et al. (2003);](#_bookmark73) and (iii) occupational exposure to various indi- cators of technology built upon data on investments, patents and R&D expenditure.

The main ﬁnding is that compared to non-green jobs, green occupations exhibit a stronger intensity of high-level cognitive skills. Also, occupations that are changing qualitatively, i.e. in terms of their skill content, have on average more formal education, more work experience and more on-the-job training relative to non- green jobs. Interestingly, on-the-job training is a distinctive feature only of the new occupations that are emerging as a consequence of higher demand for environmental speciﬁc skills. While prelimi- nary, our empirical exercise highlights important shortcomings of the binary logic of ‘green versus brown’ jobs that dominates the scholarly and the policy debates. Indeed, 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 organised as follows. Section [2](#_bookmark9) presents an overview of existing research on green employment and green skills. Section [3](#_bookmark17) outlines the data and the empirical methodology. Section [4](#_bookmark27) elaborates the empirical analysis. The last section concludes and summarises.

# Green employment vs. green skills

This section provides an overview of the relevant literature. First, we focus on studies that gauge the employment effect of environmental regulation and of innovation. It will be argued that

* 1. *Net employment effects of environmental regulation and innovation*

The pursuit 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](#_bookmark103) [Commission,](#_bookmark103) [2010)](#_bookmark103) or the Green Jobs Act in the US are instances of the kind of public com- mitment in support of smart, sustainable and inclusive economic growth. Unsurprisingly the effectiveness, and even the desirabil- ity, of government intervention in this remit is a divisive issue (see, e.g. [Jaffe et al., 1995; Bowen, 2012)](#_bookmark85) and even when there is consensus about active government involvement, how this should be implemented is equally controversial. The spectrum of possible actions is wide and encompasses options such as pigouvian taxes, cap-and-trade schemes, R&D subsidies and command-and-control regulation, as well as a variety of routes for implementation ([Aghion](#_bookmark68) [et al., 2009; Mowery et al., 2010).](#_bookmark68) Moreover, as the [OECD (2007)](#_bookmark100) remarks, the existing instruments are usually embedded within a policy mix that aims at multiple, at times contrasting, goals.

Turning to the labour market, the empirical evidence on the effects of environmental policy and regulation is mixed. Some scholars deem it either cost-ineffective ([Michaels](#_bookmark92) [and](#_bookmark92) [Murphy,](#_bookmark92) [2009;](#_bookmark92) [Hughes,](#_bookmark92) [2011)](#_bookmark92) or conducive to job destruction ([Álvarez,](#_bookmark70) [2009;](#_bookmark70) [Morriss](#_bookmark70) [et al.,](#_bookmark70) [2009).](#_bookmark70) This contrasts with optimistic views based on the expectation that policy has the potential to induce the expansion of markets for environmental goods and services that are normally labour intensive ([Engel and Kammen, 2009; Selwyn](#_bookmark102) [and Leverett, 2006; UNEP, 2008).](#_bookmark102) Further evidence is available from studies on direct interventions such as the enforcement of emission criteria which in the US, for example, is enacted by the federal gov- ernment via mandates to implement plant-speciﬁc interventions

such as the installation of state-of-the-art technology.[1](#_bookmark10) The evi-

dence on this is also mixed. A recent review of empirical studies by [Dechezleprêtre and Sato (2014)](#_bookmark96) concludes that environmental reg- ulation yields negative employment effects in pollution intensive sectors. Some scholars ascribe the employment effects of envi- ronmental regulation to industry speciﬁcities (e.g. [Morgenstern](#_bookmark94) [et al., 2002; Belova et al., 2013),](#_bookmark94) plant characteristics (e.g. [Becker,](#_bookmark81) [2005;](#_bookmark81) [Becker](#_bookmark81) [et al.,](#_bookmark81) [2013)](#_bookmark81) or type of pollutant (e.g. [Greenstone,](#_bookmark71) [2004).](#_bookmark71) Accordingly, some report job losses (e.g. [Henderson, 1996;](#_bookmark75) [Greenstone, 2002; Walker, 2013),](#_bookmark75) others ﬁnd no signiﬁcant impact (e.g. [Berman](#_bookmark86) [and](#_bookmark86) [Bui,](#_bookmark86) [2001;](#_bookmark86) [Morgenstern](#_bookmark86) [et al.,](#_bookmark86) [2002;](#_bookmark86) [Cole](#_bookmark86) [and](#_bookmark86) [Elliott, 2007)](#_bookmark86) while some (i.e. [Bezdek et al., 2008)](#_bookmark87) observe job cre- ation due to environmental regulation. More recently [Mulatu and](#_bookmark97) [Wossink](#_bookmark97) [(2014)](#_bookmark97) and [Kahn](#_bookmark88) [and](#_bookmark88) [Mansur](#_bookmark88) [(2013)](#_bookmark88) ﬁnd that energy- intensive and polluting industries tend to relocate and, hence, to destroy jobs as a consequence to ER respectively in European countries and US states. Yet another strand of studies argues that employment effects are irrelevant to the debate on green policy ([Jaffe et al., 1995; Portney, 1994; Goodstein, 1996).](#_bookmark85) In a similar vein, a comprehensive study on environmental products manufacturers at establishment-level by [Becker and Shadbegian (2009)](#_bookmark83) concludes that there is nothing unique about the green industry in terms of performance, wage premia or job creation.

Another strand of literature focuses more speciﬁcally on the

effects of environmental technological change on employment (see [Yi,](#_bookmark118) [2014](#_bookmark118) for a review). From a theoretical point of view product

this research disregards important qualitative dimensions concern-

ing the adaptation of work activities to environmental criteria. Subsequently we evaluate the merits and the shortcomings of different methodologies that have been used to identify green employment. Finally, we propose an alternative roadmap based on literature that focuses on the human capital and the skill content of occupations.

1 In the US a national organisation, the Environmental Protection Agency (EPA), and individual states have a prominent role in enforcing compliance with emission standards. For instance, state regulation programmes 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](#_bookmark82) [and Henderson, 2000).](#_bookmark82)

innovations are expected to have a positive, demand-related, effect ([Harrison et al., 2014)](#_bookmark74) while process innovations to a negative effect due to increased labour productivity ([Cainelli et al., 2011).](#_bookmark91) Some studies distinguish employment effects depending on the speci- ﬁcities of the attendant technology. Thus, the adoption of upstream clean production methods is found to have a positive employment effect ([Pfeiffer and Rennings, 2001)](#_bookmark106) in contrast to end-of-pipe solu- tions which have instead a negative effect ([Rennings et al., 2004).](#_bookmark114) Likewise, positive employment effects of innovation in materials and energy savings, which increase competitiveness and stimulate job creation, contrast with the negative outcomes of innovation in air and water processes where end-of-pipe solutions are more common ([Horbach and Rennings, 2013).](#_bookmark80) Other scholars distinguish labour market outcomes depending on whether innovation has speciﬁc environmental nature or not. Again, the evidence is not conclusive. [Horbach (2010)](#_bookmark77) and [Gagliardi et al. (2016)](#_bookmark110) ﬁnd positive effects for environmental innovations while [Licht and Peters (2013,](#_bookmark89) [2014)](#_bookmark89) observe positive but not signiﬁcant differences between environmental and non-environmental product innovations.

This review is testimony to the diversity of views on the relation

between innovation, employment and the environment. Arguably, however, the literature reviewed above neglects that the emer- gence of new technologies challenges also qualitative dimensions of employment, by inducing the expansion of new occupations, or new forms of organisation or new types of know-how, as well as the inevitable decline of certain professions and skills ([Vona and](#_bookmark116) [Consoli, 2015).](#_bookmark116) Such an issue should be especially attractive to inno- vation scholars 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., 2014).](#_bookmark95) Recent studies in labour economics (e.g. [Autor et al., 2003)](#_bookmark73) and in organisation studies (e.g. [Cohen, 2013)](#_bookmark93) indicate a promising route towards the analysis of qualitative transformations in the organisa- tion of labour. Therein jobs are conceptualised as of discrete group of tasks, and the division of labour across occupations is understood as a design choice driven by the match between work activities and workers’ skills. Before we operationalise these insights, however, we ﬁrst review the literature on green jobs and skills.

* 1. *Green employment and skills*

In spite of an intense debate on the opportunities and the chal- lenges that environmental sustainability is expected to bring about in the world of work, there is no standard deﬁnition of green employment and no consistent criteria on how to classify this particular class of occupations ([ILO,](#_bookmark84) [2011a;](#_bookmark84) [Jagger](#_bookmark84) [et al.,](#_bookmark84) [2013;](#_bookmark84) [Strietska-Ilina](#_bookmark84) [et al.,](#_bookmark84) [2011;](#_bookmark84) [OECD/Cedefop,](#_bookmark84) [2014).](#_bookmark84) We argue that understanding what green jobs are, whether they differ from non- green ones, and what are their deﬁning traits is important to inform educational policies aimed at facilitating a faster adoption of sus- tainable practices and technologies.

To date, four approaches have emerged in the effort of identify- ing 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 focuses on the association between *products and services* that are known to contribute to environmental and conserva- tion objectives and the workforce involved in their production or delivery (see, e.g. [US Department of Commerce, 2010).](#_bookmark114) The identi- ﬁcation of products and services follows the descriptions provided by federal procurement programmes and encompasses ‘usual sus- pects’ such as hybrid or electric automobiles, insulation products or energy monitoring systems. Similar approaches, based on the employment of the environmental goods and services sector can be

found in the System of Environmental Accounting Central Frame- work of the [European Commission, FAO, IMF, OECD, United Nations](#_bookmark105) [and World Bank (2012)](#_bookmark105) and implemented by Eurostat ([Eurostat and](#_bookmark107) [ICEED, 2009).](#_bookmark107) Our view is that while referring to tangible and eas- ily recognisable items is a virtue, this approach relies on ad-hoc deﬁnitions that may well yield many false negatives, for exam- ple by overlooking green activities that are not directly associated with the production of a particular product or service like energy conservation within a ﬁrm. The third method to identify green employment relies on selecting *industries* that have a high fraction of ﬁrms actively engaging environmental and conservation objec- tives such as, for example, the manufacturing of energy-efﬁcient appliances, ﬁlters or wind turbines. Similar to the ﬁrst approach reviewed above, this carries the advantage of capturing employ- ment 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 prod- ucts 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).](#_bookmark104)

The common ingredient across the three approaches reviewed

so far is that green jobs are deﬁned indirectly by assimilating the environmental properties of industry to those of the attendant work activities. We see this logic as ill-suited for the goal of deﬁn- ing green occupations since it enforces an isomorphism between the structure and organisation of knowledge at industry level and at occupation level. This criticism resonates with a latent thread among economic geographers who indeed warn about the inac- curacy of predicting high-tech occupational employment based on industry structure (see, e.g. [Feser,](#_bookmark109) [2003;](#_bookmark109) [Markusen](#_bookmark109) [and](#_bookmark109) [Schrock,](#_bookmark109) [2006).](#_bookmark109)

The alternative is to use an occupational-based lens for pro- bing the distinctive characteristics of employment associated with environmental sustainability. The ‘Green Economy’ programme developed by the Occupational Information Network (O\*NET) under the auspices of the US Department of Labour offers a suitable source to operationalise this. O\*NET is a comprehensive repository of occupation-speciﬁc information such as work tasks, education and experience requirements as well as characteristics of the work context. 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 con- tent is revised and expanded periodically by means of surveys (e.g. [Smith and Campbell, 2006).](#_bookmark118) The ‘Green Economy’ programme within O\*NET focuses on activities “*related to reducing the use of fos- sil fuels, decreasing pollution and greenhouse gas emissions, increasing the efﬁciency of energy usage, recycling materials, and developing and adopting renewable sources of energy*” ([Dierdorff et al., 2009, p. 3).](#_bookmark99) In this context, the greening of occupations refers to “*the extent to which green activities and technologies increase the demand for existing occupations, shape the work and worker requirements needed for occupational performance, or generate unique work and worker requirements*” ([Dierdorff et al., 2009, p. 11).](#_bookmark99) Accordingly, green jobs are identiﬁed by means of mixed methods such as reviews of the literature; the compilation, review and sorting of job titles; the clustering of titles to identify occupations; the identiﬁcation of occupational sectors; the identiﬁcation, research, determination, and compilation of new and emerging occupations. This exercise yields three groups of green occupations:

* + 1. existing occupations that are expected to experience signiﬁ- cant employment growth due to the greening of the economy (*Green Demand*);
    2. existing occupations that are expected to undergo signiﬁcant changes in terms of task content (*Green Enhanced Skills*); and
    3. new occupations that emerge as a response to speciﬁc needs of the green economy (*Green Emerging*).

What are the advantages of analyzing green occupations through the lenses of this data-driven method? For what concerns the methodology, the main information source is rather com- prehensive since data collection draws on large-scale surveys at establishment-level.[2](#_bookmark19) From a conceptual viewpoint this approach carries the strength of focusing directly on occupations, arguably the natural unit of analysis for the study of employment. The under- lying rationale goes back to two areas of research. On the one hand is the traditional human capital literature, and within it the iden- tiﬁcation of the main pathways through which different types of knowledge stock are built. The ﬁrst is formal education, which is typically portrayed as a source of general skills, and the other channel is on-the-job training, which is normally considered as a source of know-how tailored around speciﬁc needs ([Becker, 1962;](#_bookmark79) [Mincer,](#_bookmark79) [1962).](#_bookmark79) While the main beneﬁt of the former is the ease of transfer across work contexts over the long-term, experien- tial learning acquired within a ﬁrm is commonly understood as a short-term response to sudden spikes in the demand for spe- ciﬁc, often narrow, skills. The notion of human capital proffered by this literature has been recently enriched by the more nuanced view proposed by [Autor et al. (2003).](#_bookmark73) Therein occupations are par- titioned on the basis of 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 analytical*), 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 mental activities (*routine cognitive*), such as book-keeping or monitoring, or standardised *routine manual* activ- ities like sorting and assembling. Routine tasks are prevalent in contexts where work activities can be easily codiﬁed into rules, and the key skills concern processing, rather than generating, informa- tion (see [Simon, 1969).](#_bookmark119)

The task-based approach is an attractive complement to the traditional human capital theory and indeed it has become the standard to understand the transformation of the world of work in economics ([Autor, 2013).](#_bookmark76) A testimony to that is the existence of several empirical studies extending the basic intuition beyond the original context in which it emerged (the diffusion of Information and Communication Technologies in the US), in particular the anal- ysis of cross-country empirical evidence ([Goos et al., 2009),](#_bookmark66) of other major technological transitions (electriﬁcation in the XIX century: [Gray, 2013)](#_bookmark69) as well as the study of the impact of globalisation ([Autor](#_bookmark78) [et al., 2013; Consoli et al., 2014).](#_bookmark78) Building on this conceptual frame- work and on the data wealth of the ‘Green Economy’ programme in O\*NET we now turn to the empirical analysis of green jobs in the US.

# Skill measures, methodology and data

In this section, we ﬁrst present data and discuss measurement issues (Section [3.1)](#_bookmark12) and subsequently explain the methodology we adopt to compare the skill content of green and non-green occupa- tions (Section [3.2).](#_bookmark22)

2 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.,](#_bookmark104) [2011; Pollack, 2012).](#_bookmark104)

* 1. *Measures and data*

Our selection of cross-sectional data contains information on 905 occupations (8-digit of the Standard Occupational Classiﬁca- tion,[3](#_bookmark13) SOC henceforth) in the US.[4](#_bookmark14) Employment data (count of employees) are available at 6-digit SOC occupation and 4-digit NAICS (short for North American Industry Classiﬁcation System) industry for years 2011–2012 (Source: Bureau of Labour Services, BLS henceforth).[5](#_bookmark15) For what concerns green jobs, as anticipated ear- lier, our main source is the ‘Green Economy’ programme of O\*NET. From this we extract information on *Green Enhanced Skills* and *Green Emerging* occupations.[6](#_bookmark16) The analysis of the skill content of these occupations draws on the O\*NET database (release 17.0, July 2012).[7](#_bookmark18) As already remarked, O\*NET data refer only to occupa- tional categories and have no inherent connection with industry data. Data collection consists in drawing together descriptive rat- ings from questionnaire responses by workers (sampled randomly within establishments), occupation experts and analysts ([Dierdorff](#_bookmark99) [et al., 2009).](#_bookmark99)

[Table 1](#_bookmark21) shows a summary of O\*NET items that are relevant for the present paper.

The occupation-speciﬁc descriptors in O\*NET are the entry point into the analysis of the skill content of green jobs. A ﬁrst group of items contains standard human capital measures, namely mini- mum years of education required for the job (a proxy of general skills), required years of training (a proxy of speciﬁc skills) and required years of experience (a proxy of learning on the job). Another block of items encompasses task-based measures of skills: non-routine abstract tasks (including analytical 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 Rou-

tine Intensity Index (RTI henceforth, see [Table 1](#_bookmark21) for details).[8](#_bookmark20) All

these measures are computed as raw averages of items’ scores, each ranging between 1 and 5 and, to facilitate their interpretation, are normalised to vary between 0 and 1.

Finally, we combine occupation-speciﬁc information (impor- tance scores for a large selection of detailed skills and work

3 The SOC Classiﬁcation is a hierarchical taxonomy of occupations used by Fed- eral statistical agencies in the US. This is revised periodically to accommodate the emergence or the disappearance of occupations in the economy, and is organised on six levels of aggregation: 2-digit, 3-digit, 5-digit, 6-digit and 8-digit.

4 From the initial set of 974 occupations we end up with 905 occupations after

excluding employment in non-business industries (NAICS code 92 ‘Public Admin- istration’) and agriculture-related industries (NAICS code 11 ‘Agriculture, Forestry, Fishing and Hunting’).

5 Following the literature reviewed in Section [2.1,](#_bookmark8) we select employees in the

private non-agricultural sector. We exclude NAICS codes 11 (Agriculture, Forestry, Fishing and Hunting) and 92 (Public Administration).

6 The *Green Demand* group was left out because it includes only pre-existing

occupations that do not undergo signiﬁcant changes in terms of the labour force characteristics that are the main focus of the present paper. Clearly, the identiﬁca- tion of non-green matches (see Section [3.2)](#_bookmark22) would have been hardly meaningful for this particular group. For a complete list and description of green occupations see <https://www.onetcenter.org/green.html?p=2>(accessed 17 October 2015).

7 For illustrative purposes [Table A1](#_bookmark63) contains a description of the green occupations

with the greatest employment share and [Table A2](#_bookmark64) shows the top ﬁve industries by green employment. Interestingly, this selection includes mostly service sectors with the exception of Building Equipment Contractors (NAICS code 2382). It is also noticeable that the selection of green employment based on O\*NET differs from that of the ‘Green Goods and Services’ (GGS). If we use information from the BLS survey on GGS, the ﬁrst 4-digit industry from our selection of top-industries in terms of green employment we ﬁnd in terms of share employment in GGS is Architectural, Engineering, and Related Services (NAICS 5413), 23rd in the ranking (out of 299 4-digit industries), with about 30 percent of employees working in GGS plants.

8 These items are selected to operationalise the constructs used in prior literature,

especially [Autor](#_bookmark73) [et al.](#_bookmark73) [(2003).](#_bookmark73) The task and skill items used here are the same as [Acemoglu and Autor (2011).](#_bookmark67) See [Vona et al. (2015)](#_bookmark117) for a methodology that allows the identiﬁcation of skills that are closely tied to the characteristics of green occupations.

**Table 1**

Skill measures.

Indicator Task items in O\*NET Description of task items in O\*NET

*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

*Non-routine*

Non-routine analytical (NRA)

Non-routine interactive (NRI) Routine

Routine cognitive (RC)

Routine manual (RM)

Non-routine manual (NRM)

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

4.A.4.a.4 (IM) Establishing and maintaining interpersonal relationships

* + - * 1. (IM) Guiding, directing, and motivating subordinates
        2. (IM) Coaching and developing others

4.C.3.b.4 (CX) Importance of being exact or accurate

* + - * 1. (CX) Importance of repeating same tasks
        2. (CX, reverse) Structured versus unstructured work

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

4.A.3.a.4 (IM) Operating vehicles, mechanised 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)](#_bookmark72) log(1 + 4.5 \* RC + 4.5 \* RM) − log(1 + 4.5 \* NRA + 4.5 \* NRI)

activities, required levels of education, training and experience, employment ﬁgures by occupation-industry) with industry-level measures of technology exposure. Thus, for each occupation we consider the extent to which workers employed are, on average, exposed to technology. This is useful to account for additional con- ditioning factors in the skill proﬁling of green occupations.

* 1. *Methodology*

To estimate the difference in skill content between green and non-green occupations we estimate the following equation:

*Skilli* = *ˇ*1*Green enh skill*0*,*1 + *ˇ*2*Green emerg*0*,*1

To illustrate: ‘Environmental engineers’ (SOC 17-2081.00) fall in the *Green enhanced skills* group within the 3-digit occupation (SOC 17-2) ‘Engineers’. While some non-green occupations in the SOC class 17-2 are suitable for comparison with ‘Environmental engineers’, others are rather heterogeneous. This is the case of ‘Environmental economists’ (SOC 19-3011.01) which are compared to a large selection of social scientists (SOC 19-3 ‘Social Scientists and Related Workers’), including, for example, ‘School Psycholo- gists’ (SOC 19-3031.01).[10](#_bookmark25)

Eq. [(1)](#_bookmark23) is estimated by an OLS with occupations weighted by employment share and standard errors clustered by 3-digit SOC occupation. We assign the same weight to each 8-digit occu- pation belonging to a certain 6-digit group (see Section [3.1).](#_bookmark12)

*i i* This is to maintain detailed information on skills for narrow

0*,*1

+ *SOC* 3*digiti* + *εi* (1)

where *Skilli* is a set of skill measures for occupation *i*;

*Green enh skill*0*,*1 and *Green emerg*0*,*1 are dummy variables that

occupations. While this may, in principle, lead to systematic over- or under-estimation of some occupations, we feel conﬁdent because for the majority of occupations we can establish a per- fect one-to-one matching between the 8-digit and the 6-digit SOC

*i i*

are equal to 1 for occupations that have been identiﬁed by O\*NET respectively as *Green enhanced skill* and *Green emerging* (see Sec- tion [2.2),](#_bookmark11) and zero otherwise; *SOC* 3*digit*0*,*1 is a full set of 3-digit SOC (Standard Occupational Classiﬁcation) dummy variables; *εi* is the residual.

*i*

As will be discussed in Section [4,](#_bookmark27) 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

level.

Estimates of Eq. [(1)](#_bookmark23) are simple mean comparisons and are pro- gressively enriched with the addition of indicators of occupational exposure to technology. The idea is that differences in skill content between green and non-green occupations may be driven by dif- ferential 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 organisational factors. Our indicator of technology exposure is:

Σ.

driven by heterogeneity in the average skill content across macro- occupations rather than true speciﬁcities of green occupations. Accordingly, we look beyond mere differences across macro-

*Tech Exposureocc* =

*ind*

*Techno* log *yind Employmentind*

× *Employmentocc,ind*Σ

(2)

occupations and narrow the comparison groups to non-green occupations that are expected to be similar to our set of green occu- pations. This is operationalised by including 3-digit SOC dummies that allow us to control for other features such as general job com- plexity and required level of training. Moreover we focus on those 3-digit SOC macro-occupational groups wherein at least one green

occupation (either *Green enhanced skills* or *Green emerging*) exists.[9](#_bookmark25)

This is interpreted as the average intensity of investment (or patents) per employee for each worker in a speciﬁc occu- pation, independently on the industry where he is employed. 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 stocks. Since occupational data are

9 This leads to the exclusion of 440 occupations that cannot be used to assess differences between green and non-green occupations, and leaves us with a total of 465 occupations (111 *Green enhanced skills* and *Green emerging* occupations).

10 We acknowledge that this may generate some noise in our estimates. However, a narrower selection of occupations (e.g. occupations within the same 5-digit SOC group rather than 3-digit SOC) is not feasible in our data.

**Table 2**

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

|  |  |  |  |
| --- | --- | --- | --- |
| SOC 2-digit | Total *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 |

more aggregated (6-digit SOC) than those within O\*NET (8-digit), technology exposure is computed at the 6-digit SOC level only (about 700 occupations) and is assumed as constant across SOC 8-digit occupations within the same SOC 6-digit occupation.[11](#_bookmark28) Fur- ther details on data sources and on the construction of the variables are reported in [Appendix 1.](#_bookmark60)

Following on the earlier example, exposure to ‘environmen- tal 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), which is included in the same SOC 3-digit group, is about ten times smaller (0.186). Thereby differences in the skill proﬁles of ‘Agri- cultural 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)](#_bookmark11) rather to than actual speciﬁcities of the green occupation relative to the non-green one. Accounting for these speciﬁcities will allow us to capture the peculiarities of the skill content (or absence thereof) beyond simple differences due to complementarity or substitutability between skills and technology. Last but not least, our measure of technology exposure accounts for both general investments in capital and in ICTs as well as for environment-related R&D and patents.

# Results

In this section we operationalise the empirical strategy laid out in Section [3.2](#_bookmark22) in two steps. After having presented aggregate evi- dence on green employment in the US, the ﬁrst subsection includes a comparison between green and non-green jobs within similar 3-digit SOC classes. Subsequently we enrich the skill proﬁling by considering various proxies of technology.

11 In the absence of employment data for 8-digit occupations within 6-digit groups, we compute technology exposure at the 6-digit SOC level only (about 700 occupa- tions) and assume that it is constant across SOC 8-digit occupations within the same SOC 6-digit occupation. While for the majority of occupations (i.e. 665) there is just

* + 1. *Skill proﬁling of green occupations*

[Table 2](#_bookmark26) shows the count of 8-digit SOC occupations, split by macro-occupation (2-digit SOC) and green and non-green occupa- tions. *Green enhanced skills* and *Green emerging* jobs concentrate in macro-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 Man- agement (SOC 2-digit: 11), Business and Financial Operations (SOC 2-digit: 13) or Architecture and Engineering (SOC 2-digit: 17), all of which belong to the top quartile in terms of average importance of non-routine analytical and interactive skills. The remaining are in mid-skill occupational groups such as Construction and Extraction (SOC 2-digit: 47) or Production workers (SOC 2-digit: 53).

To gauge the scale of green employment we report employment shares by macro-occupation in [Table 3.](#_bookmark30) As discussed in Section [3.1,](#_bookmark12) we cannot observe employment ﬁgures at the 8-digit level but only at the 6-digit level. Accordingly we assume a uniform distribution across 8-digit occupations within the same 6-digit occupation. If 8-digit green occupations were systematically smaller (bigger) in terms of employment compared to non-green occupations within the same 6-digit group, aggregate green employment 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 occupa- tions 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 occu- pations within the 6-digit group with at least one green occupation. This is clearly at variance with estimates of US green employ- ment from other sources such as BLS and OECD, which usually

range between 2 and 4 percent (see also [Deschênes, 2013).](#_bookmark98)[12](#_bookmark29) But,

as anticipated in Section [2.2,](#_bookmark11) these approaches focus on employ- ees of the Green Goods and Services sector deﬁned at industry or establishment level. To illustrate, occupations that are labelled

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.

12 See BLS News Release 2013 (last access 10/02/2015), or [http://www.oecd.org/](http://www.oecd.org/els/emp/50506901.pdf) [els/emp/50506901.pdf](http://www.oecd.org/els/emp/50506901.pdf) (OECDı´s Employment Outlook 2012, last access 10/02/2015).

**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% |  |

as green therein include jobs that are not necessarily associ- ated to environmental issues such as Financial Analysis or Metal Sheet Workers. Our estimate of the size of green jobs is there- fore an upper bound of the actual work engagement in green activities.

Looking at the distribution of employment ([Table 3)](#_bookmark30) we observe that green occupations are overrepresented in few main groups, particularly those intensive in abstract or routine-manual tasks. 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.[13](#_bookmark31) This indicates a low pro-

ﬁle of ICTs in this early phase of greening of the economy. Looking at low-skill 2-digit SOC occupations, 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; OECD, 2010; ILO,](#_bookmark115) [2011b; OECD/Cedefop, 2014).](#_bookmark115)

[Table 4](#_bookmark32) contains descriptive statistics on our skill measures for the 465 occupations of interest (i.e. the ones for which at least one *Green emerging* or *Green enhanced skills* occupation was present within the 3-digit SOC group) while [Table 5](#_bookmark33) reports results based on the task measures of [Autor et al. (2003)](#_bookmark73) and [Acemoglu and Autor](#_bookmark67) [(2011).](#_bookmark67) Accordingly, we observe clear-cut signiﬁcant differences between green occupations and similar non-green occupations that use intensively cognitive skills. In particular, non-routine ana- lytical 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 emerg- ing* 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*) indicates a signiﬁcant negative difference between green occupations, although this is only near signiﬁcant for *Green emerging occupations*, and non-green occupations within their com- parison group. The lower statistical signiﬁcance of the coefﬁcients for *Green emerging* occupations, with magnitude in line with that of *Green enhanced skills* occupations, may be due to greater mea- surement 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 occu- pations compared to the revision of scores for existing occupations, for which a consolidated proﬁle exists already and only requires an update.[14](#_bookmark31)

Since our skill measures are intrinsically qualitative, a quan- tiﬁcation based on standard deviation differences would be inappropriate. For this reason we opt for an interquartile range (IQRs) approach. Starting with *Green enhanced skills* (to reiterate, existing occupations that are evolving in response to changing demands of environmental sustainability) differences are modest but not negligible: compared to similar non-green occupations, the intensity of high-level cognitive skills is 0.13 IQRs higher while the intensity of routine cognitive skills is 0.2 IQRs lower. The overall dif- ference plunges to 0.086 IQRs when using the RTI indicator which includes also NRI and RM skills. The only signiﬁcant gap between *Green emerging* jobs and similar non-green ones is in routine skills,

0.32 IQRs smaller, while the coefﬁcient for RTI is not signiﬁcant (p-value 0.147), with a difference with respect to non-green occu- pations of about 0.1 IQRs.

To put matters in context, recall that non-routine tasks require analytical and interpersonal skills to deal with non-predictable work environments while routine skills are intensive in occu- pations based on the execution of explicit instructions (e.g. book-keeping, clerical work, automated productions) ([Autor et al.,](#_bookmark73) [2003; Levy and Murnane, 2004).](#_bookmark73) Our results suggest that the task content of green occupations – both green emerging and green

13 We should remark that some ICT occupations (15-1133.00 Software Developers, Systems Software) are in the *Green demand* group that is left out from the analysis (see Section [3.1).](#_bookmark12)

14 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.

**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 analytical 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) (2) (3) (4) (5) (6)

NR analytical NR interactive R cognitive R manual NR manual RTI index

Green emerging 0.0293 −0.00737 −0.0320[\*](#_bookmark34) −0.0152 −0.00291 −0.0692

(0.0187) (0.0205) (0.0192) (0.0149) (0.0364) (0.0476)

Green enhanced skills 0.0297[\*\*](#_bookmark35) 0.00404 −0.0198[\*](#_bookmark34) −0.00508 0.0152 −0.0583[\*\*](#_bookmark35)

(0.0130) (0.0145) (0.0108) (0.0155) (0.0162) (0.0269)

Joint sign. green occ dummies (F) 3.309[\*\*](#_bookmark35) 0.120 2.489[\*](#_bookmark34) 0.519 0.456 2.996[\*](#_bookmark34)

*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.

enhanced – is less routinised than that of their peer non-green jobs. That is to say, the spectrum of work activities has not reached a level of maturity so that they can be speciﬁed in instructions. This is especially so for analytical tasks, and resonates with the remark 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).](#_bookmark116)

Moving to other dimensions of human capital, education, expe- rience and on-the-job training ([Table 6),](#_bookmark36) the differences between green occupations and similar non-green occupations are more substantial. This is especially the case for *Green enhanced skills* occu- pations which require 1.9 percent more years of education than comparable non-green occupations, about 13 weeks when evalu- ated 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 train- ing (41 percent, corresponding to about 15 weeks when evaluated

**Table 6**

Proﬁling of green occupations: education, experience and training.

at the overall sample mean). For what concerns *Green emerging* occupations no differences are found in terms of years of education and years of experience, while they require 18 percent more years of training than non-green occupations (slightly less than seven weeks when evaluated at the overall sample mean). These results point to interesting differences within the group of green occupa- tions, and the prominence of on-the-job training programmes as opposed to formal education for new *Green emerging occupations* resonates with the basic tenet of human capital theory (e.g. [Becker,](#_bookmark79) [1962).](#_bookmark79)[15](#_bookmark39)

* + 1. *Green skills and exposure to technology*

As anticipated earlier (Section [3.2)](#_bookmark22) differences in skills within narrow comparison groups may be driven by the relation between work activities and the use of technology rather than by actual speciﬁcities in the skill proﬁle of green occupations. For this reason we check whether green occupations differ from similar non-green jobs (within the same 3-digit SOC group) in terms of exposure to technology. Results are reported in [Table 7.](#_bookmark41)

*Green enhanced skills* are signiﬁcantly more exposed to all measures of technology except ICTs. Conversely *Green emerging*

occupations exhibit higher exposure to investments in ﬁxed assets

(1) (2) (3)

as well as to general R&D and patents relative to similar non-green

log(years of educ)

log(years of exp)

log(years of train)

occupations. Interestingly, no differences emerge between *Green emerging* occupations and non-green ones in terms of exposure to

Green emerging 0.0205 −0.0515 0.168[\*](#_bookmark37)

(0.0221) (0.124) (0.0998)

environmental technologies. No doubt, this result requires a more

detailed analysis that goes beyond the scope of this paper but it

Green enhanced skills

Joint sign. green occ dummies (F)

0.0191[\*\*](#_bookmark38) 0.357[\*\*\*](#_bookmark40) 0.341[\*\*\*](#_bookmark40)

(0.00861) (0.113) (0.129)

2.609[\*](#_bookmark37) 5.982[\*\*\*](#_bookmark40) 3.815[\*\*](#_bookmark38)

hints at a scenario in which the work tasks of new green occupations are clearly not ‘hands on’ machinery type of activities. Furthermore, the magnitude of these differences, considering that the variation is within 3-digit occupational groups. This is especially so in the

*N* 465 465 465

OLS estimates weighted by employment share. Robust standard errors in parenthe- sis.

\* *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.

case of general patents (about 0.6 log points for *Green enhanced*

15 An interesting complement to our evidence comes from a study by [Pollin et al.](#_bookmark111) [(2009)](#_bookmark111) focusing on the potential creation of additional jobs enhanced by investments in clean energy (as opposed to conventional fossil fuel energy). Their evidence points to a higher share of additional low-skilled jobs (proxied by lower formal education and hourly wage) with respect to medium- and high-skilled ones.

**Table 7**

Exposure of green occupations to green technology.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Green emerging | Green enhanced skills | Joint sign. green occ dummies (F) | *N* |
| log(R&D tot/L) | 0.331[\*\*](#_bookmark42) | 0.277[\*\*\*](#_bookmark44) | 6.717[\*\*\*](#_bookmark44) | 465 |
|  | (0.142) | (0.0915) |  |  |
| log(R&D env/L) | 0.0566 | 0.0861[\*\*\*](#_bookmark44) | 5.209[\*\*\*](#_bookmark44) | 465 |
|  | (0.0499) | (0.0285) |  |  |
| log(pat tot/L) | 0.477[\*](#_bookmark43) | 0.597[\*\*\*](#_bookmark44) | 5.039[\*\*\*](#_bookmark44) | 465 |
|  | (0.248) | (0.206) |  |  |
| log(pat env/L) | 0.0798 | 0.161[\*\*\*](#_bookmark44) | 4.490[\*\*](#_bookmark42) | 465 |
|  | (0.0727) | (0.0550) |  |  |
| log(investments/L) | 0.192[\*\*](#_bookmark42) | 0.123[\*](#_bookmark43) | 3.348[\*\*](#_bookmark42) | 465 |
|  | (0.0962) | (0.0635) |  |  |
| log(ICT/L) | 0.129[\*](#_bookmark43) | 0.0555 | 2.634[\*](#_bookmark43) | 465 |
|  | (0.0668) | (0.0410) |  |  |

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 8**

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

(1) (2) (3) (4) (5) (6)

NR analytical NR interactive R cognitive R manual NR manual RTI index

Green emerging 0.0155 −0.0139 −0.0338[\*](#_bookmark46) −0.0196 −0.00516 −0.0573

(0.0196) (0.0218) (0.0184) (0.0157) (0.0362) (0.0500)

Green enhanced skills 0.0252[\*\*](#_bookmark47) 0.00224 −0.0201[\*\*](#_bookmark47) −0.00479 0.0174 −0.0528[\*](#_bookmark46)

(0.0122) (0.0142) (0.0101) (0.0154) (0.0151) (0.0278)

log(R&D non-env/L) 0.0379[\*\*](#_bookmark47) 0.0202 0.0118 0.0357[\*](#_bookmark46) 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[\*\*](#_bookmark47) −0.00294

(0.0447) (0.0518) (0.0374) (0.0570) (0.0455) (0.106)

log(ICT/L) 0.0583[\*\*\*](#_bookmark48) 0.000224 0.0333[\*\*](#_bookmark47) −0.0121 −0.0231 −0.0213

(0.0202) (0.0221) (0.0165) (0.0204) (0.0241) (0.0481)

log(investments/L) −0.00100 0.0140 −0.0210[\*\*](#_bookmark47) 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[\*\*](#_bookmark47) 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 9**

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

(1) (2) (3)

*skills* occupations and 0.5 log points for *Green emerging* occupa- tions) and general R&D (about 0.3 log points for both *Green emerging skills* and *Green enhanced skills* occupations).[16](#_bookmark52) On the other hand,

log(years of educ)

log(years of exp)

log(years of train)

differences in exposure to green-speciﬁc technologies (environ- mental patents and environmental R&D) are only signiﬁcant for

Green emerging 0.0102 −0.124 0.138

(0.0230) (0.133) (0.110)

*Green enhanced skills* though the magnitude is smaller for green- speciﬁc technologies compared to general technologies. For what

Green enhanced skills

log(R&D

non-env/L)

0.0137[\*](#_bookmark49) 0.291[\*\*\*](#_bookmark51) 0.301[\*\*](#_bookmark50)

(0.00778) (0.107) (0.128)

0.0294[\*\*\*](#_bookmark51) 0.00216 −0.124

(0.0111) (0.0984) (0.118)

concerns investments in ﬁxed capital and in ICT capital, the differ- ence in exposure between green occupations and other occupations is larger 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

log(R&D env/L) −0.0118 0.641[\*\*](#_bookmark50) 0.653[\*\*](#_bookmark50)

(0.0261) (0.256) (0.269)

log(ICT/L) 0.0241[\*](#_bookmark49) −0.108 −0.125

(0.0139) (0.0991) (0.127)

log(investments/L) −0.00131 0.227[\*\*\*](#_bookmark51) 0.210[\*\*](#_bookmark50)

(0.00971) (0.0796) (0.0894)

(resp. ICT capital) about 0.19 (resp. 0.13) log points greater than similar non-green occupations.

To check whether skill differences between green and non- green occupations are inﬂuenced by the relation between work

activities and the attendant technology rather than other speci-

Joint sign. green occ dummies (F)

1.557 5.188[\*\*\*](#_bookmark51) 2.869[\*](#_bookmark49)

ﬁcities of green occupations, we enrich the baseline speciﬁcation of Eq. [(2)](#_bookmark24) with variables that capture exposure of occupations to

*N* 465 465 465

OLS estimates weighted by employment share. Robust standard errors in parenthe- sis.

\* *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.

technology (see Section [3.1).](#_bookmark12) In particular, following the literature

16 To ﬁx ideas since our measures of technology are in log, a difference of 0.6 log points in patents per worker occupations means that exposure is 82 percent higher (100 \* (e0.6 − 1)) for green emerging compared to non-green occupations.

**Table 10**

Proﬁling of green occupations: skill measures (conditional on investments and patents).

(1) (2) (3) (4) (5) (6)

NR analytical NR interactive R cognitive R manual NR manual RTI index

Green emerging 0.0202 −0.0105 −0.0307[\*](#_bookmark54) −0.0154 −0.00141 −0.0576

(0.0193) (0.0214) (0.0186) (0.0142) (0.0360) (0.0487)

Green enhanced skills 0.0251[\*\*](#_bookmark55) 0.00198 −0.0212[\*\*](#_bookmark55) −0.0105 0.0147 −0.0582[\*\*](#_bookmark55)

(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[\*\*](#_bookmark55) 0.0363[\*](#_bookmark54) 0.0172 0.0433

(0.0155) (0.0170) (0.0135) (0.0211) (0.0205) (0.0377)

log(ICT/L) 0.0690[\*\*\*](#_bookmark56) 0.00567 0.0433[\*\*\*](#_bookmark56) −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[\*\*\*](#_bookmark56) −0.0198 0.00872 −0.0595[\*](#_bookmark54)

(0.0138) (0.0156) (0.0121) (0.0173) (0.0158) (0.0336)

Joint sign. green occ dummies (F) 2.361[\*](#_bookmark54) 0.141 2.951[\*](#_bookmark54) 0.663 0.436 2.484[\*](#_bookmark54)

*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.

reviewed in Section [2,](#_bookmark9) 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) mea- sured, alternatively, by R&D (total and green R&D – [Tables 8 and 9)](#_bookmark45) and patents (total and green patents – [Tables 10 and 11).](#_bookmark53) It is impor- tant to reiterate 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.

In general, exposure to technology, measured either by R&D or patents, does not inﬂuence the estimated differences in the skill and human capital content of green occupations relative to non-green occupations. The only difference is that no signiﬁcant gap exists in terms of years of training between Green emerg-  ing occupations and non-green occupations. On the other hand,

**Table 11**

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

differences between the skill contents of green and non-green occupations 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 ([Tables 5 and 6).](#_bookmark33)

In sum, with the exception of on-the-job training for *Green emerging* occupations, differences between green and non-green occupations do not seem to depend on job-speciﬁc characteristics associated with the use of technology but, rather, on other charac- teristics of green activities that affect the workforce proﬁle such as, for example, organisational changes. Before concluding, a caveat is obligatory: this study is a preliminary attempt to elucidate 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.

(1) (2) (3)

# Concluding remarks

log(years of educ)

log(years of exp)

log(years of train)

This paper has proposed an empirical analysis of the skill content

Green emerging 0.0139 −0.110 0.154

(0.0226) (0.127) (0.104)

of green occupations, a theme that will no doubt attract consid- erable interest in the near future among scholars of innovation

Green enhanced

skills

log(patent non-env/L)

0.0142[\*](#_bookmark57) 0.307[\*\*\*](#_bookmark59) 0.316[\*\*](#_bookmark58)

(0.00818) (0.106) (0.124)

0.00739 0.0321 −0.0498

(0.00454) (0.0332) (0.0384)

and science and technology policy. The motivation of our study is the acknowledgement 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

log(patent env/L) 0.00460 0.144 0.301[\*\*\*](#_bookmark59)

(0.0110) (0.114) (0.109)

log(ICT/L) 0.0404[\*\*\*](#_bookmark59) 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)

changes in the organisation of production map onto the recon- ﬁguration of work. We explore the characteristics of green jobs by means of both traditional measures of human capital as well as task-based indicators that have been developed to study the

relationship between technology and employment. Drawing on a

Joint sign. green occ dummies (F)

1.569 5.633[\*\*\*](#_bookmark59) 3.424[\*\*](#_bookmark58)

comprehensive database of occupation-speciﬁc information in the US we identify two categories of jobs that are readily associated

N 465 465 465

OLS estimates weighted by employment share. Robust standard errors in parenthe- sis.

\* *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.

with the greening of the economy, namely: existing occupations that experience a change in work content and wholly new occu- pations. We then draw a comparison between these and similar non-green jobs.

The main result is that in general green occupations exhibit sig- niﬁcant differences from non-green ones in that they exhibit higher levels of non-routine (e.g. creative problem solving) analytical skills

as well as higher intensity of standard human capital indicators of formal education, work experience and on-the-job training. The evidence also indicates that the work content of green jobs is on average less routinised than that of non-green jobs. If we interpret routinisation as the mark of ‘maturity’ whereby job activities can be codiﬁed in the form of simple instructions, such as the case of many occupations that have been signiﬁcantly affected by the advent of ICTs – for example, clerical or machine operators – our results indi- cate that the process of reconverting production and distribution activities towards more sustainable standards is a path currently under construction. Accordingly, environmental technologies are still at early stages of the life cycle, occupational boundaries are sub- ject to frequent mutations, the division of labour across occupations is constantly being redeﬁned and, as it often happens before these transitions reach maturity, skills like cognitive adaptability and problem-solving are prominent in fast-changing work contexts.

Our results also draw attention to differences between types of green jobs. In particular, traditional dimensions of human capital such as formal education, work experience and on-the-job train- ing are more prominent among existing occupations (i.e. those that are undergoing change in work content) while for new green occupations (i.e. those that are emerging in the current effort of greening the economy) only on-the-job training emerges as a dis- tinctive trait. The implication is that educational policy 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 sector *consortia* and inter-ﬁrm associa- tions 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 indicate promising direc- tions for future research. First, in this exploratory study we rely on established, but rather general, dimensions of human capital and skill content of occupations which may or may not ﬁt to the pecu- liarities framework of environmental sustainability. It is plausible that the sequence of incremental improvements that will confer a direction to the greening trajectory will call upon speciﬁc, con- ceivably novel, skills as well as new skill combinations that have little connection with those that we are familiar with (see [Ghisetti](#_bookmark113) [et al.,](#_bookmark113) [2015).](#_bookmark113) Recent research has taken initial steps towards the identiﬁcation of the skill endowment of environmental-speciﬁc occupations (see [Vona et al., 2015),](#_bookmark117) but a lot remains to be done. Another promising route is the exploration of skill transferability across occupations. A cogent question is: to what extent are exist- ing (i.e. non-speciﬁcally green) skills relevant for green jobs? The analysis presented here identiﬁes average skill differences between green and non-green jobs but says nothing on the extent to which the skill of the latter may be transferable to the work demands of the former. According to the standard human capital literature job displacement following radical technological transitions, such as the greening of the economy, are more costly both for work- ers and society when skills are highly occupation-speciﬁc and not easily transferable ([Poletaev and Robinson, 2008; Gathmann and](#_bookmark108)

is hoped that future studies will explore these and other relevant issues in this promising line of research.

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# Appendix 1. Sources and other information about the creation of the measures of exposure to technology

We retrieve information on investment (total investments and investments in ICTs) by NAICS industry for the 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 the 3-digit or 4-digit NAICS level (depending on the industry) are retrieved from the *2010 Annual Capital Expendi- tures Survey*, Tables 4a and b.

R&D expenditure (2008–2010) are available through the National Science Foundation (NSF). We split total R&D into the amount of R&D related to environmental protection and energy applications. This is deemed relevant because it captures the extent to which future technological developments account for environ- mental 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 percent. Patent stocks have been assigned to NAICS industries by using the IPC-NAICS

concordance matrix developed by [Lybbert](#_bookmark90) [and](#_bookmark90) [Zolas](#_bookmark90) [(2014).](#_bookmark90)[18](#_bookmark61)

Environmental patents have been identiﬁed by using the list of environmentally-relevant IPC classes complied by the OECD (OECD-ENVTECH). Environmental patents identiﬁed by the OECD pertain to the following technology ﬁelds: renewable energy gen- eration technologies, emission abatement and fuel efﬁciency in transportation, general environmental management, energy efﬁ- ciency in buildings and lighting. Relevant IPC classes are reported in [Table A3.](#_bookmark65)

[Schönberg,](#_bookmark108) [2010).](#_bookmark108) Gauging the extent to which policy can curb

potential skill gaps by facilitating knowledge transfer across occu- pations would be an important addition to the ongoing debate.[17](#_bookmark62) It

17 A preliminary attempt to quantify skill distance across occupations can be found in an early version: [https://www.sussex.ac.uk/webteam/gateway/](https://www.sussex.ac.uk/webteam/gateway/file.php?name=2015-16-swps-consoli-etal.pdf&site=25) [ﬁle.php?name=2015-16-swps-consoli-etal.pdf&site=25](https://www.sussex.ac.uk/webteam/gateway/file.php?name=2015-16-swps-consoli-etal.pdf&site=25). While no clear patterns emerge from this ﬁrst exploration, we feel that such a ‘non-result’ lends further support to the argument that the transition towards green growth is still at early stages.

18 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 has been developed 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, differently from other approaches such as that of [Schmoch et al. (2003),](#_bookmark116) it acknowledges that each speciﬁc (IPC 4-digit) technology may be relevant for a plurality of industries, this resulting in multiple assignment of IPCs and industry-speciﬁc weights.

**Table A1**

Examples of green occupations.

|  |  |  |  |
| --- | --- | --- | --- |
| *SOC-Code* | *Green enhanced skills* Number of employees  (2011–2012) | Employment share (2011–2012) | Description |
| 11-1021.00  53-3032.00 | General and 1,892,730 Operations Managers  Heavy and 1,550,143 | 1.50%  1.23% | Plan, direct, or coordinate operations of organisations; formulate policies, plan the use of materials and human resources. Duties are diverse and general in nature, with respect to functional area of management. Drive a tractor-trailer combination or a truck with high |
| 49-9071.00 | Tractor-Trailer Truck Drivers  Maintenance and 1,234,933 | 0.98% | capacity. May be required to unload truck. Requires commercial drivers’ license.  Keep machines, equipment, or the structure of an |
| 47-2061.00 | Repair Workers, General  Construction Labourers 806,270 | 0.64% | establishment in repair. Duties include: pipe ﬁtting; insulating, repairing electrical or mechanical equipment; installing, aligning, and balancing new equipment.  Perform tasks involving physical labour at construction |
| 43-5071.00 | Shipping, Receiving, 685,390 | 0.54% | sites. Duties include: operating hand and power tools of all types; cleaning and preparing sites; cleaning up rubble, debris and other waste materials.  Verify and maintain records on incoming and outgoing |
|  | and Trafﬁc Clerks |  | shipments. Prepare items for shipment. Duties include: assembling, shipping merchandise or material; receiving, unpacking; arranging for the transportation of products. |
| *SOC-Code* | *Green emerging* Number of employees (2011–2012) | Employment share (2011–2012) | Description |
| 51-9199.01  13-1199.05 | Recycling and 217,006 Reclamation Workers  Sustainability 189,116 | 0.17%  0.15% | Prepare and sort materials or products for recycling. Identify and remove hazardous substances; dismantle components of products.  Address organisational sustainability issues, such as |
| 13-1199.01 | Specialists  Energy Auditors 189,116 | 0.15% | waste management, green building practices, and green procurement plans.  Conduct energy audits of buildings, building systems, |
| 41-4011.07 | Solar Sales 182,193 | 0.14% | or process systems. May also conduct investment grade audits of buildings or systems.  Contact new or existing customers to determine their |
| 17-2051.01 | Representatives and Assessors  Transportation 129,067 | 0.10% | solar equipment needs, suggest systems or equipment, or estimate costs.  Develop plans for surface transportation projects, |
|  | Engineers |  | according to engineering standards and construction policy. Prepare designs, speciﬁcations and modiﬁcation for transportation facilities. |
| *SOC-Code* | *Green demand* Number of employees (2011–2012) | Employment share (2011–2012) | Description |
| 53-7062.00  43-4051.00 | Labourers and Freight, 2,164,057 Stock, and Material  Movers, Hand  Customer Service 1,150,358 | 1.72%  0.91% | Manually move freight, stock, or other materials or perform other general labour. Includes all manual labourers not elsewhere classiﬁed.  Interact with customers to provide information in |
| 51-2092.00 | Representatives  Team Assemblers 1,005,793 | 0.80% | response to inquiries about products and services and to handle and resolve complaints.  Work as part of a team having responsibility for |
| 51-1011.00 | First-Line Supervisors 569,597 | 0.45% | assembling an entire product or component of a product. Can perform all tasks conducted by the team in the assembly process and rotate.  Directly supervise and coordinate the activities of |
| 47-2111.00 | of Production and Operating Workers  Electricians 524,940 | 0.42% | production and operating workers, such as precision workers, machine setters and operators, assemblers, fabricators.  Install and maintain electrical wiring, equipment, and |
|  |  |  | ﬁxtures. Ensure that work is in accordance with relevant codes. May install or service street lights, intercom or electrical control systems. |

**Table A2**

Employment in green occupations by industry (top 5).

|  |  |  |
| --- | --- | --- |
| NAICS code | NAICS description | % of total empl in green enhanced skills occ |
| *Top 5 industries for green enhanced skills* |  |  |
| 4841 | General Freight Trucking | 5.8% |
| 2382 | Building Equipment Contractors | 4.6% |
| 5413 | Architectural, Engineering, and Related Services | 4.4% |
| 5613 | Employment Services | 2.6% |
| 5511 | Management of Companies and Enterprises | 2.5% |
| *Top 5 industries for green emerging* |  |  |
| 5413 | Architectural, Engineering, and Related Services | 7.7% |
| 5511 | Management of Companies and Enterprises | 6.0% |
| 5613 | Employment Services | 6.0% |
| 5416 | Management, Scientiﬁc, and Technical Consulting Services | 4.0% |
| 6113 | Colleges, Universities, and Professional Schools | 3.9% |
| *Top 5 industries for green demand* |  |  |
| 5613 | Employment Services | 7.4% |
| 2382 | Building Equipment Contractors | 5.3% |
| 4931 | Warehousing and Storage | 2.6% |
| 3363 | Motor Vehicle Parts Manufacturing | 2.0% |
| 2361 | Residential Building Construction | 1.9% |

**Table A3**

Environmental patent classes.

Macro-category Sub-category IPC (CPC) classes

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

General environmental management

Energy generation from renewable and non-fossil sources

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

Fertilisers 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

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

Technologies for improved output efﬁciency (combined combustion)

Y02E20/1 (CPC)

mitigation potential

Climate change

Technologies for improved input efﬁciency Y02E20/03 (CPC) CO2 capture or storage Y02C10 (CPC)

mitigation

Capture or disposal of greenhouse gases other

than CO2

Y02C20 (CPC)

Potential or indirect contribution to emissions mitigation

Emissions abatement and fuel efﬁciency in transportation

Energy storage Y02E60/1 (CPC)

Hydrogen technology Y02E60/3 (CPC)

Fuel cells Y02E60/5 (CPC)

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 using electric motor

B60K1, B60L7/10-20, B60L11, B60L15, B60R16/033, B60R16/04, B60S5/06, B60W10/08, B60W10/26, B60W10/28, B60K16, B60L8

Energy efﬁciency in buildings and lighting

*Source*: ENV-TECH Indicator, OECD (2013).

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

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

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