Environmental regulation and green skills : an empirical exploration

Francesco Vona, Giovanni Marin, Davide Consoli, David Popp

Environmental Regulation and Green Skills: An Empirical Exploration

Francesco Vona, Giovanni Marin, Davide Consoli, David Popp

Abstract: This paper provides new evidence on the workplace skills most relevant in the transition toward environmentally sustainable economies. Using a novel data-driven methodology, we identify two main sets of green skills, namely, engineering skills for the design and production of technology, and managerial skills for implementing and monitoring environmental organizational practices. Exploiting exogenous geographical variation in regulatory stringency, we also evaluate the effect of environmental regulation on the demand of green skills for a panel of US metropolitan and nonmetropolitan areas over the period 2006–14. The main finding is that while these changes in environmental regulation have no impact on overall employment, they create significant, if modest, gaps in the demand for some green skills, especially those related to technical and engineering work tasks.

JEL Codes: J24, Q52

Keywords: Environmental regulation, Green skills, Task model, Workforce composition

THE CATCHWORD "GREEN SKILLS" has become a staple of both policy debates and plans, as exemplified by the stimulus package that committed substantial resources to training programs for "green jobs" under President Obama. Yet in spite of a raging debate on the effectiveness of these actions, there is little systematic empirical research to guide public intervention for meeting the demand for skills that will be needed to oper-

Francesco Vona is at the Observatoire Français des Conjonctures Economiques (OFCE) and SKEMA Business School, Université Côte d'Azur (GREDEG), France (francesco.vona@sciencespo.fr). Giovanni Marin is in the Department of Economics, Society and Politics, University of Urbino "Carlo Bo," Italy (giovanni.marin@uniurb.it). Davide Consoli is at Ingenio CSIC-UPV, Spain (davide.consoli@ingenio.upv.es). David Popp is in the Department of Public Administration and International Affairs, Maxwell School, Syracuse University, United States, and National Bureau of Economic Research, United States (dcpopp@maxwell.syr.edu). We wish to thank Dan Phaneuf, the editor, and three referees for their constructive comments and suggestions. We also thank Alex Bowen, Carmen Carrion-Flores, Mark Curtis, Olivier Deschenes, Ann Ferris, Jens Horbach, Karly-

ate and develop green technology. We argue that understanding the extent to which greening the economy can induce significant changes in the demand for certain skills and, most cogently, which skills these might be, is a crucial first step to inform the design of training and educational policies in the future. The main contribution of the present paper is a new data-driven methodology to identify skills demanded in the green economy. Our descriptive data provide a first look at these green skills and allow us to compare the skill content of green and brown jobs, that is, those jobs mainly employed in polluting industries. Using the Occupational Information Network (O*NET) data set, we identify two core sets of green skills for which green jobs differ from non-green jobs: engineering skills for design and production of technology, and managerial skills for setting up and monitoring environmental organizational practices. When limiting the comparison to green and brown jobs, skill differences appear less pronounced. We use these data to provide new evidence on the effect of environmental regulation on the demand for green skills for a panel of US metropolitan and nonmetropolitan areas over the period 2006–14. Our findings suggest that, while these recent changes in environmental regulation have no impact on overall employment, they create significant, but quantitatively modest, gaps in the demand for some green skills, especially those related to technical and engineering skills.

Environmental policy advocates often note that increased regulation will help the economy through the creation of "green jobs." For example, the summary for policy makers of the United Nations Environmental Programme's report on the green economy (UNEP 2011) touts the employment benefits of a greener economy. At the same time, critics of climate policy point to the job losses that they are sure will follow.[1] Empirical evidence of environmental regulation's effect on employment is mixed (e.g., Green-

gash Kuralbayeva, Maurizio Iacopetta, Leonard Lopoo, Stefania Lovo, Joelle Noailly, Edson Severnini, Kelly Stevens, and Elena Verdolini for useful comments and discussions. This paper benefits from comments at the following seminars and conferences: the Maxwell School of Syracuse University, SKEMA Business School (Nice), Triangle Resource and Environmental Economics Seminar, the third annual meeting of the Italian Association of Environmental and Resource Economists (Padova), University of Ferrara, 21st annual conference of the European Association of Environmental and Resource Economists (Helsinki), London School of Economics conference on innovation and the environment (London), American Economic Association (San Francisco), 28th EALE meeting (Ghent), and 3rd IZA Workshop on Labor Market Effects of Environmental Policies (Berlin) for their comments. Francesco Vona and Giovanni Marin gratefully acknowledge the funding received from the European Union's Seventh Framework Programme for research, technological development, and demonstration under grant agreement no. 320278 (RASTANEWS). Francesco Vona wishes to thank Maxwell School of Citizenship and Public Affairs at Syracuse University for the kind hospitality during the initial writing of this paper. Davide Consoli acknowledges the financial support of the Spanish Ministerio de Economia y Competitividad (RYC-2011-07888).

1. Bowen and Kuralbayeva (2015) provide a good summary of the policy debate surrounding green jobs.

stone 2002; Morgenstern et al. 2002), but recent studies such as Kahn and Mansur (2013) suggest the possibility of larger effects, particularly in energy-intensive industries. One reason that some studies find limited effects is that they focus on reallocation, so that job losses following a reduction in one sector's scale of activity are offset by gains in other sectors, including increased demand for pollution control equipment or of workers required to comply with regulation and use new green technologies (e.g., Morgenstern et al. 2002). At the same time, however, previous research ignores that job displacement may entail various types of adjustment costs (Smith 2015) such as long-term earnings losses (Davis and von Wachter 2011; Walker 2013) or the obligation to migrate (Kumioff et al. 2015). Walker (2013) finds that workers in sectors affected by the 1990 Clean Air Act lose 20% of their pre-regulatory lifetime earnings, with most of the burden falling upon displaced workers. Moreover, workers displaced by environmental regulation are more likely to take longer to find a new job and more likely to find their new job in a different industry where they lose valuable industry-specific skills. While Walker notes that these costs are significantly lower than the aggregate benefits of the Clean Air Act, he also suggests that the distributional effects of environmental regulation on workers may be significant.

Both the popularity of the green jobs concept within the environmental policy community and the studies cited above highlight the growing prominence of green jobs and of the possible adjustment costs of changes in employment patterns in response to environmental regulation. The adjustment costs from job losses can be exacerbated when the skill profile of expanding jobs does not match the skill profile of contracting jobs. Labor research shows that workers' relocation costs crucially depend on the skill similarity between occupations and that skill specificity is more tied to occupations than to a particular firm (Poletaev and Robinson 2008; Kambourov and Manovskii 2009; Gathmann and Schönberg 2010). Consider an economy reshaped by high carbon taxes to dramatically reduce carbon emissions from fossil fuel consumption. An engineer who works drilling for petroleum may find his skills readily transferable to similar drilling for carbon sequestration. In contrast, would the skills of a displaced coal miner be easily transferable to the manual tasks used for installing new wind turbines or solar panels?

To understand the potential adjustment costs of greening the economy, we identify a set of skills used more intensively in green occupations than non-green ones. Our data-driven methodology searches within the broad range of skills contained in the O*NET data set to identify skills prominent in green occupations. For each occupation, the O*NET data set distinguishes tasks specific to that job from general skills that are used both in that occupation and elsewhere. Using this information we identify, first, jobs having a significant share of green specific tasks over total tasks and, second, the sets of general skills also associated with these jobs. We use these *Green General Skills* to compare the similarity of workforce skills across occupations, with a particular interest in assessing whether these general skills are substantially different from the skills of those particular workers that are more likely to be displaced by environmental regulation, that is, brown workers. While the skill gap between green jobs and brown jobs within groups of similar occupations is generally small, interesting exceptions emerge. In particular, the largest skill gaps between green and brown jobs occurs within construction and extraction occupations. As these occupations include workers in the oil and mining industries, these differences are important for climate policy. Recent political events demonstrate how workers in these sectors are worried about future employment effects of climate regulation.

In the second part of the paper we also provide an initial empirical application of our green skills measures. Adapting a standard empirical strategy to identify the employment effect of environmental policies (e.g., Greenstone 2002; Walker 2011), we estimate the effect of switches to nonattainment status on skill demand controlling for a host of observable and unobservable regional characteristics. In particular, using variations in employment shares of occupations across US regions, we construct aggregate skill measures for each US metropolitan and nonmetropolitan area for 2006–14 and estimate the effect of environmental regulation changes on the demand for green skills. We argue that a positive net impact of environmental regulation on any of these skill measures indicates the existence of gaps between the skills possessed by jobs that benefit from regulation and those possessed by jobs that contract due to regulation. Identifying these gaps informs the development of training and educational policies designed to mitigate the negative employment effects that are traditionally associated with environmental regulation.

While evidence on the labor market outcomes of environmental regulation is abundant for the United States,[2] only two recent studies find heterogeneous effects for different groups of workers. Curtis (2017) shows that incumbent workers are sheltered from the negative regulatory impact and that the main driver is a slowdown in hiring of young workers. Walker (2013) estimates large earnings losses for workers displaced by environmental regulation who change sector, thus corroborating the idea that specific skills are important in energy-intensive industries. However, these papers do not directly explore possible changes in the content of work and, thus, of the skills demanded from employers in greener activities compared to brown ones. These occupation-specific features are particularly relevant in light of skill similarity at the job, rather than industry, level (Gathmann and Schönberg 2010).

2. Some empirical studies find that the employment effect is negligible (Berman and Bui 2001; Morgenstern et al. 2002; Gray et al. 2014), while others find a negative and modestly large effect concentrated in energy-intensive industries (e.g., Greenstone 2002; Walker 2011; Kahn and Mansur 2013). With the exception of the United Kingdom, there is far less research on other countries. Cole and Elliott (2007) also find a negligible effect for a short panel of UK industries. This result is corroborated by a recent plant-level study that exploits exogenous variation in the eligibility of a carbon tax discount in the UK (Martin et al. 2014).

To the best of our knowledge, only Becker and Shadbegian (2009) examine the relationship between green production and workforce skills. Their descriptive evidence shows that for a given level of output and factor usage, plants producing green goods and services employ a lower share of production workers. This lends support to a variant of the skill-bias technical change hypothesis postulating that at the onset of a new wave of technological change the demand for high-skilled workers increases and subsequently dissipates inasmuch as codification facilitates the use of new technologies by the less talented workers (Aghion et al. 2002; Vona and Consoli 2015). By analogy, since most green technologies are still at an early stage, we expect that their adoption will be associated with an increase in the demand of highly skilled workers. However, since insights drawn from the skill-bias technical change literature can shape our expectations only to a limited extent, in the remainder of the paper we rely on an empirical approach to adapt more precisely the concept of "appropriate" skills to the case of green technologies and production methods.

This study contributes to the literature in three ways. Most importantly, we propose a new methodology to identify the workplace skills important for particular occupations. In this application, we use the methodology to identify skills important to green jobs likely to be in high demand in a world with increasing environmental regulation. However, our data-driven measures build upon prior work on changes in the demand for skills (Autor et al. 2003) and could be generalized to identify the skills relevant for any specific occupational group. Having identified green skills, we next explore qualitative evidence of the skill requirements for occupations both likely to see increases and decreases in demand following environmental regulation. Finally, we provide an initial empirical application of the data to assess how environmental regulation affects skill demand. Although limited availability of data is a hurdle for causal inference, our paper is the first to assess how environmental regulation affects the demand for different skill sets and can be extended to analyze the distributional impacts of environmental policies through changes in the returns to skills.

The available data present two challenges for a clean identification of causal effects. First, compared to related studies we use data on metropolitan and nonmetropolitan areas, rather than county (see, e.g.. Greenstone 2002; Walker 2013; Curtis 2017). This higher level of aggregation makes our estimates of the labor market impact of nonattainment designation less reliable and requires auxiliary assumptions on the construction of the final data set that are tested for robustness. Our choice is, however, consistent with prior studies in labor economics using metro area data to account for workers' commuting (e.g., Autor and Dorn 2013). Second, the changes in environmental regulation that are relevant to our paper are evaluated over a short time span and potentially amplified by the concurrent shock of the great recession between 2007 and 2009. As adjustments to skill gaps take time, we cannot rule out the possibility that our estimated impact of regulation on workforce skills is a short-term phenomenon. We conclude by discussing the possibility of richer empirical analysis using extensions of the data presented here.

1. IDENTIFICATION AND MEASUREMENT OF GREEN SKILLS

In this section, we introduce our measure of green skills in five parts. Table 1 defines and summarizes the construction of our green skills measures. First, we briefly explain the data we use to link green jobs to green skills. Second, we introduce our novel data-driven methodology for identifying green skills within the US workforce. Third, we provide descriptive evidence of our green skill measures vis-à-vis other human capital measures. Fourth, we construct an index of the importance of these green skills across occupations. Finally, we compare different skill measures for green and brown jobs.

1.1. The Green Economy Program of O*NET

In spite of much interest on green skills there is, to the best of our knowledge, no standard definition for such a concept. Policy reports and a still scant academic literature conflate green skills with "green jobs," namely, the workforce of industries that produce environmentally friendly products and services (see, e.g., Deitche 2010; US Department of Commerce 2010; Deschenes 2013). The "Green Economy" program maintained by the Occupational Information Network (O*NET) under the auspices of the US Department of Labor is a notable exception in that it details the work tasks of green jobs.

In O*NET green occupations are classified in three groups: (i) existing occupations that are expected to be in high demand due to the greening of the economy; (ii) occupations that are expected to undergo significant changes in task content due to the greening of the economy (green enhanced); and (iii) new occupations in the green economy

Table 1. Construction and Analysis of Green General Skills Importance

Step 1: Calculate Greenness: a continuous measure of the greenness of occupations (sec 1.2)
- Data used: counts of green and non-green specific skills in each occupation, from O*NET

Step 2: Identify Green General Skills—general workplace skills more strongly associated with greener occupations (sec 1.2)
- Data used: importance scores for general skills listed for each occupation in O*NET
- We identify 16 Green General Skills, which we group into four macro groups of related skills (sec 1.3)

Step 3: Construct Green General Skill importance index for each occupation (sec 1.4)
- Data used: importance scores for general skills listed for each occupation in O*NET
- Compare GGS importance with other skill measures (sec 1.4) and between green and brown occupations (sec 1.5)

Step 4: Map Green General Skill importance index for each occupation to metropolitan areas, based on the distribution of occupations in each metro area (sec 2.1)
- Data used: GGS importance indices from author calculations and the Bureau of Labor Statistics Occupational Employment Statistics
- Regress importance of each GGS in each metro area on changes in environmental regulation (secs. 2.2–2.3)

(new and emerging) (see Dierdoff et al. 2009, 2011). However, involvement with environmental activities is more clearly identifiable in the last two groups compared to the first, which can be considered at best indirectly "green" (see Consoli et al. [2016] for more details). One important feature of O*NET is that it allows for a finer distinction of the importance of green activities within an occupation. O*NET includes information on both tasks (e.g., what workers are expected to do at the workplace—the demand side) and skills (e.g., the abilities and competences that workers should possess to perform work tasks—the supply side). Tasks are further divided into "general" tasks, which are common to all occupations, and "specific" tasks that are unique to each occupation.[3] Finally, for new and emerging and green-enhanced occupations, O*NET partitions specific tasks into green and non-green specific tasks. For example, sheet metal workers perform both green specific tasks, such as "constructing ducts for high efficiency heating systems or components for wind turbines," and non-green specific tasks, such as "developing patterns using computerized metal working equipment." Similarly, electrical engineers can "plan layout of electric power generating plants or distribution lines" and, at the same time, can "design electrical components that minimize energy requirements."

We exploit this complementary information to (1) define the greenness of an occupation based on the number of specific green tasks required and (2) to identify sets of Green General Skills associated with greener occupations. Defining the greenness of an occupation based on the number of green specific tasks affords a more accurate distinction of green and non-green jobs compared to the O*NET classification, which uses a binary classification to identify green jobs. By constructing a continuous measure of greenness, we place greater weight on occupations whose primary tasks are clearly green.

1.2. A Methodology for the Identification of Green Skills

Using the distinction between green and non-green specific tasks, we compute a *Greenness* measure for each occupation. We then use this index to identify Green General Skills, which are general skills more strongly associated with greener occupations. We define *Greenness* as the ratio between the number of green specific tasks and the total number of specific tasks performed in occupation k:

$$\text{Greenness}_k = \frac{\#\text{green specific tasks}_k}{\#\text{total specific tasks}_k}. \tag{1}$$

This indicator can be interpreted as a proxy of the relative importance of a particular class of job tasks related, more or less directly, with environmental sustainability. The

3. O*NET is a comprehensive database containing occupation-specific information on skill occupational requirements and tasks performed on the job since early 2000. These data provide detailed requirements for each occupation, such as detailed tasks performed, skills, education, and training requirements. Using questionnaire data from a representative sample of US firms, expert evaluators and job incumbents assign importance scores to different task or skill items, such as problem solving.

Greenness ratio allows an arguably finer distinction between types of green job than the O*NET definition in that it captures the spectrum of greenness across various occupations, as shown by the examples in table 2.[4] As expected, occupations like environmental engineers, solar photovoltaic installers, or biomass plant technicians have the highest Greenness score by virtue of the specificities of their job content to environmental activities. Occupations that exhibit complementarity with environmental activities but that also include an ample spectrum of non-green tasks have an intermediate score, such as electrical engineers, sheet metal workers, or roofers. At the bottom end of the greenness scale are jobs that carry out environmental tasks but cannot be considered full-fledged green, such as traditional engineering occupations, marketing managers or construction workers.

For illustrative purposes, we highlight a few occupations that have respectively high and low levels of greenness and that require high or low levels of training.[5] Environmental engineer (SOC [Standard Occupational Classification] 17-2081; Greenness = 1) is a prototypical high-level job (e.g., above average requirements of formal education and on the job training; above average wage; low incidence of routine tasks that can be easily automated) that, according to O*NET, entails "research, design, plan, or perform duties in the prevention, control, and remediation of environmental hazards." O*NET reports several job titles that it classifies as environmental engineers, such as air pollution control engineer, environmental analyst, hazardous substances engineer, and regulatory environmental compliance manager. Environmental engineers exhibit a common trait of high-end (green and non-green) occupations whose core work tasks include technical analysis (i.e., "Design or supervise the design of systems, processes, or equipment for control, management, or remediation of water, air, or soil quality") as well as interaction with other high-level professionals (i.e., "Serve as liaison with federal, state, or local agencies or officials on issues pertaining to solid or hazardous waste program requirements"). Another high greenness occupation, solar photovoltaic installers (SOC 47-2231; Greenness = 1), is defined in O*NET as "Assemble, install, or maintain solar photovoltaic systems on roofs or other structures in compliance with site assessment and schematics." This is representative of technical occupations that perform hands-on work tasks and that require lower education and training than, say, environmental engineers. Examples of such tasks include standardized procedures ("Determine appropriate sizes, ratings, and locations for all system overcurrent devices, disconnect devices, grounding equipment, and surge suppression equipment"), some degree of problem solving ("Identify electrical, environmental, and safety hazards associated with photovoltaic (PV) installations") as well as physical dexterity (i.e., "Install module array interconnect wiring, implementing mea-

4. The full list of green occupations and their greenness is reported in table A1 in app. A.

5. We thank an anonymous referee for encouraging us to provide a more detailed description of the selection of occupations and, thus, to improve the clarity of our empirical analysis.

Table 2. Examples of Green Occupations by Level of Greenness

	Greenness = 1	Greenness between .5 and .3	Greenness < .3
Green enhanced occupations	Environmental engineers, environmental science technicians, hazardous material removers	Aerospace engineers, atmospheric and space scientists, automotive speciality technicians, roofers	Construction workers, maintenance and repair workers, inspectors, marketing managers
New and emerging green occupations	Wind energy engineers, fuel cell technicians, recycling coordinators	Electrical engineering technologists, biochemical engineers, supply chain managers, precision agriculture technicians	Traditional engineering occupations, transportation planners, compliance managers

sures to disable arrays during installation") and work in hazardous conditions (i.e., "Test operating voltages to ensure operation within acceptable limits for power conditioning equipment, such as inverters and controllers").

Turning to occupations with a low incidence of green tasks, and thus a lower Greenness ratio, we see examples where green and non-green tasks overlap. Risk management specialist (SOC 13-2099; Greenness = 0.085) is a high-skill/low-greenness job involving cognitive activities (i.e., "Analyzing and managing risk management issues by identifying, measuring, and making decisions on operational or enterprise risks") which can occasionally be further developed to cope with environmental risks (i.e., "Determine potential environmental impacts of new products or processes on long-term growth and profitability"). Conversely, machine setters, operators, and tenders (SOC 51-9012; Greenness = 0.05) is a technical job that combines cognitive (i.e., "Monitor material flow or instruments such as temperature or pressure") and manual (i.e., "Set up or adjust machine controls to regulate conditions such as material flow, temperature, or pressure") routine tasks. Their only green activity is "Operating machines to process materials in compliance with applicable safety, energy, or environmental regulation."

While nonexhaustive, these examples highlight both the substantial heterogeneity of green tasks and the shortcomings of a binary view of occupations as either green or non-green that is so common in policy debates. Nonetheless, using Greenness as a pure measure of skills has limitations for formulating policy recommendations. An indicator based on specific tasks is by definition not suitable to compare the skill profiles of green and non-green occupations and, thus, to identify which non-green skills can be successfully transferred to green activities and which green skills should be the target of educational programs. Such a comparison is essential to estimate (re)training costs considering that workers' relocation from brown to green jobs depends on the extent to which skills are portable and can be reused in expanding jobs (e.g., Poletaev and Robinson 2008).

To overcome these limitations and broaden the policy relevance of our study, we use the Greenness indicator as a search criterion to identify Green General Skills (GGS henceforth). This procedure uses measures of general tasks (e.g., the general activities that workers carry out at the workplace) and skills (e.g., the skills that are required to perform work tasks) retrieved from O*NET (version 17.0) wherein importance scores for 108 general tasks and skills are reported for 912 SOC (Standard Occupational Classification) eight-digit occupations. For these general tasks and skills, O*NET provides an importance score for all 912 occupations, thus allowing a controlled comparison of the skill profiles of green and non-green jobs.[6] Accordingly, we regress the importance score of each general task (or skill) l in occupation k on our Greenness indicator plus a set of three-digit occupational dummies:

$$\text{Task\_Imp}_k^l = \beta^l \times \text{Greenness}_k + \phi^{\text{SOC}-3\text{d}} + \epsilon_k. \tag{2}$$

Occupational dummies at the three-digit SOC level ($\phi^{\text{SOC\_3d}}$) are included to allow the comparability of the skill profiles of similar occupations. In addition, we use only three-digit SOC occupations containing at least one job with positive greenness, thus eliminating broad occupations that bear no relevance on sustainability, such as, that is, Personal Care and Service.[7] For the three-digit occupations that contain at least one eight-digit green occupation, eight-digit occupations without any green specific tasks receive a Greenness score of 0. Thus, we identify GGS by comparing green (characterized by heterogeneous intensity of greenness) and non-green occupations for a subset of three-digit SOC occupations that are similar in task content and skill requirements. Here, a positive (negative) and significant β^l denotes that general task (or skill) l is used more (less) intensively in greener occupations. We label a general task or skill as green when the estimated $\hat{\beta}^l$ is positive and statistically significant at the 1% level. This procedure generates the set of 16 GGS listed in table 3. These items are mostly skills, rather than tasks and are labeled accordingly in what follows.

The validity of this exercise depends crucially on the definition of greenness because occupations with higher greenness contribute more to the GGS selection than occupations with lower greenness. Our green skills selection compares non-green occupations with both occupations that are clearly green (e.g., a Greenness indicator of 1) and with those that are only partially green (e.g., a low Greenness indicator). While one may be

6. We focus on "Knowledge" (32 items), "Work activities" (41 items), and "Skills" (35 items), while we exclude "Work context" (57 items) because the items in it concern the characteristics of the workplace rather than actual know-how applied in the workplace. O*NET data have been matched with Bureau of Labor Statistics data using the 2010 SOC code. Details are available in app. B. Importance scores in O*NET vary between 1 (low importance) and 5 (high importance). We have rescaled the score to vary between 0 (low importance) and 1 (high importance).

7. The list of three-digit occupations containing at least one green job is reported in table A2 of app. A, while table A3 of app. A includes a list of the three-digit occupations that do not contribute to the GGS selection. Overall, we use 475 of the 912 eight-digit occupations to obtain the GGS.

Table 3. Green General Skills Identified from O*NET

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

concerned that including these partially green occupations biases the results, one advantage of our methodology is that, by using the full range of Greenness in equation (2), occupations with lower Greenness indicators have less influence on the selection of green general tasks than do fully green occupations. Various robustness tests (in app. A; apps. A–E are available online) confirm that the selection of green skills is not affected by the exclusion of marginally green tasks from the measure of Greenness of occupations.[8]

1.3. A First Take on Green Skills

Our set of Green General Skills includes several closely related skills. To simplify the presentation and to highlight the key features, we first group our Green General Skills into macro groupings of related skills. Since we have no a priori theoretical justification for these groups, we use principal component analysis as a guide to select Green General Skills items that explain a sufficient amount of the difference in skill profiles between green and non-green jobs. Accordingly, items that mainly load into principal compo-

8. We exclude marginally green tasks using a keyword search on the task description. See app. A for details.

nents with eigenvalue much lower than one are excluded,[9] which leaves us with 14 green skill items classified into one of four main groups: engineering and technical, operation management, monitoring, and science. A clear benefit of this method is that it provides us with a ranking of the importance of each GGS. The engineering and technical principal component explains the bulk of the variance in green skills (share of variance explained 34.9%). Operation management is next in importance, explaining 24.5% of the variance, followed by monitoring (8.4%) and science (6.2%). Table 3 lists the task items in each broader skill type. We believe that these four main skill groups are consistent with the requirements commonly thought to be important to environmental tasks.

First, engineering and technical skills encompass the whole spectrum of the technology life cycle, including design, development, and installation. Installation is the professional domain of mid- and low-skill occupations with technical skills requiring vocational or associate degrees such as solar installers, roofers, and technicians. Conversely, technology development, such as the creation of new clean energy technologies, relies on "hard" engineering know-how, such as solar energy system engineers or environmental engineers.

Operation management captures skills related to the organization of green activities and to managing the integration of various phases of the product cycle. Several recent studies find evidence of the positive effect of management on energy efficiency and environmental performance (e.g., Martin et al. 2012; Hottenrott and Rexhauser 2015). Moreover, in a study of US manufacturers, Boyd and Curtis (2014) show that performance-based managing skills may have beneficial spillovers to energy efficiency. Such skills fit well with our concepts of systems analysis and systems evaluation. Relevant examples are professions intensive in operation management skills that integrate green knowledge into organizational practices, that is, climate change analysts and sustainability specialists, or jobs requiring adaptive management. Adaptive management requires capacity to identify environmental needs and to stir the dialogue across different stakeholders' groups, as is the case for chief sustainability officers and supply chain managers.

Our third Green General Skill, monitoring, includes legal, administrative, and technical activities necessary to comply with regulatory standards. Examples of occupations that use these tasks intensively include environmental compliance inspectors, govern-

9. Our exception to this rule is including the Green General Skill science, which has an eigenvalue of 0.99. This allows us to separate the role of basic sciences (physics and biology) from applied engineering and technical skills. We exclude two Green General Skills Geography and Operating Vehicles, Mechanized Devices, or Equipment, for two reasons. First, the loads of these two items are small on the four macro groups. Second, the largest loads for these skills appear in the seemingly unrelated macro group of monitoring. In sensitivity analysis presented in section 2.4, we explore the effect of environmental regulation on these two skills individually and find that it is indeed smaller than for the skills included in our four macro groups.

ment property inspectors, emergency and management directors, and legal assistants. Finally, our last Green General Skill, science, explains less of the variation in skill profiles between green and non-green occupations, with an eigenvalue of just 0.99 in the principal component analysis.

Finally, science skills relate to innovation and technological development in a more general way than engineering. Indeed, occupations with high scores in this skill can either possess specific knowledge applicable to environmental issues, such as environmental scientists, materials scientists, or hydrologists, or be more general-purpose occupations, such as biochemists, biophysicists, and biologists. The nature of environmental technologies may explain the greater importance of engineering and technical skills. Rather than creating new basic knowledge, most environmental technologies entail the application of general scientific knowledge to specific problems, that is, material science for renewable and transport technologies, or physics of conductors and insulators for energy efficient solutions. Thus, rather than requiring purely scientific knowledge, these applications require engineering to facilitate the adaptation of these technologies to new domains of practice.

1.4. The Importance of Green General Skills by Occupation

Our next task is to map Green General Skills to the occupations where they are most prominently used. For each of these four skill sets, we construct a *Green general skill importance index* for each occupation, *k*, by taking the simple average of the importance scores in occupation *k* for each O*NET item belonging to the macro group. For instance, for the macro group science, the Green general skill index for each occupation is the simple average of the importance score of "biology" and "physics" (see table 3). Thus, we can interpret the GGS index for each skill type as the importance of each Green General Skill in a given occupation.

Table 4 lists the average GGS importance index for various two-digit SOC occupations, sorted by each occupation's Greenness index. Table 4 also includes the average education and years of training for each occupation, as well as that occupation's routine task index (RTI), which measures the extent to which a job performs routine tasks as opposed to nonroutine ones (Autor and Dorn 2013).[10] Greenness is particularly high in less-routine occupations requiring advanced degrees, such as science and engineering. To better illustrate the relationship between education and green skills, figures 1 and 2 show the correlation between each individual GGS importance index and either the RTI or educational requirement of each occupation.

10. In this case a negative number implies a greater intensity of nonroutine/complex tasks. The formula for the RTI index is $RTI = \log(1 + 4.5*RC + 4.5*RM) - \log(1 + 4.5*NRA + 4.5*NRI)$, where NRI is nonroutine interactive, NRA nonroutine analytical, RC routine cognitive, and RM routine manual. Table B1 in app. B reports the O*NET task items used to build NRI, NRA, RC, and RM.

Table 4. Average Green Skills by Two-Digit SOC Macro Occupation

	#Gr. Occ.	Greenness	Eng./Tech.	Op. Mngmt.	Science	Monitoring	RTI	Yr. Trng.	Yr. Ed.
11 Management	9	.091	.309	.609	.144	.592	–.875	15.297	1.717
13 Business and Financial Operations	8	.090	.196	.591	.086	.625	–.726	15.276	1.715
15 Computer and Mathematical	1	.002	.288	.647	.112	.443	–.567	15.391	1.434
17 Architecture and Engineering	15	.186	.661	.599	.367	.541	–.614	15.574	1.654
19 Life, Physical, and Social Science	14	.151	.274	.586	.439	.547	–.679	16.801	1.889
21 Community and Social Services	0	.000	.058	.583	.087	.591	–.916	15.905	1.730
23 Legal	1	.000	.069	.551	.087	.885	–.692	17.764	2.855
25 Education, Training, and Library	0	.000	.130	.512	.215	.487	–.929	15.940	3.249
27 Arts, Design, Entertainment, Sports, and Media	2	.029	.218	.479	.106	.369	–.612	14.601	2.073
29 Healthcare Practitioners and Technical	1	.001	.157	.564	.435	.576	–.550	15.619	1.666
31 Healthcare Support	0	.000	.112	.381	.147	.444	–.370	12.709	1.267
33 Protective Service	0	.000	.147	.411	.140	.629	–.441	12.276	.893
35 Food Preparation and Serving Related	0	.000	.123	.322	.099	.353	–.232	10.917	1.791
37 Building and Grounds Cleaning and Maintenance	0	.000	.208	.290	.104	.338	–.166	11.533	1.727
39 Personal Care and Service	0	.000	.123	.386	.151	.387	–.508	12.414	1.827
41 Sales and Related	1	.015	.153	.410	.076	.330	–.478	12.286	1.179
43 Office and Administrative Support	1	.003	.076	.383	.046	.439	–.318	12.931	1.205
45 Farming, Fishing, and Forestry	0	.000	.228	.271	.232	.280	–.052	11.137	3.291
47 Construction and Extraction	10	.081	.551	.393	.225	.480	–.241	12.098	2.152
49 Installation, Maintenance, and Repair	6	.094	.505	.475	.227	.454	–.324	12.658	1.881
51 Production	8	.037	.305	.363	.122	.372	–.048	11.841	1.484
53 Transportation and Material Moving	3	.030	.239	.353	.115	.420	–.131	11.726	1.119
Total	80	.028	.205	.436	.142	.451	–.424	13.206	1.613

Note. Variables weighted by two-digit SOC occupations using employment weights in 2012 (BLS-OES). RTI = routine task index. #Gr. Occ. = no. green occupations; Eng./Tech. = engineering and technical; Op. Mngmt. = operation management; Yr. Trng. = years of training; Yr. Ed. = years of education.

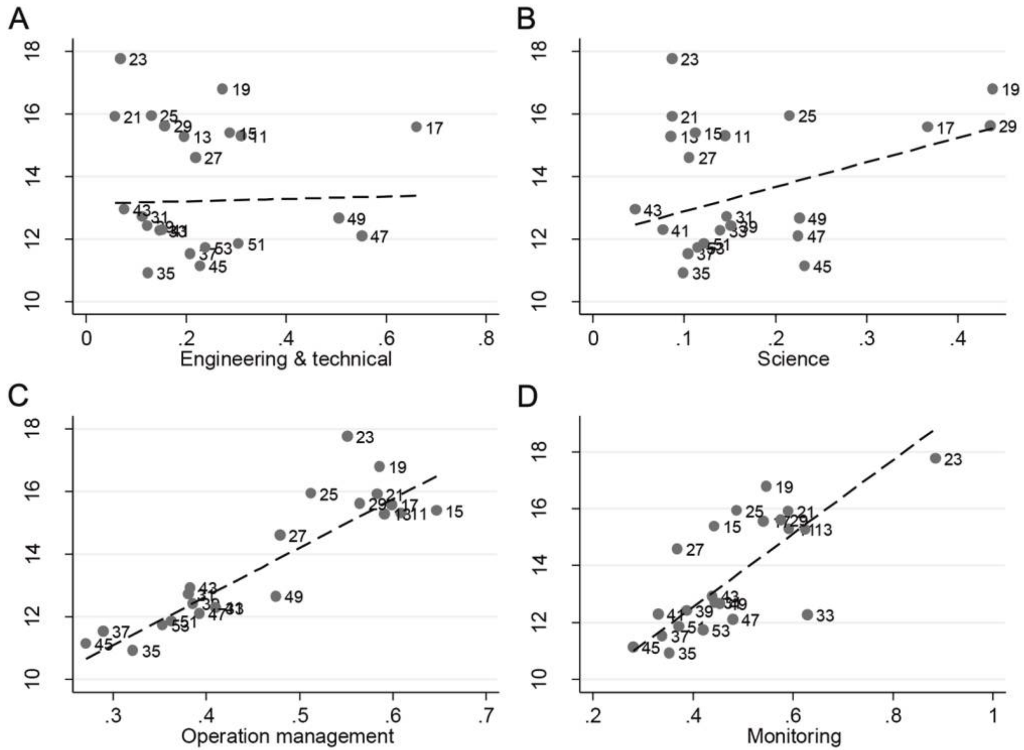

Figure 1. Correlations between GGS importance and education. GGS importance and required years of education weighted by two-digit SOC occupations using employment weights in 2012 (BLS-OES).

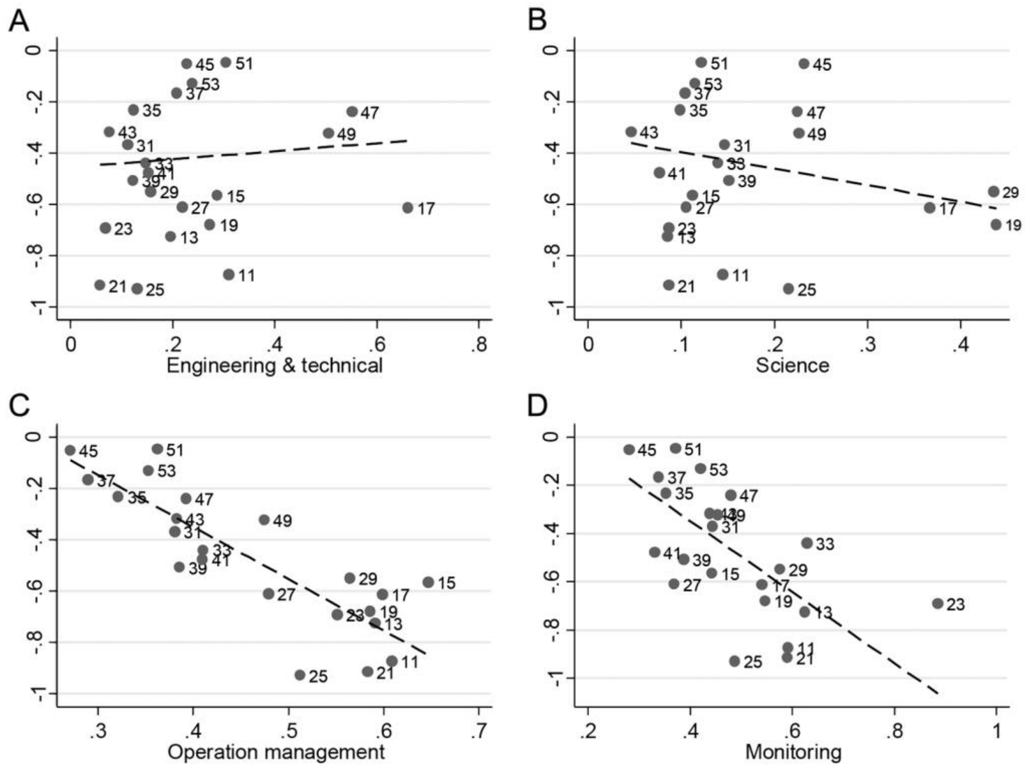

Figure 2. Correlations between GGS importance and RTI index. GGS importance and routine task intensity index weighted by two-digit SOC occupations using employment weights in 2012 (BLS-OES).

Note that the importance of both operation management and monitoring Green General Skills is higher in occupations that require more education and exhibit lower routine intensity. Similarly, there is positive correlation between occupations with high scientific GGS importance and high educational requirement. Occupations with high scientific GGS importance are also slightly less routine, although the correlation there is weaker than for education. This is consistent with previous research showing that new occupations such as several green ones are relatively more complex and exposed to new technologies than existing occupations (Lin 2011). Coherent with the lower share of explained variance for science skills, we see in table 4 that even in occupations with high Greenness, the importance of science is generally lower than that of other GGSs

In contrast, green engineering and technical skills appear in both high- and low-education occupations. Engineering skills are important for both low-education occupations such as Construction and Extraction and Installation and Maintenance, as well as high-education ones such as Architecture and Engineering. Table 5 shows the average education and training requirements for each of the six subcomponents of the engineer-

Table 5. Education and Training Requirements for Engineering and Technical Skills

	% Master's Degree	% College	Years of Education	Years of Training
Engineering and technical—aggregate:				
Mean	.054	.219	13.341	1.950
SD	.118	.341	1.580	.881
Engineering and technology:				
Mean	.109	.430	14.462	1.921
SD	.191	.383	1.682	1.081
Design:				
Mean	.090	.412	14.253	1.933
SD	.159	.368	1.706	1.036
Building and construction:				
Mean	.051	.235	13.362	1.910
SD	.105	.307	1.558	.876
Mechanical:				
Mean	.020	.083	12.679	1.675
SD	.049	.180	.980	.944
Drafting:				
Mean	.051	.185	13.062	1.598
SD	.104	.323	1.548	.851
Estimating quantifiable characteristics:				
Mean	.051	.185	13.062	1.598
SD	.104	.323	1.548	.851

Note. Occupations in the top decile for each item, weighted by employment in 2012 (BLS-OES).

ing and technical skill set for occupations that lie at the top decile for each specific subcomponent. The first two subcomponents, engineering and technology and design, have a significantly higher educational requirement than the remaining skills.

1.5. Skill Measures: Green versus Brown Jobs

The expected effect of environmental regulation on employment depends on the skill distance between occupations that may benefit and those that instead may be harmed by new environmental regulations. To compare the skill requirements in occupations likely to be harmed by environmental regulation with those skills required in green jobs, we first identify a set of "brown" occupations that are prevalent in highly polluting industries and, subsequently, compare the importance of our Green General Skills in these brown occupations to the importance in green occupations within the same two- or three-digit SOC occupation class.

To begin, we must first define pollution-intensive industries. As the focus in the empirical work that follows is on air pollution regulation, we consider emissions of the six criteria air pollutants. Given increased focus on climate change, we also consider CO_2 emissions. We identify pollution-intensive industries as those four-digit North American Industry Classification System (NAICS) industries in the 95th percentile of pollution intensity (measured in terms of emissions per worker) for at least three pollutants (CO_2 and emissions that contribute to criteria pollutants regulated by the Environmental Protection Agency: CO, VOC, NOx, SO_2, PM10, PM2.5, and lead).[11] This definition yields a set of 62 brown industries.

Next, after exploring a number of alternatives, we identify brown occupations that are most prevalent in these industries by selecting those with a probability of working in polluting sectors seven times higher than in any other job.[12] Brown jobs exist in six separate two-digit SOC occupations (see table 6). Of these six macro professions, only two are high skilled: SOC-17, Architecture and Engineering, and SOC-19, Science, while the remaining four are mostly low-skilled macro occupations. This reflects the high share of low-skilled jobs in highly polluting sectors and contrasts with the high incidence of high-skilled jobs for environmentally friendly activities (see table 4).

Table 6 presents our comparison between the skill portfolios of green and brown jobs. Occupations for which the GGS importance index is more than 0.05 higher for

11. Details on the procedure and the data used to identify brown jobs are in app. C.

12. We also considered cutoffs of 5 and 10 times higher. Our goal was to find a cutoff that included clearly relevant brown occupations (such as mining and geological engineers, which are not included using a cutoff of 10 times higher) while avoiding seemingly irrelevant occupations (such as microbiologists, which are included using a 5 times higher cutoff). There are some cases where green and brown occupations overlap. For example, because the power sector generates air pollution, all workers in that sector are potentially brown. In cases where green and brown occupations overlap we define the occupation as green. Examples include occupations related to renewable energy generation (e.g., wind turbine service technicians) or nuclear power generation (e.g., nuclear power reactor operators). These occupations were considered green only in our analysis.

green jobs are in bold font, while occupations 0.05 more important for brown jobs are in italic. For this comparison, we define green jobs as those occupations with a Greenness index greater than 0.1. Importantly, each of the six two-digit occupations with a brown job also contain green jobs, permitting comparison between the general skills required by two groups under reasonable ceteris paribus conditions. We present comparisons aggregated at the two-digit level for low-skill workers and at the three-digit level for high-skill workers. Low-skilled brown jobs are intensive in manual tasks that are not associated with specific educational requirements. Thus, the transition from different jobs within a similar two-digit group is likely to be accomplished with little additional training. In contrast, for high-skilled occupations the cost of switching across three-digit groups (e.g., from an architect, SOC17-1, to an engineering job, SOC17-2) is substantial, so that a comparison at 3-SOC level better captures the skill specificity of these occupations.

We begin with the weighted mean GGS importance for green and brown jobs in all these occupations. We then compute the mean GGS importance for the brown and the green group weighting each occupation within the respective group by its total employment. For each Green General Skill, the importance index for brown jobs falls between that of green jobs and other types of jobs. This suggests that, in many cases, workers displaced from brown jobs by environmental regulation may be reemployed in new green jobs more easily than other workers might. The difference between green and brown jobs is largest for engineering, although this may be due in part to a larger range in the GGS importance index for engineering.

Differences between green and brown jobs are often less pronounced when looking at specific occupations. This is particularly true within the lower-skilled two-digit occupations, where the requirements for green and brown occupations are often similar. One important exception here is construction and extraction workers. Not only are the gaps between green and brown workers large, but for all Green General Skills except science the importance of GGS in other jobs is closer to green jobs than to brown jobs. This suggests that workers in brown jobs displaced by environmental regulation in these jobs may face particular challenges finding new employment. As this SOC category includes workers in the oil and mining industries, these differences are of relevance for climate policy.

In high-skilled occupations, the skill portfolio of green and brown jobs is different, but not always in the expected direction. Indeed, while Green General Skills are more important in green jobs for physical scientists (SOC 19-2) and science technicians (SOC 19-4), for life scientists (SOC 19-1) and engineers (SOC 17-2) we observe that the importance of GGS is greater in brown jobs than in green jobs.[13]

13. Note, however, that in the case of life scientists this difference is all driven by one brown occupation, food scientists. Table C3 in app. C reports the list of detailed occupations used for the three-digit comparison.

Table 6. Green Skills Indexes in Green and Brown Occupations

SOC	Brown	Green	Nor Brown or Green	SOC	Brown	Green	Nor Brown or Green
Engineering and Technical				Science			
17-2 Engineering jobs	**.585**	**.719**	.566	17-2 Engineering jobs	*.502*	*.426*	.366
19-1 Life scientists	.430	.390	.317	19-1 Life scientists	*.695*	*.585*	.641
19-2 Physical scientists	.390	.386	.421	19-2 Physical scientists	**.430**	**.542**	.599
19-4 Science technicians	.383	.416	.319	19-4 Science technicians	.403	.391	.439
47 Construction and extraction	**.403**	**.580**	.486	47 Construction and extraction	**.235**	**.307**	.188
49 Installation, maintenance, and repair	.553	.529	.519	49 Installation, maintenance, and repair	.286	.245	.203
51 Production	.317	.362	.309	51 Production	**.114**	**.220**	.111
53 Transportation and material moving	*.388*	*.320*	.293	53 Transportation and material moving	.168	.196	.124
Total	.398	.557	.322	Total	.205	.316	.161

Operation Management				Monitoring			
17-2 Engineering jobs	*.697*	*.632*	.628	17-2 Engineering jobs	.558	.562	.493
19-1 Life scientists	.623	.613	.659	19-1 Life scientists	*.696*	*.613*	.518
19-2 Physical scientists	**.502**	**.636**	.629	19-2 Physical scientists	**.561**	**.623**	.441
19-4 Science technicians	**.453**	**.547**	.485	19-4 Science technicians	**.460**	**.562**	.495
47 Construction and extraction	**.383**	**.554**	.397	47 Construction and extraction	**.459**	**.612**	.596
49 Installation, maintenance, and repair	.474	.453	.436	49 Installation, maintenance, and repair	.471	.450	.383
51 Production	*.393*	*.327*	.340	51 Production	.380	.417	.407
53 Transportation and material moving	.314	.334	.343	53 Transportation and material moving	**.390**	**.466**	.358
Total	.421	.507	.376	Total	.426	.499	.396

Note. Skill intensity by macro occupation weighted by employment in 2012 (BLS-OES). Occupations for which the GGS importance index is more than 0.05 higher for green jobs are highlighted in bold, and occupations 0.05 more important for brown jobs are highlighted in italic. SOC = Standard Occupational Classification.

Finally, we consider the implications of these descriptive data for environmental regulation. First, since environmental regulation will mostly curb jobs in polluting industries where brown jobs are concentrated (Greenstone 2002; Kahn and Mansur 2013), the relatively lower skill distance between green and brown jobs (compared to other jobs) could translate into a small net effect of regulation on workforce skills. However, there are exceptions to this, such as the importance of engineering and technical skills in green jobs for engineering (SOC 17-2) and construction (SOC 47). Knowing where the gaps are highest can inform the design of training programs aimed at assisting workers displaced by environmental regulation.

Second, note that the share of employment in high-skilled occupations is substantially higher in green than in brown jobs. Approximately 50% of workers in green occupations are employed in high-skilled occupations (SOC 11, 13, 15, 17, and 19). Within brown jobs, only 6% of workers are employed in high-skilled occupations. Recall from figures 1 and 2 that Green General Skills are more important in occupations that require more education and that are less routine intensive. As a result, changes in the composition of the workforce itself may amplify the skill gap brought about by the substitution of brown with green activities, with a particular impact on lower skilled workers. The next section focuses on possible changes in workforce composition.

2. EFFECTS OF REGULATION ON GREEN GENERAL SKILLS: A QUASI-EXPERIMENTAL APPROACH

The descriptive analysis in the preceding section identifies skills likely to be of importance as environmental regulation increases and suggests occupations where differences between the skills of green and brown jobs are most likely to matter. However, environmental regulation may have additional effects on the workforce. Environmental policies stimulate the adoption of technologies and organizational practices that reduce the environmental burden of production processes, which in turn require specific competences and skills needed to monitor environmental performance, evaluate compliance with regulatory standards, and even develop new production processes or, more generally, new technologies. These may lead to increases or reductions in demand for specific occupations and, thus, changes in the skill composition within an economy. We argue that a positive net impact of environmental regulation on any of our skill measures (GGS importance or standard measures) signals the existence of gaps between the skills possessed by jobs that benefit from regulation and those possessed by jobs that instead contract due to regulation. Ours is the first study to explore the relation between more stringent environmental regulation and workforce skills.

The main challenge is correctly identifying the effect of environmental regulation on green skills. Any positive shocks on GGS importance may reduce the cost of hiring workers required to comply with regulations. If GGS abundance reduces the burden of environmental regulation on exposed firms, one may find a positive effect of environmental regulation on GGS demand simply because effective regulatory stringency depends on the availability of the appropriate skills. In such a case, environmental regulation could be affected by unobserved shocks on GGS supply that are independent of regulation, for example, a new training program.

To identify the effect of environmental regulation, we use a quasi-experimental research design that exploits variation in regulatory stringency at the regional level due to approval of new emission standards at the federal level.[14] The US Clean Air Act (CAA) sets federal level standards for the concentration of six criteria pollutants (National Ambient Air Quality Standards, or NAAQS). Counties that fail to meet concentration levels for one or more of the six criteria pollutants are designated as nonattainment areas for that pollutant, and the corresponding states are required to put in place implementation plans to meet federal concentration standards within 5 years.[15] We consider how changes in attainment status affect our GGS importance measures using a panel of 537 metropolitan and nonmetropolitan areas over the period 2006–14.

2.1. Data Construction

During the time under analysis the Environmental Protection Agency (EPA) issued new environmental standards for four criteria pollutants: PM (particulate matter smaller than 2.5 micron), ozone, lead, and SO_2. Specifically, new and more stringent concentration standards have been adopted in 2006 for PM2.5, in 2008 for lead, in 2010 for SO_2, and in 2008 for ozone. Effective designation of nonattainment areas for the new standards took place with lags: in 2009 for PM2.5, 2010 for lead, 2011 for SO_2, and 2012 for ozone. Note that the time window of the shocks (i.e., designation), 2009–12, lies exactly in the middle of the period under analysis, 2006–14. These new standards had a differential impact on regulatory stringency (as defined later in this section) across counties, leading to a change in the attainment status for 81 counties that make up the 30.3% of US population in 2014.[16] Following previous literature, we exploit the fact that nonattainment counties experience more stringent regulation (treated group) than counties that preserve their attainment designation (control group). Figure 3 shows that new nonattainment areas are mainly concentrated in the upper Midwest and western United States, with a few switchers in the eastern United States as well.

---

14. Other papers using a similar strategy include Greenstone (2002), Walker (2011), and Kahn and Mansur (2013).

15. States may use a variety of policy tools to comply with concentration standards, such as creating a system of pollution permits, mandating the adoption of specific technologies (reasonably available control measures, RACM, or best available control measures, BACM, depending on the severity of the nonattainment status) or requiring that polluting emissions from new establishments must be offset by corresponding reductions in emissions from existing establishments.

16. While our regression data are aggregated at the level of metropolitan and nonmetropolitan areas as defined by the US Census Bureau, attainment status is defined by county.

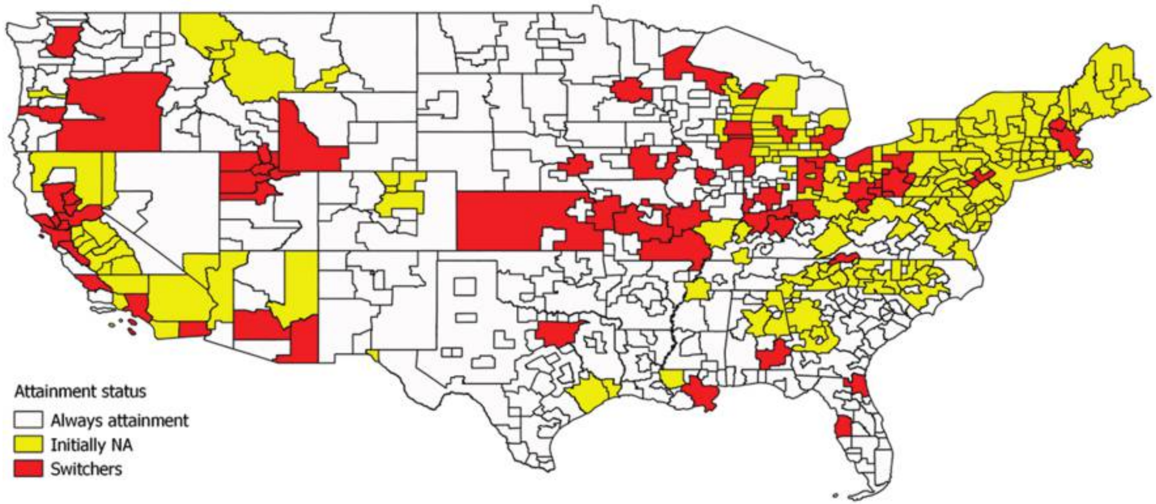

Figure 3. Attainment status by metropolitan and nonmetropolitan areas

As a first step we compute a measure of green skill importance for the local labor force in each region using employment data by occupation at the metropolitan and nonmetropolitan area level of the Bureau of Labor Statistics (Occupational Employment Statistics, OES). These data include the number of employees and average wages in 822 six-digit Standard Occupational Classification occupations for 537 metropolitan and nonmetropolitan areas over the period 2006–14. This requires one additional data assumption, as our skills data use eight-digit SOC occupations, but the employment data are only available for six-digit occupations. In our main analysis, we assume that employees are uniformly distributed across eight-digit occupations within each six-digit SOC occupation. Appendix B further discusses this assumption showing that, since most of green skills variation is at the six-digit level, our proposed aggregation of skill scores does not bias the GGS measures at the metro-area level. To be sure that this is the case also for the estimations, we explore the robustness of our results to a different assumption in appendix B. Metro and nonmetro areas are our units of analysis by necessity, since detailed occupational data are not available at the county level. As many occupations are unlikely to be affected by environmental regulation, we include only two-digit SOC occupation groups that contain at least one green job.[17] The set of two-digit occupations including brown jobs is a subset of this group. Thus, the regional GGS importance index includes occupations potentially positively and negatively impacted by environmental regulation. Pairing the employment data with our GGS importance index for each occupation k, the importance of each Green General Skill in area j is:

$$\mathrm{GGS}_{jt} = \frac{\sum_k \mathrm{GGS}^k \times L_{jt}^k}{L_{jt}}, \tag{3}$$

where GGS^k is the general green skill importance of occupation k at the national level, L_j^k is the number of employees in area j and occupation k, and L_j is the total number of employees in area j.

Since employment data by occupation is at the metro, rather than county, level the second step is to map county nonattainment status to larger metro and nonmetro areas. An area, j, is categorized as nonattainment for a particular pollutant in year t if (1) it includes at least one county that has nonattainment status in year t for that pollutant, (2) it was designated as attainment for the old standard of that pollutant in 2006. Regarding the first condition, the EPA generally classifies an entire metropolitan area as

17. These two-digit occupations are SOC codes 11, 13, 15, 17, 19, 23, 27, 29, 41, 43, 47, 49, 51, and 53. In app. E, we show that our results barely change if we build the local GGS importance index using all occupations. Overall, these occupations account for about 66% of US employment over the period 2006–14.

nonattainment for ozone and PM2.5.[18] Regarding the second condition, areas that were designated as nonattainment for the old standard of a certain pollutant (i.e., ozone-1997) should not experience a substantial change in regulatory stringency if they continue to be designated as nonattainment for the new standard of the same pollutant (i.e., ozone-2008). In addition, although an area can be in principle nonattainment for more than one pollutant, this is true only for seven of the areas under analysis. Accordingly, we simply set nonattainment to one for these areas beginning in the year in which the area goes into nonattainment for any of the regulated pollutants.[19]

Finally, our empirical strategy seeks to disentangle the effect of regulation in the two critical phases of nonattainment designation phase and implementation. The latter phase begins with the submission of the state implementation plans (SIP) describing the actions that will be undertaken to comply with the new nonattainment status (Sheriff et al. 2015). We account for the two phases by including separate dummy variables for, respectively, nonattainment "designation" and "implementation."

2.2. Methodology

While our main estimates focus on the effects of environmental regulation on our GGS importance index, we also consider the effect of regulation on overall employment, years of education, and the routine task index. Letting y represent these various dependent variables, our various regressions take the following form for 537 metropolitan and nonmetropolitan areas:

$$\begin{aligned} y_{jt} = {} & \beta \text{NA\_designation}_{j,t \geq t_{\text{NA}}} + \phi \text{NA\_designation}_{j,t \geq t_{\text{NA}}} \\ & \times \text{NA\_implementation}_{jt \geq t_{\text{impl}}} + + \varphi \text{NA}_{j0} \text{trend}_t + \boldsymbol{\gamma} \mathbf{X}_{j0}\ \text{trend}_t \\ & + \mu_j + \mu_{ts} + \epsilon_{jt}, \end{aligned} \tag{4}$$

where μ_j are area fixed effects and μ_{ts} a full set of interactions between state and time effects to capture unobservable state-level shocks, such as other policies.

The first variable of interest, $\text{NA\_designation}_{j,t \geq t_{\text{NA}}}$, is a dummy variable indicating whether area j has been designated as nonattainment in at least one new standard in year t. Since the timing of designation differs for each pollutant, the year in which nonattainment status first takes effect, t_{NA}, will vary across regions depending on the pollutant that is responsible for the switch. Given the presence of area fixed effects μ_j,

18. See https://www3.epa.gov/pmdesignations/2012standards/docs/april2013guidance.pdf for PM 2.5, and https://archive.epa.gov/ozonedesignations/web/pdf/area_designations_for_the_2008_revised_ozone_naaqs.pdf for ozone. For other standards, we considered the possibility of modeling nonattainment status as a continuous rather than a dichotomous variable. However, the share of metropolitan area population that lives in nonattainment counties clusters at 0 and 1 for most metro and nonmetro areas, making this option difficult to implement.

19. Results are unaffected by this assumption.

the effect of $\text{NA\_designation}_{j,t\geq t_{\text{NA}}}$ is identified only for these areas that switch to nonattainment status for at least one pollutant in the period.

The second variable of interest, $\text{NA\_designation}_{j,t\geq t_{\text{NA}}} \times \text{NA\_implementation}_{j,t\geq t_{\text{impl}}}$, captures the additional effect from implementation of new regulatory measures in response to nonattainment designations. The variable $\text{NA\_implementation}_{j,t\geq t_{\text{impl}}}$ equals 1 in area j beginning in the year in which the state to which the area belongs has submitted its implementation plan, t_{impl}. The full effect of nonattainment status after implementation is thus the combined effect of designation and implementation (i.e., the sum of $\hat{\beta}$ and $\hat{\phi}$).

The last variable of interest, $\text{NA}_{j0}\text{trend}_t$, allows for differential trends for areas that had nonattainment status for at least one of the old standards in 2006. This term is important for comparisons across areas since the implementation phase for old standards, such as ozone-1997 and PM2.5-1997, were not completed during the time span under analysis and because areas in nonattainment status for both the old standard and the new standard of the same pollutant are included in this group.

The set of covariates **X** facilitates a ceteris paribus comparison between treated and control group in equation (4). Our vector of covariates includes the share of employment in manufacturing, utilities, primary sector (extraction and agricultural sectors), construction, the log of population density, the log of the establishment size and trade exposure, proxied by import penetration.[20] Some of these control variables may be themselves influenced by regulation. For example, several studies show that nonattainment status has an impact on employment in industries highly exposed to regulation, that is, part of manufacturing and utilities (Kahn and Mansur 2013; Ferris et al. 2014). If environmental regulation influences our control variables, which, in turn, are correlated with changes in GGS importance, the impact of regulation on GGS importance would be biased because environmental regulation affects both the controls and our dependent variable. Angrist and Pischke (2009) refer to such variables as "bad controls." To allow for observable differences in regional characteristics to affect the skill composition while avoiding the risk of including bad controls, we fix the vector of controls **X** at levels observed at the beginning of the period (i.e., predetermined with respect to changes in environmental regulation) and interact these variables with a time trend. While differences in levels of time-invariant features are already captured by the area fixed effect, μj, the interaction of our control variables fixed at the beginning of the period with a linear trend allows the possibility of different patterns of average growth in GGS importance for areas with different initial characteristics.

20. The economic justification for these controls is quite straightforward. The shares of employment by industry account for the industrial structure and for the regional exposure to other shocks (i.e., construction for the financial crisis), population density for agglomeration effects, establishment size for both economies of scale and mechanical correlation between firm size and skill variety, import penetration for trade-induced compositional effects. Details on data sources of these variables are reported in app. B.

Finally, the policy changes analyzed in this paper co-occurred with the great recession. It has been widely argued that the global economic slump likely interacted with or exacerbated long-term trends such as the rise of global trade, the acceleration of technological progress, market deregulation, and structural changes in the composition of the labor force (see, e.g., Kalleberg and von Wachter 2017). Furthermore, the effects of the recession have been unequal across the US population not just in terms of severity but, also, of the persistence of weak economic conditions in the aftermath. This calls attention to the complex mix of structural factors that determine the exposure of local labor markets to the crisis. Recent research has documented that higher exposure to the financial crash brought about a larger decline in employment in local, namely, nontradable, activities (Mian and Sufi 2014). Because Mian and Sufi's measure of resilience to the great recession based on household net worth is available only for metropolitan areas, we could account for the local impact of large and persistent demand shocks such as the great recession indirectly at best. To overcome such a shortcoming we rely on a standard methodology in labor economics and construct a shift-share variable that captures the counterfactual change in local employment during the peak of the crisis given the initial industrial structure of the area (Bartik 1991; Diamond 2016). This allows us to measure how much local employment would have been affected if the observed sector-specific shocks were the same for all areas, as it is plausible to expect during a profound macroeconomic shock like the financial crisis. Accordingly, we multiply the vector of the local shares of sectoral employment in 2006 by the vector of 2007–10 changes in sectoral employment at the national level.[21] We use national changes net of local changes in employment to ensure that our measure of resilience is uncorrelated with unobservable shocks affecting the local labor market.

Conditional on the vector of controls, the estimated coefficients $\hat{\beta}$ and $\hat{\phi}$ identify the differential change in GGS importance induced by policy on the treated group compared to the change in GGS importance that occurred in the control group. For instance, the designation effect $\hat{\beta}$ is:

$$\begin{aligned}\hat{\beta} = {} & [E(\mathrm{GGS}_{t\geq t_{\mathrm{NA}}}|\mathbf{X}, \mathrm{NA\_designation} = 1) - E(\mathrm{GGS}_{t<t_{\mathrm{NA}}}|\mathbf{X}, \mathrm{NA\_designation} = 1)] \\ & -[E(\mathrm{GGS}_{t\geq t_{\mathrm{NA}}}|\mathbf{X}, \mathrm{NA\_designation} = 0) - E(\mathrm{GGS}_{t<t_{\mathrm{NA}}}|\mathbf{X}, \mathrm{NA\_designation} = 0)].\end{aligned} \tag{5}$$

21. In formulae:

$$\text{resilience crisis}_j = \sum_k \mathrm{Growth}_k^{07-10} \times \mathrm{Share}_{kj}^{2005},$$

where j indexes the area and k the industry (four-digit NAICS), $\mathrm{Growth}_k^{07-10}$ is the growth in employment between 2007 and 2010 for industry k observed for the United States as a whole, and $\mathrm{Share}_{kj}^{2005}$ is the share of employment in industry k in area j in 2005. Employment by four-digit NAICS for counties is retrieved from the County Business Patterns database.

In this difference-in-difference setting, the coefficient $\hat{\beta}$ measures the treatment effect on the treated under two conditions: (1) the two groups are similar in terms of observable and unobservable characteristics (including pretreatment dynamics) and (2) selection into treatment is random (Heckman et al. 1997).

We address the first identification concern by testing for the existence of observable differences in the covariates before the treatment occurs. Table 7 shows that some covariates are unbalanced. Areas that will switch were systematically more densely populated, with a smaller share of employment in primary (agriculture and mining) industries (only when using weighted averages) and the utility industry (only not weighted averages). More importantly, switching areas are also more likely to be already nonattainment for at least one criterion pollutant than areas for which no change in regulation will occur in later years. Switching areas were also systematically more endowed with green skills in general (Average GGS), operation management green skills and, to a lesser extent, monitoring green skills. Failing to consider pretreatment differences in nonattainment status for old regulatory standards is likely to influence the demand for GGS also during our estimation period and may bias our estimates of $\hat{\beta}$ and $\hat{\phi}$.

Besides evaluating systematic cross-sectional differences between areas, we also test for possible differences in pretreatment trends of GGS importance using a series of fixed effect models with our indexes of GGS importance as dependent variables and year dummies, also interacted with a time-invariant treatment dummy for switching areas in pretreatment years (2006–8). Joint significance of the interactions between treatment dummy and year dummies would indicate the existence of systematic differences in pretreatment trends. As shown in panel A of table 8, standard tests fail to reject the null hypothesis of no common pretreatment trends for all GGS both in a naïve model without controls (panel A) and in a model where control variables are added (e.g., as in eq. [4]).

The second identification issue concerns nonrandom selection into the treatment. A standard way to address this is to approximate a randomized experiment by means of propensity score matching (Rubin 2008). We use pretreatment characteristics to estimate a probit model of the probability of being treated. The propensity score allows measuring the similarity across units in a unidimensional fashion. The key identifying assumption is that, conditional on the propensity score, the probability of being treated becomes independent of observable area characteristics.

Once the propensity score is estimated, each treated unit is matched with one or more nontreated units. Since our pool of potential control groups is rather limited in size (471 nonswitching areas as opposed to 66 switching areas), we match nonswitching areas with switching areas based on the kernel of the propensity score. This method attributes decreasing weights (i.e., decreasing relative contribution to the counterfactual) the farther away “control areas” are from the corresponding treated area in terms of estimated propensity score. Weights, estimated for year 2006, are then employed as regression weights to estimate equation (4).

Table 7. Balancing of Variables across Areas (Year 2006)

	Not Weighted			Weighted by Average Employment 2006–14		
	Average Nonswitchers	Average Switchers	*t*-Test Difference	Average Nonswitchers	Average Switchers	*t*-Test Difference
log(pop density)	4.5880	5.1020	2.69***	5.6100	6.4260	6.78***
Share manufacturing sector	.1270	.1331	.63	.1060	.1150	1.66*
Share construction sector	.0538	.0554	.61	.0552	.0538	−.85
Share primary sector	.0173	.0131	−.99	.0121	.0049	−3.44***
Share utility sector	.0041	.0052	2.30**	.0040	.0044	1.41
log(establishment size)	15.8000	15.6180	−.41	16.4500	16.5266	.29
Import penetration	.0693	.0658	−1.26	.0657	.0649	−.58
Area is NA in 2006	.3510	.6420	4.65***	.5780	.7800	4.68***
Average GGS	.3140	.3159	1.85*	.3150	.3167	2.60***
Engineering and technical	.2850	.2859	.41	.2800	.2794	−.43
Science	.1180	.1177	−.19	.1150	.1140	−1.31
Operation management	.4220	.4279	2.80***	.4320	.4393	4.49***
Monitoring	.4350	.4381	1.73*	.4420	.4441	1.69*

Note. Year 2006. N = 537. N of switchers = 66. NA = nonattainment; GGS = Green General Skills.

* $p < .1$.

** $p < .05$.

*** $p < .01$.

Table 8. Pretreatment Common Trend Assumption

	Engineering and Technical (1)	Science (2)	Operation Management (3)	Monitoring (4)
A. Without control variables:				
Joint significance (F) of treatment × year dummies	1.051	1.446	1.950	.965
p-value	.350	.236	.143	.382
B. With control variables:				
Joint significance (F) of treatment × year dummies	.490	.185	.681	.558
p-value	.613	.831	.507	.573

Note. Dependent variables refer to "exposed" occupations only (SOC codes: 11, 13, 15, 17, 19, 23, 27, 41, 43, 47, 49, 51, 53). Fixed effect model weighted by average population. Standard errors clustered by area in parentheses. $N = 1{,}611$ (years 2006–8). Specification in panel A: year dummies and year dummies interacted with "treatment" dummy. Additional controls included in specification of panel B: state-specific year dummies; other controls interacted with linear trend: share of manufacturing (2005), share of primary sector (2005), share of construction sector (2005), share of utility sector (2005), import penetration (2005), log of population density (2005), log of average establishment size (2005), exposure to the crisis (2005).

* $p < .1$.

** $p < .05$.

*** $p < .01$.

Table 9 reports the probit estimates of the probability of switching. Not surprisingly, higher shares of employment in utilities and manufacturing, higher population density and initial nonattainment increase the probability of being treated. We also observe that areas initially more endowed with GGS are more likely to be treated. On the other hand, areas with higher average establishment size are less likely to be treated, while import penetration and the share of employment in primary (agriculture and mining) sector play no role. Since the endowment of each specific GGS differs substantially across areas, we estimate propensity score matching separately for each GGS and use these weights to obtain GGS-specific control groups to estimate equation (4). Results of these GGS-specific propensity scores are in appendix D and are similar to those presented here.

After matching and reweighting the group of matched nontreated areas, the difference in average observable features between treated and controls is never statistically different from zero (see table 9). Thus, matching on the propensity score balances the two groups in terms of observable pretreatment features. Therefore, following recent work by Ferris et al. (2014) and Curtis (2015), our preferred specification to estimate the effects of environmental regulation on GGS importance combines propensity score matching and difference-in-difference setting.

Table 9. Propensity Score and Balancing after Matching

	Pr(Treated = 1)	Average Matched Nontreated (Weighted by Kernel Weights)	Average Treated	*t*-Test Difference
log(pop density)	.144**	4.9707	5.1024	.40
	(.0717)			
Share manufacturing sector	2.650**	.13402	.13262	−.15
	(1.229)			
Share primary sector	−2.572	.01342	.01307	−.01
	(2.982)			
Share utility sector	48.45***	.0046	.00516	.77
	(18.55)			
Share construction sector	2.578	.05606	.05544	−.16
	(4.124)			
log(establishment size)	−.0689**	15.597	15.619	.10
	(.0286)			
Import penetration	−5.202	.06604	.06583	−.02
	(4.049)			
Area is NA in 2006	.496***	.60945	.64179	.25
	(.163)			
Average GGS	17.15**	.31687	.31745	−.13
	(7.585)			

Note. Probit model for year 2006. Standard errors in parentheses. Pseudo *R* squared: 0.0991. Number of observations: 537. Matching on propensity score based on kernel. NA = nonattainment; GGS = Green General Skills.

* $p < .1$.

** $p < .05$.

*** $p < .01$.

2.3. Results

The effects of a structural shock on workforce composition (e.g., the importance of a given GGS) will be large if (1) there is substantial job turnover in the area and (2) if the skills of the jobs that have been created do not match the skills of jobs that have been destroyed. A large contraction or expansion of employment may generate short-term skill gaps due to frictions unrelated to structural differences in the skill portfolio of expanding and contracting occupations. Thus, we begin by simply testing whether changes in environmental regulation had substantial positive or negative employment effects by using the log of total employment (instead of the GGS importance index) as dependent variable. The estimates of the employment effect are based on the difference-in-difference matching estimator described above.

Table 10. Baseline Estimates for Total Employment

	Total Employment (BLS) (1)	Total Employment (CBP) (2)	Employment in Brown Industries (3)
NA in $t = 0 \times$ trend	–.00297*	–.00131	–.00384
	(.00164)	(.00110)	(.00428)
NA designation	.00458	.00373	–.00357
	(.00392)	(.00391)	(.0112)
NA implementation	–.0107	.00303	.00115
	(.00971)	(.00491)	(.0181)
NA designation + NA implementation	–.00615	.00676	–.00242
	(.00985)	(.00474)	(.0203)
R squared	.481	.747	.446
N	4,815	4,280	4,280

Note. Fixed effect model weighted by kernel-based weights based on propensity score. Other control variables: state-specific year dummies; other controls interacted with linear trend: share of manufacturing (2005), share of primary sector (2005), share of construction sector (2005), share of utility sector (2005), import penetration (2005), log of population density (2005), log of average establishment size (2005), exposure to the crisis (2005). NA = nonattainment; BLS = Bureau of Labor Statistics; CBP = County Business Pattern.

* $p < .1$.

Table 10 shows that the net employment effect of switching to nonattainment status is near zero and that this result is robust. In column 2, we estimate the same regression using the County Business Pattern (CBP) data set to construct the employment measure at the regional level, as this data set (that has been used by recent work on the employment effect of environmental regulation, e.g., Kahn and Mansur [2013]) allows us to obtain detailed estimates of employment by industry.[22] Results are unaffected by the use of a different data source. In column 3, we use this data set to estimate the effect of regulation on employment only for brown industries as defined in section 1.4. Even for these industries most affected by nonattainment status, there is no effect of environmental regulation on employment. Interestingly, those areas that were already nonattainment under the old standards do experience a decline in employment, although it is only significant at the 10% level in the model using total Bureau of Labor Statistics employment. Thus, the decline does not seem concentrated in the industries that are particularly exposed to regulation.

Given that we are looking at short-term responses to environmental regulation, not finding significant changes in employment may be expected. However, might the com-

22. It does not, however, include breakdowns by occupation, which is why we do not use this data set for our main analysis.

position of the workforce change? That is, might the skills employed in a region differ after environmental regulation? Using the GGS importance index for each metropolitan or nonmetro area as the dependent variable in equation (4) allows us to address this question. Results in panel A of table 11 show that stricter environmental regulation does increase demand for our four Green General Skills in occupational groups including at least one green job. The *t*-test on the cumulated impact of designation and implementation dummies shows that the average treatment effect on the treated is statistically significant at conventional levels for all GGS. Changes in workforce skills occur throughout the entire adjustment process. We find differences between the designation and implementation phase of regulation for two skills: the effect of nonattainment status is largest after designation for monitoring and is largest during implementation for operation management.

For comparison, panel B of table 11 provides the effect of environmental regulation on standard human capital measures. We find little evidence that environmental regulation affects standard human capital measures. The only statistically significant effects are at the 10% level. Designation of nonattainment status increases the years of training required by 0.4%, and implementation of nonattainment status reduces the routine task index by 0.2%. The cumulated effect of designation and implementation of nonattainment status only has a small positive effect on the average years of schooling of the local workers. Even this effect is only marginally significant at the 10% level. Comparing these results with the increased demand for GGS seen in panel A lends support to the conjecture that the inducement effect of regulation is concentrated in the subset of highly specific skills that are identified by our data-driven methodology. This also contrasts with the effect of other structural shocks, such as trade and technology (Autor et al. 2003; Lu and Ng 2013) that mostly increase the demand of high general skills required to perform nonroutine tasks. While we caution that our results can only capture short-run changes in demand due to the relatively short time span of our analysis, a policy implication of this finding is that, at this stage, directing the supply of education toward technical and engineering degrees is more important to support green economy activities rather than aiming at a generalized increase of the level of education of the workforce.

Given our initial focus on short-term impacts, the magnitudes of these effects are generally small. However, two issues are important to interpret these magnitudes. First, our Green General Skills importance indices themselves display small variations over the time period considered.[23] Estimating long-run effects of regulation would require merging the O*NET data with older data sets that do not explicitly identify green skills. We leave this for future work. Second and most importantly, O*NET variables do not have a natural scale and cannot be treated as cardinal (Autor at al. 2003). This implies that

23. For example, while a 0.21% increase in the importance of engineering may appear small, for all areas in our sample, the importance of engineering GGS fell by 0.1% during our sample period.

Table 11. Baseline Estimates for Skill Composition

A. GGS Importance				
	Science	Engineering and Technical	Operation Management	Monitoring
NA in t = 0 × trend	−.000108	−.000206	.0000116	−.0000403
	(.0000805)	(.000143)	(.000111)	(.000110)
NA designation	.000314	.00115*	.000357	.000746**
	(.000378)	(.000677)	(.000441)	(.000370)
NA implementation	.000419	.000988	.000856*	.000245
	(.000387)	(.000787)	(.000459)	(.000415)
NA designation + NA implementation	.000733*	.00214***	.00121**	.000992**
	(.000377)	(.000663)	(.000530)	(.000452)
R squared	.390	.600	.614	.550
N	4,824	4,824	4,815	4,815

B. Standard Human Capital Measures				
	RTI	log(Training)	log(Education)	Share Requiring Master's Degree
NA in t = 0 × trend	−.000220	.0000832	.0000724	.000102
	(.000280)	(.000595)	(.000115)	(.0000927)
NA designation	.000408	.00444*	.000257	.000271
	(.00130)	(.00268)	(.000502)	(.000364)
NA implementation	−.00204*	−.000656	.000792	.000276
	(.00116)	(.00273)	(.000485)	(.000322)
NA designation + NA implementation	−.00163	.00378	.00105*	.000547
	(.00147)	(.00263)	(.000573)	(.000378)
R squared	.579	.313	.595	.548
N	4,815	4,815	4,815	4,824

Note. Dependent variables refer to SOC codes (two-digit) with at least one green job (SOC codes: 11, 13, 15, 17, 19, 23, 27, 41, 43, 47, 49, 51, 53). Fixed effect model weighted by kernel-based weights based on propensity score. Other control variables: state-specific year dummies; other controls interacted with linear trend: share of manufacturing (2005), share of primary sector (2005), share of construction sector (2005), share of utility sector (2005), import penetration (2005), log of population density (2005), log of average establishment size (2005), exposure to the crisis (2005). GGS = Green General Skills; NA = non-attainment; RTI = routine task index.

* $p < .1$.

** $p < .05$.

*** $p < .01$.

the usual metrics are not appropriate to gauge the magnitude of the effect of environmental regulation on our GGS importance indices. An alternative is to use changes in relative rankings induced by regulation. A small quantitative impact of environmental regulation on Green General Skills indices may be compatible with large changes in the ranking of communities. While this provides additional qualitative evidence on how the skill composition of workers in a community changes over time, it is important to bear in mind that these short-run changes in rankings result from small changes occurring in a number of communities, rather than in any single community.

To address this limitation of O*NET-based measures, we express the change in each area's ranking between 2014 and 2008 as changes in the percentile ranking in the 2008 distribution (see also Autor et al. 2003). We use 2008 as the base year because the first designation of nonattainment under the NAAQS occurred in 2009. We construct counterfactual changes in the ranking of treated regions due only to the effect of nonattainment designation and implementation. We first add the overall impact of regulation to the GGS importance index of each treated area in 2008. We then compare the rankings of each treated area before and after adding the treatment effect (table 12). Column 1 shows the mean percentile ranking change. This suggests, for example, that a treated area at the 50th percentile of monitoring skills before treatment would rise to the 52.3th percentile after treatment. Not surprisingly, the percentile change is largest for engineering, which experiences a 4.7 percentile change after treatment, nearly twice the effect observed for our other Green General Skills.

To put these changes in perspective, columns 2 and 3 show the overall change in the importance of Green General Skills from 2008–14. We do this by comparing how much higher or lower each area's 2014 GGS importance index would rank in the 2008 distribution relative to its actual 2008 value. Column 2 shows the average of this difference for treated areas, and column 3 shows the same for our control areas.[24] For example, column 2 shows that the importance of engineering skills is lower in 2014 than in 2008 for treated areas. The ranking of the engineering GGS importance for treated areas falls on average by 2.1 percentile points based on the 2008 distribution of GGS importance indices. However, column 3 shows that the ranking of engineering GGS importance falls on average by 5.4 percentile points in control areas. Thus, the ranking of treated areas is 3.3 percentile points higher than it would have been if they had not been treated.

In sum, the quantification of environmental regulation on green skills corroborates our previous conclusion: training and educational support to green activities should be specifically directed toward middle-high technical and engineering skills. This result is consistent with the fact that these skills explain the bulk of the difference between green and non-green jobs in the principal component analysis. In our next section, we

24. We weight untreated areas using their propensity scores estimated above. The difference between column 2 and column 3 is thus equivalent to a nonparametric difference-in-difference estimator of the treatment effect on the treated.

Table 12. Quantification of the Effect of Environmental Regulation on GGS Importance

	Parametric Effect (Percentile Change of Treated Areas due to Treatment) (1)	Percentile Change of Treated Areas, 2008–14 (2)	Percentile Change of Control Areas, 2008–14 (3)
Engineering and technical	4.7	−2.1	−5.4
Science	2.8	4.6	.6
Operation management	2.1	9.7	6.7
Monitoring	2.3	10.4	6.3

Note. Results refer to coefficients estimated in table 11 (panel A) based on eq. (4). GGS labels in italics denote a statistically significant ($p < .1$) effect of environmental regulation.

present three extensions that test the robustness of this conclusion and that help disentangle the heterogeneous effect of environmental regulation for specific green skills composing the four macro skill groups.

2.4. Extensions

Our results depend on several assumptions that are necessary to deal with the data limitations mentioned above. We explore the robustness of the findings in relation to four assumptions: (1) our grouping of Green General Skills, (2) the occupation-specific degree of exposure to environmental regulation, (3) our treatment of areas that were designated as nonattainment areas prior to changes in air quality standards, and (4) the timing of the effect of regulation. We briefly summarize here our main results while further details and robustness checks are in appendix E.

Overall, this set of extensions confirms that the importance of engineering and technical skills, especially those with higher educational requirement, increases due to environmental regulation. The skill gaps induced by environmental regulation on the other three GGS importance indices are smaller and less stable across specifications. There is thus insufficient evidence to recommend an expansion of training in these domains.

3. CONCLUSIONS

This paper has taken a first step toward filling a gap in our understanding of the incidence of environmental regulation in the labor market. We first identified a set of general work skills that are associated with green occupations and subsequently assessed the effect of environmental regulation on the demand for these skills. By necessity the pursuit of these ambitious goals has to adapt to the constraints of available data sources, and while our empirical strategy necessitates several assumptions to match occupational skills to local environmental regulation, our work provides an initial exploration of previously unexplored data in the area of environmental economics. The contribution to the extant literature is twofold.

First, our empirically driven selection of green skills allows the detection of skill gaps that can be used to compute measures of skill distance from brown to green occupations, or to specify in greater detail the types of general skills in high demand in specific sectors or subgroups of green jobs (e.g., those related to renewable energy). We find that the skill gap between green jobs and brown jobs is small and in most cases the general skill requirements of brown jobs are closer to those of green jobs than the general skill requirements of other jobs. At the same time, interesting exceptions emerge within specific occupations, such as the importance of green engineering skills within the architecture and construction and extraction fields. Since energy extraction occupations, such as coal mining, are likely to be heavily impacted by future climate policy regulations, this finding draws attention to the prospective adjustment costs that may be borne by workers in those sectors. Combined with the other result, that green jobs are rarely more complex than brown jobs, we conclude that policies aimed at providing education and training for green jobs should aim at expanding specific technical programs, rather than a general increase in postsecondary education.

Second, as an initial demonstration of potential applications of our Green General Skills index, we use a quasi-experimental research design to assess the impact of increased environmental regulation on both the importance of Green General Skills and on overall employment. Given the small skill gap between green and brown jobs noted above, it is not surprising that the overall effect of environmental regulation on employment is small. Similarly, we do observe some changes in the importance of Green General Skills after regulation, but these are generally not large effects. Consistent with the gaps described above, the largest effects are in the importance of high engineering skills. However, given the nature of our research design, which uses county-level changes in Clean Air Act attainment status as a proxy for changes in environmental regulation, we can say less about the employment and skill effects of environmental regulation on specific industries. Such an investigation is left for future work.

While the empirical analysis provides a first take of how the task-based approach can elucidate unexplored nuances in the effect of environmental policy on employment, there are limitations to our approach. First, as already mentioned in the introduction, the present study only identifies the short-term effects of increasing environmental regulation. Alternative data sets exist for analyzing environmental regulation over longer time frames (e.g., decadal census employment data), but the O*NET data set only covers the period post-2000. Examining longer-run effects would require merging O*NET with its precursor DOT (Dictionary of Occupational Titles) and linking that to decadal census data to accurately measure fine-grained occupational data across geographical areas. Such an effort entails significant challenges and is left for future research. A second issue that the present paper does not address, within-occupation skill changes, provides an example of further questions that could be addressed with long-run data. The work activities of a job, and thus the skills needed to perform it, can change over time. This process is best exemplified by the progressive take up of green tasks even by workers employed in non-green jobs. Some current skills will become obsolete due to structural changes in the labor market and employment shifts both within and across sectors. At the same time, demand for some new skills will emerge, both as existing occupations are increasingly pressed to support adaptation and mitigation strategies and as completely new positions come into play. For instance, the position of chief sustainability officer as a subset of chief executives is a recent creation. Third, environmental regulation may affect upstream input suppliers (e.g., creating jobs for manufacturing pollution control equipment, reducing employment for extraction of fossil fuels) and downstream customers through changes in price. As recently acknowledged by the EPA, computable general equilibrium (CGE) models may be a promising avenue for better understanding the adjustment costs associated with changing employment (Smith 2015). We hope that by focusing on the demand for specific skills, rather than specific occupations, our skills measures provide useful information for calibrating such models.

REFERENCES

Aghion, Philippe, Peter Howitt, and Luca G. Violante. 2002. General purpose technology and within-group wage inequality. *Journal of Economic Growth* 7:315–45.

Angrist, Joshua, and Jörn-Steffen Pischke. 2009. *Mostly harmless econometrics*. Princeton, NJ: Princeton University Press.

Autor, David, and David Dorn. 2013. The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review* 103 (5): 1553–97.

Autor, David, Frank Levy, and Richard Murnane. 2003. The skill content of recent technological change: An empirical exploration. *Quarterly Journal of Economics* 118 (4): 1279–1333.

Bartik, Timothy. 1991. *Who benefits from state and local economic development policies?* Kalamazoo, MI: W. E. Upjohn Institute for Employment Research.

Becker, Randy A., and Ronald J. Shadbegian. 2009. Environmental products manufacturing: A look inside the green industry. *BE Journal of Economic Analysis and Policy* 9 (1): 1–25.

Berman, Eli, and Linda T. M. Bui. 2001. Environmental regulation and labor demand: Evidence from the south coast air basin. *Journal of Public Economics* 79 (2): 265–95.

Bowen, Alex, and Karlygash Kuralbayeva. 2015. Looking for green jobs: The impact of green growth on employment. Grantham Research Institute on Climate Change and the Environment Policy Brief, London.

Boyd, Gale A., and Mark E. Curtis. 2014. Evidence of an "energy-management gap" in US manufacturing: Spillovers from firm management practices to energy efficiency. *Journal of Environmental Economics and Management* 68 (3): 463–79.

Cole, Matthew A., and Robert J. Elliott. 2007. Do environmental regulations cost jobs? An industry-level analysis of the UK. *BE Journal of Economic Analysis and Policy* 7 (1): 1–27.

Consoli, Davide, Giovanni Marin, Alberto Marzucchi, and Francesco Vona. 2016. Do green jobs differ from non-green jobs in terms of skills and human capital? *Research Policy* 45 (5): 1046–60.

Curtis, Mark E. 2015. The short-run employment impact of tightening the ozone non-attainment standards: Evidence from the 2004 expansion. Paper presented at the 2015 IZA Workshop: Labor Market Effects of Environmental Policies, Bonn.

———. 2017. Who loses under power plant cap and trade programs? Estimating the impact of the NOx budget trading program on manufacturing employment. *Review of Economics and Statistics*, Online first.

Davis, Steven J., and Till von Wachter. 2011. Recessions and the costs of job loss. Brookings Papers on Economic Activity 1–55, Brookings Institution, Washington, DC.

Deitche, Scott M. 2010. *Green collar jobs: Environmental careers for the 21st century*. Santa Barbara, CA: ABC-CLIO.

Deschenes, Olivier. 2013. Green jobs. IZA Policy Paper no. 62, IZA, Bonn.

Diamond, Rebecca. 2016. The determinants and welfare implications of US workers' diverging location choices by skill: 1980–2000. *American Economic Review* 106 (3): 479–524.

Dierdorff, Erich C., Jennifer J. Norton, Donald W. Drewes, Christina M. Kroustalis, David Rivkin, and Phil Lewis. 2009. Greening of the world of work: Implications for O*NET-SOC and new and emerging occupations. National Center for O*NET Development, Raleigh, NC.

Dierdorff, Erich C., Jennifer J. Norton, Christina M. Gregory, David Rivkin, and Phil Lewis. 2011. Greening of the world of work: Revisiting occupational consequences. National Center for O*NET Development.

Ferris, Ann E., Ronald J. Shadbegian, and Ann Wolverton. 2014. The effect of environmental regulation on power sector employment: Phase I of the Title IV SO_2 trading program. *Journal of the Association of Environmental and Resource Economists* 1 (4): 521–53.

Gathmann, Christina, and Uta Schönberg. 2010. How general is human capital? A task-based approach. *Journal of Labor Economics* 28 (1): 1–50.

Gray, Wayne B., Ronald J. Shadbegian, Chunbei Wang, and Merve Meral. 2014. Do EPA regulations affect labor demand? Evidence from the pulp and paper industry. *Journal of Environmental Economics and Management* 68 (1): 188–202.

Greenstone, Michael. 2002. The impacts of environmental regulations on industrial activity: Evidence from the 1970 and 1977 Clean Air Act amendments and the census of manufactures. *Journal of Political Economy* 110 (6): 1175–1219.

Heckman, James J., Hidehiko Ichimura, and Petra E. Todd. 1997. Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *Review of Economic Studies* 64 (4): 605–54.

Hottenrott, Hanna, and Sascha Rexhauser. 2015. Policy-induced environmental technology and inventive efforts: Is there a crowding out? *Industry and Innovation* 22 (5): 375–401.

Kahn, Matthew E., and Erin T. Mansur. 2013. Do local energy prices and regulation affect the geographic concentration of employment? *Journal of Public Economics* 101:105–14.

Kalleberg, Arne L., and Till M. von Wachter. 2017. The U.S. labor market during and after the Great Recession: Continuities and transformations. *Russell Sage Foundation Journal of the Social Sciences* 3 (3): 1–19.

Kambourov, Gueorgui, and Iourii Manovskii. 2009. Occupational specificity of human capital. *International Economic Review* 50 (1): 63–115.

Kuminoff, Nicolai V., Todd Schoellman, and Christopher Timmins. 2015. Environmental regulations and the welfare effects of job layoffs in the United States: A spatial approach. *Review of Environmental Economics and Policy* 9 (2): 198–218.

Lin, Jeffrey. 2011. Technological adaptation, cities, and new work. *Review of Economics and Statistics* 93 (2): 554–74.

Lu, Yu, and Travis Ng. 2013. Import competition and skill content in U.S. manufacturing industries. *Review of Economics and Statistics* 95 (4): 1404–17.

Martin, Ralf, Mirabelle Muûls, Laure B. de Preux, and Ulrich J. Wagner. 2012. Anatomy of a paradox: Management practices, organizational structure and energy efficiency. *Journal of Environmental Economics and Management* 63 (2): 208–23.

Martin, Ralf, Laure B. de Preux, and Ulrich J. Wagner. 2014. The impact of a carbon tax on manufacturing: Evidence from microdata. *Journal of Public Economics* 117:1–14.

Mian, Atif, and Amir Sufi. 2014. What explains the 2007–2009 drop in employment? *Econometrica* 82:2197–2223.

Morgenstern, Richard, William Pizer, and Jhih-Shyang Shih. 2002. Jobs versus the environment: An industry-level perspective. *Journal of Environmental Economics and Management* 43 (3): 412–36.

Poletaev, Maxim, and Chris Robinson. 2008. Human capital specificity: Evidence from the Dictionary of Occupational Titles and Displaced Worker Surveys, 1984–2000. *Journal of Labor Economics* 26 (3): 387–420.

Rubin, Donald B. 2008. For objective causal inference, design trumps analysis. *Annals of Applied Statistics* 2 (3): 808–40.

Sheriff, Glenn, Ann E. Ferris, and Ronald J. Shadbegian. 2015. How did air quality standards affect employment and generation at U.S. power plants? The importance of stringency, geography, and timing. NCEE Working Paper Series Working Paper 15-01.

Smith, Kerry V. 2015. Should benefit-cost methods take account of high unemployment? Symposium introduction. *Review of Environmental Economics and Policy* 9 (2): 165–78.

UNEP (UN Environmental Programme). 2011. Towards a green economy: Pathways to sustainable development and poverty eradication; A synthesis for policy makers. www.unep.org/greeneconomy.

US Department of Commerce. 2010. Measuring the green economy. Department of Commerce, Economics and Statistics Administration, Washington, DC.

Vona, Francesco, and Davide Consoli. 2015. Innovation and skill dynamics: A life-cycle approach. *Industrial and Corporate Change* 24 (6): 1393–1415.

Walker, Reed W. 2011. Environmental regulation and labor reallocation: Evidence from the Clean Air Act. *American Economic Review* 101 (3): 442–47.

———. 2013. The transitional costs of sectoral reallocation: Evidence from the Clean Air Act and the workforce. *Quarterly Journal of Economics* 128 (4): 1787–1835.