Environmental Regulation and Green Skills: an empirical exploration

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Abstract

We present a data-driven methodology to identify occupational skills that are relevant for environmental sustainability. We find that these green skills are mostly engineering and technical know-how related to the design, production, management and monitoring of technology. We also evaluate the effect of environmental regulation on the demand of green skills exploiting exogenous geographical variation in regulatory stringency for a panel of US metropolitan and non-metropolitan areas over the period 2006-2014. Our results suggest that, while these recent changes in environmental regulation have no impact on overall employment, they create significant gaps in the demand for some green skills, especially those related to technical and engineering skills.

Keywords: Green Skills, Environmental Regulation, Task Model, Workforce Composition.

JEL codes: J24, Q52

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1 Introduction

The catchword 'green skills' has become common parlance in policy circles, exemplified by the Obama stimulus package committing substantial resources, as much as $90 billion, to training programs for 'green jobs'. 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 operate and develop green technology.[1] 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. Using a new data-driven methodology to identify green skills in the Occupational Information Network (O*NET) dataset, we find that these skills are mostly engineering and technical know-how related to the design, production, management and monitoring of technology. We evaluate the effect of environmental regulation on the demand of green skills exploiting exogenous geographical variation in regulatory stringency for a panel of US metropolitan and non-metropolitan areas over the period 2006-2014. Our findings suggest that, while these recent changes in environmental regulation have no impact on overall employment, they create significant 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 policymakers 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 often point to the job losses that they are sure will follow.[2] Empirical evidence of environmental regulation's effect on employment is mixed. While many studies present limited evidence of job losses from environmental regulations (e.g. Greenstone 2002), recent studies such as Kahn and Mansur (2013) suggest the possibility of larger effects, particularly in energy-intensive industries. One reason that studies often find limited effects is that there are reallocation effects such that job losses due to a reduction in the scale of economic activity in one sector are offset by gains in other sectors, including increased demand for pollution control equipment or of

[1] Further details on the Recovery Act at: http://www.whitehouse.gov/administration/eop/cea/factsheets-reports/economic-impact-arra-4th-quarterly-report/section-4 For a review of studies on the effects of the package see: http://www.washingtonpost.com/blogs/wonkblog/post/did-the-stimulus-work-a-review-of-the-nine-best-studies-on-the-subject/2011/08/16/gIQAThbibJ_blog.html. For an assessment of the specific part of the program devoted to green jobs see http://usatoday30.usatoday.com/news/washington/story/2012-01-30/obama-green-jobs-program-failure/52895630/1

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

workers required to comply with regulation and use new green technologies. At the same time, however, this research strand ignores important adjustment costs (Smith 2015). Job loss may entail other social costs, such as the stigma displaced workers experience (Bartik 2015) or the need for workers to relocate (Kumioff *et al*. 2015). Even if workers who lose their jobs in response to regulation are re-employed, higher unemployment spells mechanically lead to long-run reduction in wages for these workers (Davis and von Watcher, 2011). Walker (2013) finds that workers in sectors affected by the 1990 Clean Air Act lose 20% of their preregulatory earnings, with most of the losses 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. While Walker notes that these costs are significantly lower than the aggregate benefits of the Clean Air Act, they do suggest 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 suggest that consideration of green jobs and the possible adjustment costs of changes in employment patterns in response to environmental regulation is important. 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 skill the 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 a displaced coal miner find his skills easily transferable to the manual labor 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 that are used more intensively in green occupations relative to non-green ones. Specifically, we obtain our green skills constructs using a data-driven methodology that searches within the broad range of skills contained in the O*NET dataset. For each occupation, the O*NET dataset allows distinguishing 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 those of the particular workers that are displaced by environmental regulation.

To see how environmental regulation changes the demand for green skills, we use variations in employment shares of occupations across US regions to construct aggregate skill measures for each US metropolitan and non-metropolitan areas for 2006-2014. 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. 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 to environmental regulation.

Empirical evidence on the labor market effects of environmental regulation provides mixed results. Some studies predict job losses driven by reallocation of workers among industries rather than net job loss economy-wide (Arrow et al, 1996; Henderson, 1996; Greenstone, 2002), while others find negligible outcomes (e.g. Berman and Bui, 2001; Morgenstern et al, 2002; Cole and Elliott, 2007; Ferris et al., 2014). Consistent with these findings, Mulatu et al. (2010) for European countries and Kahn and Mansur (2013) for US states find that energy-intensive and polluting industries relocate in response to environmental regulation. Other studies use plant-level data to understand the extent to which employment changes come from higher layoff rates (job destruction) or decreasing hiring rates (job attrition). Walker (2011) finds that a significant portion of employment adjustments are due to increases in job destruction, and that this effect is stronger among newly regulated plants. Partially in contrast with these findings, Curtis (2014) shows that incumbent workers are sheltered by the negative regulatory impact, and that the main driver is a slow-down in hiring of young workers. Although recent analyses assess the cost of regulation for different experience groups (Curtis 2014) or in terms of losses of industry-specific human capital (Walker 2013) , they do not explore possible changes in the content of work and thus of the skills demanded from employers. These occupational-specific features are particularly important in light of the documented importance of skill similarity at the job rather than at industry level (Gathmann and Schönberg 2010).

To the best of our knowledge, only Becker and Shadbegian (2009) examine the relationship between green productions 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 finding 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 increase and subsequently dissipates inasmuch as codification facilitate 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-biased 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. First, we propose a new methodology to identify the types of know-how that are important for certain occupations, green ones in our case. Our data-driven measures build upon prior work on changes in the demand for skills (Autor, Levy and Murnarne, 2003) and can be generalized to identify the skills relevant for any specific occupational group. Second, our paper is the first to complement quantitative assessments of the effect of environmental regulation on employment (e.g. Greenstone, 2002; Walker, 2013) with more qualitative aspects regarding the composition of workforce skills. Third, we extend the literature on the effect of structural shocks, such as trade and technology (e.g., Autor and Dorn, 2013), on skill demand by focusing on a different driver, i.e. environmental regulation.

The remainder of the paper is organized as follows. Section 2 presents the methodology for the construction of green skills measures. Sections 3 empirically assesses the effect of environmental regulation on our newly created green skills indexes exploiting exogenous geographical variation in regulatory stringency for a panel of US metropolitan and non-metropolitan areas. Section 4 provides additional evidence that the effect of environmental regulation on the demand of green skills is mostly concentrated in industries highly exposed to regulation. Section 5 concludes.

2 Identification and Measurement of Green Skills

This section is organized in four parts. The first briefly explains the data that we use to link green jobs to green skills. The second subsection details a novel data-driven methodology for identifying green skills within the US workforce. In the third part we provide descriptive evidence of our green skill measures vis-à-vis other human capital measures, while the fourth part compares different skill measures for green and brown jobs.

*2.1 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 an admittedly scant academic literature often conflate green skills with ‘green jobs’, namely the workforce of industries that produce environmentally friendly products and services (see e.g. US Department of Commerce, 2010; Deitche, 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 distinguishes between green jobs and green skills, namely the skills that are used intensively in green jobs.

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, henceforth GE); and (iii) new occupations in the green economy (new & emerging, henceforth NE) (see Dierdoff et al, 2009; 2011). However, the involvement with environmental activities is more clearly identifiable in the last two groups compared to the first one, which can be considered at best indirectly 'green' (see Consoli et al, 2015 for details).

One important feature of the O*NET database is that it allows for a finer distinction of the importance of green activities within an occupation. In particular, O*NET provides information on 'general' tasks, which are common to all occupations, and tasks that are instead specific to each occupation.[3] The Green Task Development Project further enriches this distinction for 'New & Emerging' and 'Green-Enhanced' occupations by partitioning the set of specific tasks into green and non-green. For example, Sheet Metal Workers perform both green tasks, such as 'constructing ducts for high efficiency heating systems or components for wind turbines', and non-green 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'. Unfortunately, different from general tasks whose importance is defined on a continuous scale, these specific tasks are not comparable across occupations because specific tasks are binary characteristics of any given occupation.

We exploit this complementary information to (1) define the greenness of an occupation based on the number of specific green tasks required and (2) use this information 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 allows for a more nuanced and accurate distinction of green and non-green jobs compared to the O*NET classification, which identifies 'full green' jobs like Chemical Engineers, Electric Engineers, Financial Analysis, Rail-track Operators or Sheet Metal Workers. On the other hand, the

[3] O*NET is a comprehensive database containing occupation-specific information on skill occupational requirements and tasks performed on the job since the 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.

identification of general skills used intensively in green occupations allows to address the key issue of the extent to which current workforce skills can be easily transferred to green activities.

2.2 A methodology for the identification of Green Skills

Starting from the distinction between green and non-green specific tasks we compute the *Greenness* measure, that is, the ratio between the number of green specific tasks and the total number of specific tasks performed by an occupation *k*:

$$Greenness_k = \frac{\#green\ specific\ tasks_k}{\#total\ specific\ tasks_k}. \qquad (1)$$

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 *Greenness* ratio allows an arguably finer distinction between types of green job compared to the O*NET definition in that it captures well the spectrum of greenness across various occupations, as shown by the examples in Table 1.[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 occupations whose main activity occasionally involves the execution of environmental tasks but that cannot be considered full-fledged green jobs, such as traditional Engineering occupations, Marketing Managers or Construction Workers.

[Table 1 about here]

Using the *Greenness* indicator as a pure measure of skills has limitations for formulating policy recommendations. Specifically**,** an indicator based on specific tasks is by definition not suitable to compare the skill profiles of green and non-green occupations and, thus, limits our understanding of 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 the cost of training programs 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 create a Green General Skills index (GGS henceforth). The identification is based on measures of general tasks retrieved from the release 17.0 of the O*NET database. Importance scores for 108 general

[4] The full list of green occupations and their greenness is reported in Table 1 in Appendix A.

skills and tasks are reported for 912 SOC 8-digit occupations.[5] We use a two-step procedure. First, 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:

$$Task\_Imp_k^l = \alpha + \beta^l \times Greenness_k + D_k^{SOC\_3d} + \varepsilon_k. \quad (2)$$

Occupational dummies ($D_k^{SOC\_3d}$) 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 item with positive greenness, thus eliminating occupations that bear no relevance on sustainability, such as Personal Care and Service. Here, a positive (negative) and significant β^l denotes that task l is used more (less) intensively in greener occupations. We identify a general task as green when the estimated $\hat{\beta}^l$ is positive and statistically significant at 99%. This generates a set of 16 GGS.

[Table 2 about here]

The second step is grouping these items into coherent macro-groups using principal component analysis (PCA) and keeping only the selected green general tasks that load into principal components with eigenvalue greater than 1.[6] This leaves us with a list of 14 green task items that we group into 4 main skill types: engineering and technical, science, operation management, and monitoring.[7] Table 2 lists the task items in each broader skill type. The principal component analysis yields Green General Skills constructs that resonate with insights provided by policy reports and recent papers on organizational change and energy efficiency.[8]

[5] 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 BLS data using the 2010 SOC code. Details are available in the data Appendix 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).

[6] In fact, we chose a slightly lower cut-off of 0.98 to include the GSS Science. Science appears together with engineering a core GGS when using more demanding selection criteria. Note that the PCA analysis leads us to exclude two task items: 'Geography' and 'Operating Vehicles, Mechanized Devices, or Equipment.' The reason is that the loads of these two items is small on the four principal components selected by our analysis. In Appendix A we present further robustness exercises with different approaches to select our set of green general skills.

[7] The fifth component includes only one item, *Geography*, and was thereby excluded. Geographic skills pertain to urban planning and analysis of emission dynamics (several profession intensive of Geography skills are green, such as Environmental Restoration Planners, Landscape Architects and Atmospheric and Space Scientist). Due to the specificity of this last component that only refers to one general skill we do not include it in the main analysis. Baseline results for Geography and all single items are reported in 20 in Appendix D.

[8] Martin et al (2012) find that energy managers have a positive impact on climate friendly innovation. Similarly, Hottenrott and Rexshouser (2015) report productivity improvements due to complementarity between the implementation of organizational practices and environmental technology adoption.

After having clustered items into coherent macro-groups by means of PCA, we build the final GGS skill indices of occupation *k* for each of the four broad skill sets by taking the simple average of the importance scores of each O*NET item belonging to a given macro-group. For instance, for the macro-group Science, the GGS index for each occupation is the simple average between the importance score of 'Biology' and the importance score of 'Physics' (see Table 2). Thus, we can interpret the GGS for each skill type as the importance of each GGS in a given occupation. Note that macro-group 'Engineering and Technical' is the first principal component that accounts for the bulk of the difference in skill profiles between green and non-green occupations.

2.3 A first take on Green Skills

Table 3 lists the GGS index for various 2-digit SOC occupations, sorted by each occupation's greenness index. The concentration of green jobs in high-level occupational groups explains in part the prevalence of high skills in our selection of GGS. 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).

Table 3 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 non-routine ones (Autor and Dorn, 2013).[9] To better illustrate the relationship between education and green skills, Figures 1 and 2 show the correlation between each individual GGS index and either the RTI or educational requirement of each occupation. Note that the importance of both "Operation Management" and "Monitoring" green general skills are higher in occupations that require more education and that exhibit lower routine intensity. In contrast, green Engineering and Technical skills appear in both high- and low-education occupations. We discuss the traits of each green general skill in more detail below.

[Figure 1 and Figure 2 about here]

The first GGS, Engineering and Technical (E&T henceforth) encompasses the whole spectrum of the technology life cycle, namely: 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 relies on 'hard'

[9] In this case a negative number implies a greater intensity of non-routine/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 non-routine interactive, NRA non-routine analytical, RC routine cognitive and RM routine manual. Table 7 in Appendix B reports the O*NET task items used to build NRI, NRA, RC and RM.

engineering know-how possessed by green ‘Architecture and Engineering’ professions, such as Wind Energy or Environmental Engineers. This heterogeneity is apparent in the first panel of Figure 1, which shows a high GGS engineering index in both low-education occupations such as Construction & Extraction’ and ‘Installation & Maintenance’, as well as high-education occupations such as Architecture and Engineering. Table 4 shows the education and training requirements for each of the six subcomponents of the Engineering and Technical skill set. The first two subcomponents, ‘Engineering and Technology’ and ‘Design’ have a significantly higher educational requirement than the remaining skills. As a result, in our analysis we partition the E&T GGS into High and Low engineering, with High engineering representing the two skills requiring higher educational attainment.

[Table 4 about here]

The second GGS construct, Science, is also related to innovation and technological development, although in a more general way. 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 Biologist. Not surprisingly, Figure 1 shows a positive correlation between occupations intensive in scientific GGS and required education levels. Occupations with a high scientific GGS are also slightly less routine, although the correlation there is weaker than for education (see Figure 2). Finally, note from Table 3 that even in occupations with high greenness, the importance of science is generally lower than the other GGS.

The third GGS, Operation Management (O&M henceforth), captures skills related to the organization of green activities and to managing the integration of various phases of the product cycle. Examples of professions intensive in these skills are jobs that integrate green knowledge into organizational practices, i.e., Climate Change Analysts and Sustainability Specialists, or jobs requiring adaptive management. Adaptive management requires the 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. As these skills are concentrated in managerial, legal and mathematical occupations, this GGS is associated with a high educational requirement and an extremely low routine intensity.

Finally, Monitoring GGS refers to legal, administrative and technical activities necessary to comply with regulatory standards. Examples of such occupations include Environmental Compliance Inspectors, Government Property Inspectors, Emergency and Management Directors and Legal Assistants. Monitoring skills are similar to O&M skills as they are positively correlated with the educational requirement of occupations and are less routine, although the correlation is partially driven by the outlier legal profession (SOC-23, see bottom panel of Figure 1). Given that these pertain to different professional domains, in the empirical analysis the two items, legal and technical, will be considered both together and separately.

2.4 *Skill measures: green vs. brown jobs*

The expected effect of environmental regulation on employment will depend on the skill distance between occupations that may benefit and those that instead may be harmed by the implementation of 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 identify a set of brown occupations that are prevalent in highly polluting industries. As in Curtis (2014), we first identify as 'pollution-intensive industries' those manufacturing sectors with greater share of energy costs over total production.[10] We then define brown occupations as those with a share of employment in these polluting sector above 10%.[11] Since we are interested in the skills required to green our economies, we compare the skills required in brown jobs to those in occupations with a greenness index greater than 0.1, using the metrics of GGS.

Brown jobs exist in 5 separate 2-digit SOC occupations. Interestingly, each of these five 2-digit occupations also contain green jobs, permitting comparison the general skills required by green and brown jobs under ceteris paribus conditions. Of these five macro professions only one is high skill, namely SOC-17 'Architecture and Engineering', while the remaining four are mostly low-medium skill jobs. This clearly reflects the high share of low-skilled jobs in highly polluting sectors.

[Table 5 about here]

Table 5 presents the main results of this comparison. Looking at the total GGS for green and brown jobs in these occupations, for each of our four GGS, the GGS index for brown jobs in these occupations falls between that of green jobs and other types of jobs.[12] This suggests that, in many cases, workers

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[10] In addition to the 'Mining, Quarrying, and Oil and Gas Extraction' (NAICS 21) and 'Electric Power Generation, Transmission and Distribution' (NAICS 2211) industries, we identified as 'pollution-intensive industries' those manufacturing sectors with greater share of energy costs over total production, similarly to Curtis (2014). We included manufacturing industries (4-digit NAICS) in the top decile for this measures, that is: 3112, 3131, 3133, 3221, 3251, 3252, 3271, 3272, 3272, 3274, 3279, 3311, 3313, 3315 and 3328. Details are in Appendix B.

[11] Notice that the employment shares in brown industries is only 1.75%. Thus, a 10% share to identify brown jobs is remarkably greater than the share that would prevail if we randomly assign jobs to industries. Our results are however robust to more or less strict definition of both brown and green jobs. Notice also that from this selection of brown occupations we excluded those occupations related to renewable energy generation (e.g. Wind Turbine Service Technicians) or nuclear power generation (e.g. Nuclear Power Reactor Operators) as most of them are employed in the non-fossil part of the Electric power generation, transmission and distribution (NAICS 2211) industry.

[12] The total is computed as the weighted mean of the GGS in all of the 2-digit occupations considered in Table 3.

displaced from brown jobs by environmental regulation may find re-employment in newly created green jobs easier than other workers might. The education requirements for brown jobs also fall between that of green and other jobs, but are much closer to the requirements for other jobs. However, both brown and other jobs are less routine intensive than green jobs.

That said, there are important differences across occupations. For example, green E&T skills are more important in green than brown jobs in both architecture (SOC 17) and construction and extraction (SOC 47). Note that the engineering GGS index for other jobs (those neither brown nor green) is similar to that of green jobs in the construction and extraction industry, suggesting that workers in brown jobs displaced by environmental regulation in this sector may face particular challenges finding new employment. A similar pattern appears for the monitoring skill in SOC 47, although the magnitude of differences between green and brown jobs is smaller. In contrast, within installation, maintenance and repair (SOC 49), production (SOC 51) and transportation (SOC 53), the importance of GGS is rarely different between green and brown jobs. Indeed, in some cases a GGS is more important in brown jobs than in green jobs, such as O&M in production jobs. Also note that the difference between routine task intensity in green and brown jobs is primarily driven by construction and installation jobs. Indeed, in architecture, green jobs are a bit less routine intensive than brown jobs, although in all cases architecture is the least routine intensive of the five occupations listed.

Taken together, these descriptive data highlight two facts relevant for the analysis of how environmental regulation might affect the skill composition of the workforce. First, since environmental regulation will mostly curb jobs in polluting industries where brown jobs are concentrated (Greenstone 2002; Kahn and Mansur 2014), the low skill distance between green and brown jobs should translate into a small net effect of regulation on workforce skills. The one exception to this is engineering and technical skills, particularly in architecture and construction. Second, while green jobs are high skill jobs they are rarely more complex (i.e. less routine intensive) than brown jobs. Thus, policies aimed at providing education and training for green jobs should target an expansion of specific technical programs rather than the development of advanced educational programs.

3 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 workplace. 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 standard and even develop new production processes or, more generally, novel technical responses to regulation. These may lead to increases or reductions in specific occupations, and thus changes in the mix of skill levels observed within an economy. To assess the extent of these changes on the skill composition of the workforce we analyse how changes in environmental regulation within US metropolitan and non-metropolitan areas affect the importance of each of our green general skills. We argue that a positive net impact of environmental regulation on any of these skill 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 that assesses the impact of a more stringent environmental regulation on several skill measures, including our new GGS measures.

The main challenge is correctly identifying the effect of ER on green skills. Any positive shocks on GGS may reduce the cost of hiring workers required to comply with regulation. 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, our main analysis uses 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.[13] The US Clean Air Act (CAA) sets county-specific attainment 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.[14] We consider how changes in attainment status affect our GGS measures using a panel of 537 metropolitan and non-metropolitan areas over the period 2006-2014.

[13] Other papers using a similar strategy include Greenstone (2002), Walker (2011), and Kahn and Mansur (2014).

[14] 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.

3.1 *Data construction*

During the time under analysis the Environmental Protection Agency (EPA) issued new environmental standards for four criteria pollutants: PM (smaller than 2.5 micron), Ozone, Lead and SO2. Specifically, new and more stringent concentration standards have been adopted in 2006 for PM 2.5, in 2008 for lead, in 2010 for SO2 and in 2008 for ozone. Effective designation of nonattainment areas for the new standards took place with lags: in 2009 for PM 2.5, 2010 for Lead, 2011 for SO2, and 2012 for Ozone. Note that the time window of the shocks, 2009-2012, lies exactly in the middle of the period under analysis, 2006-2014. 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.[15] 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 NA areas are mainly concentrated in densely populated areas in the Ozone Transport Region (that includes 12 states in the North-East of the US) and in California.

[Figure 3 about here]

As a first step we compute a measure of green skill intensity 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 6-digit Standard Occupational Classification occupations for 537 metropolitan and non-metropolitan areas over the period 2006-2014 (see Appendix B for details). Metro and non-metro areas are our units of analysis since detailed occupational data are not available at a finer regional level, i.e. county. Pairing these data with our GGS index for each occupation, the intensity of each green general skill in area *j* is:

$$GGS_j^k = \frac{\sum_k GGS^k \times L_j^k}{L_j} \tag{3}$$

where GGS^k is the skill intensity of occupation *k* at the US-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*.[16]

[15] While our regression data are aggregated at the level of metropolitan and non-metropolitan areas as defined by the U.S. Census Bureau, attainment status is defined by county.

[16] As an alternative, we could have used data from the American Community Survey (ACS, available from the IPUMS - Integrated Public Use Microdata Series). In the Appendix B we show that the within-area volatility in our

The second step is to develop an indicator of regulatory status for each region. To do so, we map county NA status to larger metro and non-metro 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, we follow the criterion of the Environmental Protection Agency of considering metropolitan areas with at least one nonattainment county as nonattainment areas and extend it to non-metropolitan areas (see Sheriff et al., 2015). 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-2012). 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.[17]

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

3.2 Methodology

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

$$y_{jt} = \beta \mathrm{NA\_designation}_{j,t \geq t_{NA}} + \phi \mathrm{NA\_implementation}_{\mathrm{jt \geq t_{impl}}} + \varphi \mathrm{NA}_{j0} trend_t + \boldsymbol{\gamma} \mathbf{X}_{j0} trend_t + \mu_j + \mu_{ts} + \varepsilon_{jt}, \quad (4)$$

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 (i.e. policies, effect of crisis).

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skill constructs is implausibly high when we use this data. Thus, we opt for BLS data as our identification strategy relies on within-area variation only.

[17] Results are unaffected by this assumption.

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

The second variable of interest, $\text{NA\_implementation}_{\text{jt}\geq \text{t}_{\text{impl}}}$, captures the implementation of new regulatory measures in response to nonattainment designations. It equals 1 in area j from year t_{impl} (year in which the state to which the area belongs has submitted the implementation plan) onwards. We evaluate the combined effect of designation and implementation by testing the statistical significance of the sum of $\widehat{\beta}$ and $\widehat{\phi}$.

The last variable of interest, $\text{NA}_{j0}trend_t$, gauges 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.[18] 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, i.e. part of manufacturing and utilities (Ferris et al., 2014; Kahn and Mansur, 2013). If environmental regulation influences our control variables which, in turn, are correlated with changes in GGS, the impact of regulation on GGS would be biased because environmental regulation affect both the controls and our dependent variable. Angrist and Pischke (2009) define such variables as ‘bad controls’. To allow for observable differences in regional characteristics to affect the skill composition while avoiding the risk of

[18] The economic justification for these controls is quite straightforward. The shares of employment by industry control 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 Appendix B.

including ‘bad controls’, we fix the vector of controls $\mathbf{X}$ 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, μ_j, 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 for areas with different initial features.

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

$$\widehat{\beta} = \left[E\left(GGS_{t\geq t_{NA}}|\,\mathbf{X}, \text{NA\_designation} = 1\right) - E\left(GGS_{t<t_{NA}}|\,\mathbf{X}, \text{NA\_designation} = 1\right)\right] -$$

$$\left[E\left(GGS_{t\geq t_{NA}}|\,\mathbf{X}, \text{NA\_designation} = 0\right) - E\left(GGS_{t<t_{NA}}|\mathbf{X}\,, \text{NA\_designation} = 0\right)\right]. \qquad (5)$$

In this difference-in-difference setting (DID), 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 pre-treatment 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, i.e. $\text{E}(\mathbf{X}_{t<t_{NA}}|\text{ NA\_designation} = 1)$ and $\text{E}(\mathbf{X}_{t<t_{NA}}|\text{ NA\_designation} = 0)$. Table 6 shows that only four covariates are unbalanced. Areas that will switch were systematically more densely populated, with smaller share of employment in primary (agriculture and mining) industries and more likely to be already nonattainment for at least one criteria pollutant than areas for which no change in regulation will occur in later years. Switching areas were also systematically more endowed with O&M green skills. Failing to consider pre-treatment 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 $\hat{\phi}$.

[Table 6 about here]

Besides evaluating systematic cross-sectional differences between areas, we also test for possible differences in pre-treatment trends of GGS by means a series of fixed effect models with our indexes of GGS as dependent variables and year dummies, also interacted with a time-invariant treatment dummy for switching areas in pre-treatment years (2006-2008). Joint significance of the interaction between treatment dummy and year dummies would indicate the existence of differences in pre-treatment trends. As shown in Panel A of Table 7, we reject the null hypothesis of no common pre-treatment for Engineering and Technical skills in a naïve model without controls. However, when control variables are added (equation 4) the null hypothesis of common pre-treatment common trends cannot be rejected for all GGS. Thus, allowing different trends for areas with different initial features is necessary to satisfy the assumption of pre-treatment common trends.

[Table 7 about here]

The second identification issue concerns non-random 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 pre-treatment characteristics to estimate a probit model of the probability of being treated. The propensity score allows measuring the similarity across units in a uni-dimensional fashion. The key identifying assumption is that, conditional on the propensity score, the probability of being treated is independent of observable area characteristics.

Once the propensity score is estimated, each treated unit is matched with one or more non-treated units. Since our pool of potential control groups is rather limited in size (471 non-switching areas as opposed to 66 switching areas), we match non-switching 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 using the same specification as in our baseline results.

Table 8 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 that were 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.

[Table 8 about here]

After matching and re-weighting the group of matched non-treated areas, the difference in average observable features between treated and controls is never statistically different from zero (see Table 8). Thus, matching on the propensity score balances the two groups in terms of observable pre-treatment features. Therefore, following recent related papers by Ferris et al. (2014) and Curtis (2014), our preferred specification of the effect of environmental regulation on GGS combines propensity score matching and DID.

3.3 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. 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 specification described in equation 4 with the log of total employment (instead of the GGS index) as dependent variable. Table 9 shows that the net employment effect of switching to NA status is near zero, and that this result is robust. In Column 2, we estimate the same regression using the County Business Pattern (CBP) dataset to construct the employment measure at regional level, as this dataset (that has been used by recent work on the employment effect of environmental regulation, e.g. Kahn and Mansur, 2014) allows us to obtain detailed estimates of employment by industry. Results are unaffected by the use of a different data source. In Column 3, we estimate the effect of regulation on employment only for the industries more exposed to regulation, i.e. manufacturing, construction and utilities. Again, the effects are not statistically different from zero. It is worth noting that only areas that were NA for the old standards seem to experience a significant decline in employment, i.e. φ is negative and significant in the model using total BLS employment, but such a decline does not seem concentrated in the industries that are particularly exposed to regulation.

[Table 9 about here]

In light of these results and of the ones pointing to a limited skill distance between green and brown jobs, we should expect that the recent regulatory changes analysed by our study would have little or no effects on workforce skills. Table 10 presents our estimates of equation (4) and, contrary to our expectation, suggests that stricter environmental regulation does increase demand for our four general green skills plus the two engineering & technical (low and high) and the two monitoring (law and compliance). However, the magnitude of these effects is not large. Looking specifically at Panels A and B, the average treatment effect on the treated, obtained by summing up the designation and the implementation effect, is statistically significant for most GGS (although operations management and monitoring are only significant at the 10 percent level). Science and Law skills (a sub-component of the broad GGS Monitoring) are the only two exceptions for which the joint effect of nonattainment designation and implementation are not statistically significant. However, it is worth noting that the implementation stage does increase the importance of Science GGS.

The nature of environmental technologies may explain the stronger effect of environmental regulation on engineering and technical skills than on scientific skills. Rather than creating new basic knowledge, most environmental technologies entail the application of general scientific knowledge to specific problems, i.e. 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 apply these technologies in new domains of use. Turning to monitoring, if we separate this item into two components – compliance and law – nonattainment status increases the importance of compliance skills but not of legal skills. It may be that while compliance activities must take place on-site, legal activities associated with complying with environmental regulation take place elsewhere, such as in state capitals.

[Table 10 about here]

Panel C of Table 10 contrasts the effect of environmental regulation on GGS to the effect on standard human capital measures. We find no evidence that environmental regulation leads to an increase in the demand of complex skills, measured by the RTI index, or in the share of workers with post-graduate education. Combining these results with the increased demand for green general skills seen in panels A and B lends support to the conjecture that the inducement effect of regulation is concentrated in a subset of highly specific technical skills. This contrasts with the effect of other structural shocks such as trade and technology (Autor, Levy and Murnarne, 2003; Ng and Lu, 2013), which mostly increase the demand of high general skills required to perform non-routine tasks. While we caution that our results can only capture short-run changes in demand, as a policy implication, this finding suggests that re-directing the educational supply towards technical and engineering degrees is more important to support green economy activities than merely increasing the level of education of the workforce.

To precisely quantify the effect of environmental regulation on green skills, note that the effective range of variation of our skill indicators across regions is significantly smaller than the theoretical one (i.e. 0-1). Within a given year, the largest range for any of our GGS indices is a gap of 0.239 for the GGS of High Engineering & Technical skills in 2013.[19] This helps explain the small absolute magnitude of our point estimate of the treatment effect, which just increases the importance of green skills between 0.08% (for O&M) and 0.21% (for Engineering high). To interpret the economic significance of these changes, we can consider what such a change would mean to a community that was the median for each index in our initial year of 2006. The largest increase in demand for green general skills occurs within Engineering.

[19] Table 18 in Appendix B shows the variation in our GGS measures across metro and non-metro areas.

Nonattainment status moves the median High-skilled Engineering community to the 58th percentile. The median overall E&T community moves to the 56th percentile, and the median Low-skilled Engineering community moves to the 54th percentile. The median Compliance community also moves up to the 54th percentile after nonattainment status. In contrast, the effects are smaller for Operation Management and Monitoring, where the median community moves up to just the 52nd or 53rd percentile. Recall that O&M and Monitoring skills are usually less occupation-specific and require more general education than engineering & technical skills (see Figures 1-2). In sum, the quantification of the effect of environmental regulation on green skills corroborates our previous conclusion: training and educational support to green activities should be specifically directed towards middle-high technical skills. Specifically, this result is consistent with the fact that E&T skills explain the bulk of the difference between green and non-green jobs and are the only occupations with significant differences in the GGS importance between green and brown jobs (as shown previously in Table 5).

4 Industry-specific effects

While considering changes in nonattainment status provides a quasi-experimental research design, it also limits the analysis to overall changes in workforce composition within a metro or non-metro area since attainment status applies to an entire county. However, other studies find that the effects of environmental regulation on labor can be concentrated in the most heavily regulated industries (Kahn and Mansur, 2014). Unfortunately, the availability of region- (state) and sector-specific employment data broken down by occupations are only available for the years 2012 and 2013, preventing us from adopt a similar quasi-experimental design on industry-level data.

In the face of such a shortcoming, we assess whether differential effects by industry matter using data on the distribution of the workforce by both occupation, industry (using the 4-digit NAICS), and state for the years 2012 and 2013.[20] Instead of changes in nonattainment status we use the National Emission Inventory (NEI) developed by the EPA to proxy for the stringency of environmental regulations across both state and industry. According to Brunel and Levinson (2015), when the sectoral breakdown is sufficiently narrow emissions are the best proxies of environmental regulatory and a higher emission level implies a weaker regulation. While this allows us to focus on the effects of regulation on those industries most likely to be affected, we acknowledge that the results in this section should not be interpreted

[20] In principle, the annual ACS data have time-varying information on industry-region-occupation. However, as we show in Appendix B, employment figures for each Census cells sector-state-occupation-time are not reliable and implausibly volatile over time.

causally, as we cannot use a quasi-experimental design to distinguish between the causes of regulation and the composition of the workforce.

To provide illustrative evidence on the positive effect of more stringent environmental regulation on green general skills, following Brunel and Levinson (2015) we compute an index of environmental regulation for each industry equal to the ratio between the state-level emissions per worker in industry *i* and the federal level emissions per workers in the same industry *i*, and another index for GGS built in a similar fashion.[21] We then explore the relationship between environmental regulation and green skills at the sector-state level by estimating the following equation:

$$\log\left(\frac{GGS_{ij}}{\overline{GGS}_i}\right) = \beta \log\left(\frac{ER\_pc_{ij}}{\overline{ER\_pc}_i}\right) + \boldsymbol{\gamma}\mathbf{X}_{\mathrm{ij}} + \varepsilon_{\mathrm{ij}}, \tag{6}$$

where *i* indexes sector and *j* indexes states and ε_{ij} is a conventional error term. The main variable of interest, the ratio of state and national emissions per capita in sector *i*, is in logs as its distribution is highly right-skewed. We transform the dependent variable in logs to interpret the results as elasticities. We also include a set of parsimonious controls, $\mathbf{X}_{\mathrm{ij}}$: state effects absorbing unobservable factors that affect both skill demand and ER, such as subsidies to green investments; the log of the number of monitored facilities to control for regulatory enforcement; and the 10-years log change in the level of employment to make sure that the observed relationship between environmental regulation and workforce composition is not driven by strong compositional effects. This empirical approach implicitly controls for sector fixed effects because the two variables of interests are measured in terms of deviation from the national mean for each industry, so that the coefficients can be interpreted as percentage change deviations from the national mean.

[Table 11 about here]

Table 11 presents the results of this exercise.[22] We focus on the two criteria pollutants that have been most regulated in the last two decades, Ozone and PM2.5. Recall that a higher emission level implies a weaker regulation which, in turn, leads us to expect a negative coefficient of ER on green skills. The results in Table 11 are consistent with our previous findings. In particular, more stringent regulation is significantly associated with a greater importance of GGS even though the degree of association is modest across the board. To illustrate, a 10% reduction in PM2.5 emission intensity compared to the national

[21] Details on the construction of these variables are in the data Appendix B.

[22] Notice that these results are generally robust to richer empirical specifications (including for instance import penetration and limit our analysis to the manufacturing sector) and to the use of an IV strategy to account for the endogeneity in environmental regulation. The interested reader can find these results in a previous version of this work (Vona et al., 2015).

mean leads only to a 0.05 % increase in the sectoral use of O&M skills relative to the national average. The effect remains small even if we take into account the extremely large degree of variability of environmental regulation ($ER_{pc_{ij}}/\overline{ER}_{pc_i}$). For example, in the case of PM2.5, even a one standard deviation decrease in emissions would increase the importance of O&M skills by just 1.3% and high engineering and technical skills by just 1.8%. Also, and consistent with previous results, these associations are almost twice as large for engineering high skills. The only notable differences is the large effect of regulation on science skills, which is now similar to that of engineering high skills, and the non-significant effect of Ozone on engineering low skills.

In sum, the results of the industry-level analysis reinforce the point that educational and training support should be especially directed towards high rather than middle technical skills. The emphasis on high technical and scientific knowledge is also supported by the positive and significant correlation between stringent regulation and the use of scientific skills. No doubt, these findings differ from those of previous studies and offer food for thought. Two issues in particular are worth remarking.

First, the small effects in highly exposed industries observed here may conceal indirect effects from inter-sectoral linkages between upstream equipment suppliers and downstream users. While the industries that use pollution abatement equipment are emissions intensive, many of the key upstream suppliers of pollution abatement equipment are in industries that are not emissions intensive. Therefore, our estimates of the effect of environmental regulation on GGS demand in highly exposed sectors should be seen as a lower bound of the overall effect of regulation on workforce composition, as green skills may also become more important in industries that are not heavily regulated themselves, but that benefit from increased demand under stricter environmental regulation. Indeed, as both Voigtlaender (2014) and Franco and Marin (2015) recently remarked, inter-sectoral linkages should be analyzed more in detail to further disentangle direct and indirect effects of environmental regulation on the demand of GGS. We leave such an investigation here for future work.

Second, previous studies use data sources, such as the County Business Pattern dataset, that provide richer sector-level detail but do not offer any details on employment changes at the occupation level, as we require here. Normally in these studies environmental regulation is identified using a regulatory shock (such as non-attainment status as in our section 4) that varies geographically, but not across sectors. That approach is therefore intrinsically different from ours in which variation is truly sector-by-state. We believe that these nuances and idiosyncrasies are especially enriching at this early stage of the debate on the labor market effects of environmental regulation.

5 Conclusions

This paper takes a first step in filling a gap in our understanding of the incidence of environmental regulation in the labor market. We first identify a set of general work skills that are associated with green occupations. We then assess the effect of environmental regulation on the demand for these skills. The contribution to the extant literature is twofold.

First, our empirically-driven selection of green skills allows the detection of skill gaps which can be used to compute measures of skill transferability from brown to green occupations, or to specify in even greater details the types of general skills in high demand in specific sectors or sub-groups of green jobs (e.g. those related to renewable energy). Overall, we find that the skill gap between green jobs and high-polluting "brown" jobs is small. Indeed, in most cases, the general skill requirements of brown jobs are closer to green jobs than the general skill requirements of other jobs. Nonetheless, we find exceptions within specific occupations, such as the importance of green engineering skills within the architecture and construction and extraction fields. As energy extraction occupations, such as coal mining, are likely to be heavily impacted by future climate policy regulations, this finding suggests paying attention to the adjustment costs of workers in those sectors will be important. Combined with our finding that green jobs are rarely more complex than brown jobs, this suggests that policies aimed at providing education and training for green jobs should target an expansion of specific technical programs rather to a development of advanced educational programs.

Second, 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 occupations or industries. Such an investigation is left for future work.

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Tables and figures

Figure 1 – Correlations between GGS and Education

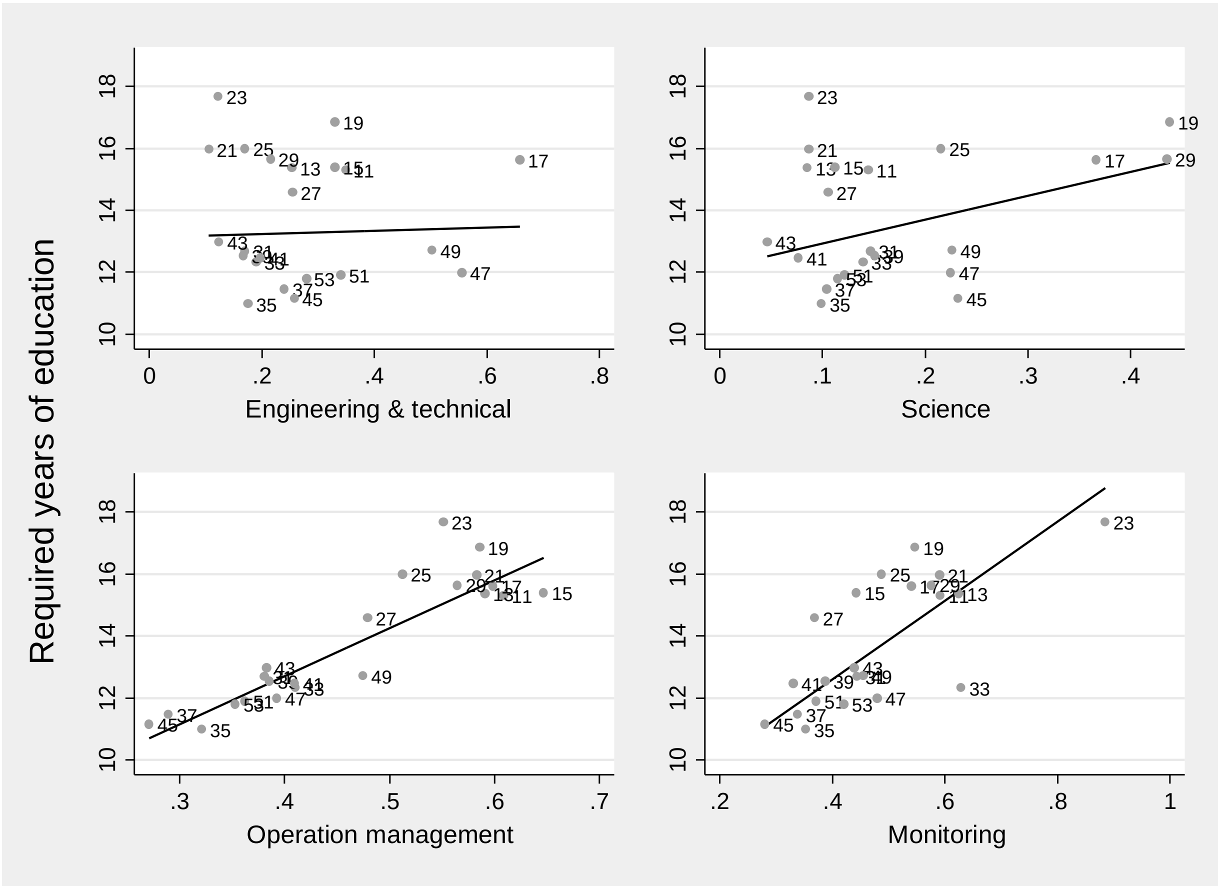

Figure 2 – Correlations between GGS and RTI index

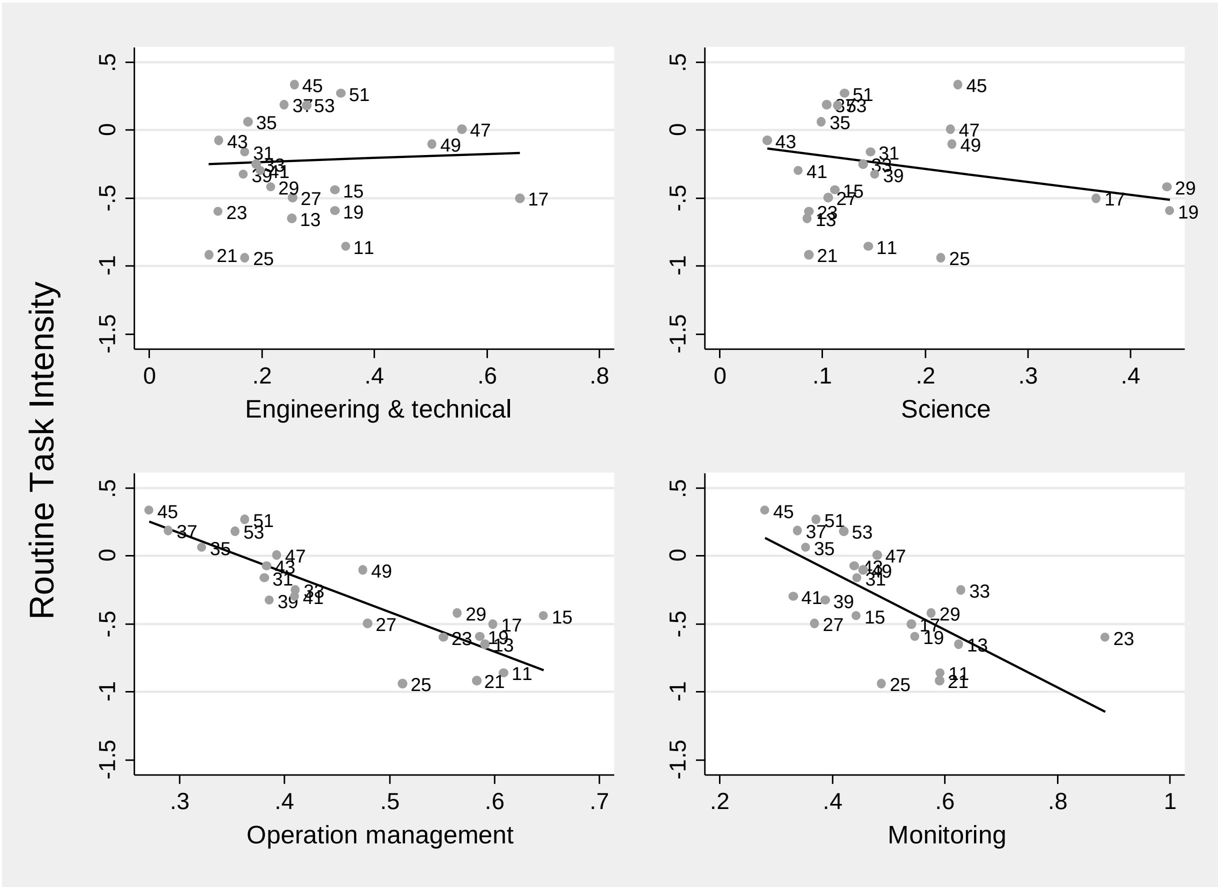

Table 1 – Examples of green occupation by level of ‘greenness’

	Greenness=1	**Greenness btw 0.5 and 0.3**	**Greenness<0.3**
Green Enhanced Occupations	Environmental Engineers, Environ Science Technicians, Hazardous Material Removers	Aerospace Engineers Atmospheric and Space Scientists, Automotive Speciality Technicians, Roofers	Construction Workers, Maintenance & 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

Table 2 – Green General Skills identified from O*NET

	Engineering & 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
	Science
2C4b	Physics
2C4d	Biology
	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

Table 3 – Average green skills by 2-digit SOC macro occupation

	# Green occ	Greenness	Engineering & technical	Operation manag	Science	Monitoring	RTI	Years of training	Years of education
17 - Architecture and Engineering	15	0.182	0.659	0.599	0.367	0.541	-0.501	1.654	15.621
19 - Life, Physical, and Social Science	14	0.152	0.330	0.586	0.439	0.547	-0.594	1.889	16.858
49 - Installation, Maintenance, and Repair	6	0.095	0.503	0.475	0.227	0.454	-0.103	1.881	12.717
11 - Management	9	0.082	0.349	0.609	0.144	0.592	-0.859	1.717	15.295
13 - Business and Financial Operations	8	0.082	0.253	0.591	0.086	0.625	-0.650	1.715	15.369
47 - Construction and Extraction	10	0.081	0.556	0.393	0.225	0.480	0.007	2.152	11.994
51 - Production	8	0.037	0.340	0.363	0.122	0.372	0.271	1.484	11.903
53 - Transportation and Material Moving	3	0.030	0.279	0.353	0.115	0.420	0.184	1.119	11.800
27 - Arts, Design, Entertainment, Sports, and Media	2	0.029	0.255	0.479	0.106	0.369	-0.495	2.073	14.574
41 - Sales and Related	1	0.009	0.197	0.410	0.076	0.330	-0.299	1.179	12.463
43 - Office and Administrative Support	1	0.003	0.124	0.383	0.046	0.439	-0.073	1.205	12.968
15 - Computer and Mathematical	1	0.002	0.330	0.647	0.112	0.443	-0.443	1.434	15.388
29 - Healthcare Practitioners and Technical	1	0.001	0.216	0.564	0.435	0.576	-0.418	1.666	15.647
21 - Community and Social Services	0	0.000	0.106	0.583	0.087	0.591	-0.918	1.730	15.977
23 - Legal	1	0.000	0.122	0.551	0.087	0.885	-0.601	2.855	17.682
25 - Education, Training, and Library	0	0.000	0.170	0.512	0.215	0.487	-0.936	3.249	16.001
31 - Healthcare Support	0	0.000	0.170	0.381	0.147	0.444	-0.162	1.267	12.681
33 - Protective Service	0	0.000	0.190	0.411	0.140	0.629	-0.250	0.893	12.319
35 - Food Preparation and Serving Related	0	0.000	0.175	0.322	0.099	0.353	0.059	1.791	10.977
37 - Building and Grounds Cleaning and Maintenance	0	0.000	0.240	0.290	0.104	0.338	0.186	1.727	11.456
39 - Personal Care and Service	0	0.000	0.167	0.386	0.151	0.387	-0.326	1.827	12.531
45 - Farming, Fishing, and Forestry	0	0.000	0.258	0.271	0.232	0.280	0.334	3.291	11.143
Total	80	0.026	0.246	0.436	0.142	0.451	-0.227	1.613	13.256

Table 4 – Education and training requirements for Engineering & technical skills

	% MA	% College	Years of Education	Years of Training
Engineering and technical - aggregate				
Mean	0.054	0.219	13.341	1.950
SD	0.118	0.341	1.580	0.881
Engineering and Technology				
Mean	0.109	0.430	14.462	1.921
SD	0.191	0.383	1.682	1.081
Design				
Mean	0.090	0.412	14.253	1.933
SD	0.159	0.368	1.706	1.036
Building & Construction				
Mean	0.051	0.235	13.362	1.910
SD	0.105	0.307	1.558	0.876
Mechanical				
Mean	0.020	0.083	12.679	1.675
SD	0.049	0.180	0.980	0.944
Drafting				
Mean	0.051	0.185	13.062	1.598
SD	0.104	0.323	1.548	0.851
Estimating quantifiable characteristics				
Mean	0.051	0.185	13.062	1.598
SD	0.104	0.323	1.548	0.851

Table 5 - Green vs brown

	Green	Brown	None	Green	Brown	None
SOC 2	Engineering and Technical			Science		
17 - Architecture and Engineering	0.69	0.59	0.60	0.39	0.51	0.30
47 - Construction and Extraction	0.57	0.47	0.56	0.28	0.20	0.20
49 - Installation, Maintenance, and Repair	0.51	0.56	0.47	0.24	0.28	0.19
51 - Production	0.35	0.38	0.33	0.19	0.12	0.12
53 - Transportation and Material Moving	0.35	0.45	0.27	0.22	0.27	0.11
Total	0.56	0.44	0.36	0.28	0.19	0.14
SOC 2	Operation Management			Monitoring		
17 - Architecture and Engineering	0.61	0.68	0.56	0.56	0.55	0.51
47 - Construction and Extraction	0.37	0.37	0.41	0.48	0.44	0.49
49 - Installation, Maintenance, and Repair	0.46	0.46	0.49	0.44	0.44	0.47
51 - Production	0.31	0.43	0.34	0.39	0.39	0.36
53 - Transportation and Material Moving	0.36	0.34	0.35	0.50	0.46	0.42
Total	0.46	0.43	0.38	0.48	0.42	0.42
SOC 2	RTI			Years of education		
17 - Architecture and Engineering	-0.54	-0.74	-0.40	15.79	16.39	15.13
47 - Construction and Extraction	-0.01	0.20	-0.03	11.97	11.58	12.10
49 - Installation, Maintenance, and Repair	-0.09	0.04	-0.17	12.85	12.54	12.61
51 - Production	0.24	0.16	0.31	12.76	12.24	11.75
53 - Transportation and Material Moving	0.35	0.36	0.18	11.66	12.06	11.80
Total	-0.14	0.12	0.13	13.24	12.30	12.03

Skill intensity by macro-occupation weighted by employment (SOC 6-digit) in 2012 (BLS).

Figure 3 - Attainment status by metropolitan and non-metropolitan areas

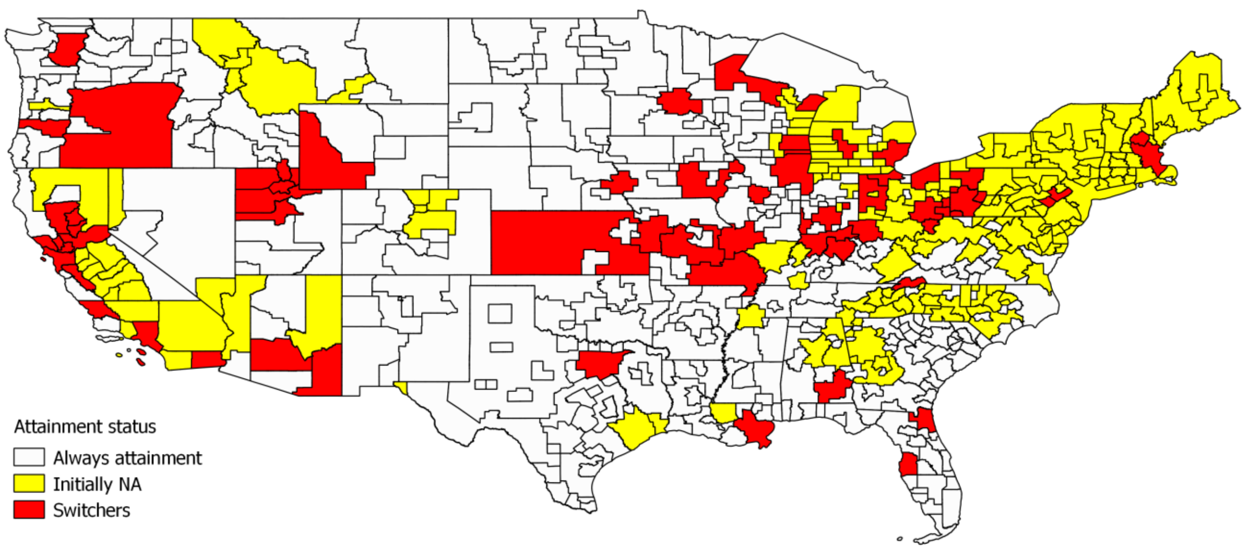

Table 6 - Balancing of variables across areas (year 2006, weighted by population)

Year 2006	Average non-switch	Average switch	t-test difference
log(pop density)	5.529	6.381	2.553
Share manuf	0.108	0.115	0.851
Share construction sect	0.055	0.054	-0.352
Share primary sect	0.014	0.005	-3.868
Share utility sect	0.004	0.005	0.697
log(estab size)	16.240	16.395	0.205
Import penetration	0.066	0.065	-0.258
Area is NA in 2006	0.564	0.778	2.398
Average GGS	0.314	0.316	1.282
Engineering & Technical	0.250	0.252	0.716
Science	0.138	0.135	-1.272
Operation Management	0.425	0.432	2.523
Monitoring	0.444	0.445	0.662

Year 2006. N=537. N of switchers: 66. Averages weighted by population in metropolitan and non-metropoligan areas.

Table 7 - Pre-treatment common trend assumption

	(1)	(2)	(3)	(4)	(5)
	Engineering & technical	Science	Operation management	Monitoring	RTI
Panel A - Without control variables					
Joint significance (F) of treatment x year dummies	2.712	0.0916	0.285	0.614	0.623
p-value	0.0673	0.913	0.752	0.542	0.537
Panel B - With control variables					
Joint significance (F) of treatment x year dummies	1.535	0.0322	0.416	0.735	0.996
p-value	0.217	0.968	0.660	0.480	0.370

Fixed effect model weighted by average population. Standard errors clustered by area in parenthesis. * p<0.1 ** p<0.05 *** p<0.01. N=1611 (years 2006-2008). 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), NA status dummy (2006).

Table 8 - Propensity score and balancing after matching

	Pr(treated=1)	Average matched non-treated (weighted by kernel weights)	Average treated	t-test difference
log(pop density)	0.148**	4.9065	5.0669	0.67
	(0.0725)			
Share manuf	2.746**	.13503	.13205	-0.23
	(1.238)			
Share primary sect	-2.422	.01366	.01337	-0.07
	(3.075)			
Share utility sect	47.68**	.00475	.00514	0.55
	(18.63)			
Share construction sect	3.061	.05644	.0555	-0.27
	(4.120)			
log(estab size)	-0.0806***	15.64	15.655	0.03
	(0.0299)			
Import penetration	-5.422	.06618	.06598	-0.06
	(4.033)			
Area is NA in 2006	0.502***	.59884	.63077	0.37
	(0.163)			
Average GGS intensity	27.50***	.3146	.31418	-0.31
	(10.44)			

Probit model for year 2006. Robust standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Pseudo R squared: 0.102. Number of observations: 537. Matching on propensity score based on kernel.

Table 9 - Baseline estimates for total employment

	Tot employment (BLS)	Tot employment (CBP)	Empl in exposed industries
NA in t=0 x trend	-0.00333*	-0.00181	-0.00311
	(0.00172)	(0.00123)	(0.00321)
NA designation	0.00329	0.00472	0.0131
	(0.00436)	(0.00416)	(0.00939)
NA implementation	-0.0113	0.00293	-0.00336
	(0.0101)	(0.00532)	(0.00989)
NA designation + NA implementation	-0.00801	0.00765	0.00974
Test: NA design + NA implement=0 (p-value)	0.451	0.115	0.420
R sq	0.466	0.747	0.817
N	4806	4272	4806

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).

Table 10 - Baseline estimates for skill composition

	Science	Engineering & technical	Engineering 'high'	Engineering 'low'
NA in t=0 x trend	-0.0000286	-0.000140	-0.000221	-0.0000986
	(0.0000817)	(0.000141)	(0.000162)	(0.000138)
NA designation	-0.000482	0.00104**	0.00130**	0.000909*
	(0.000387)	(0.000525)	(0.000596)	(0.000513)
NA implementation	0.000719**	0.000524	0.000827	0.000373
	(0.000337)	(0.000592)	(0.000684)	(0.000566)
NA designation + NA implementation	0.000237	0.001564	0.002127	0.001282
Test: NA design + NA implement=0 (p-value)	0.443	0.0111	0.00222	0.0328
R sq	0.448	0.492	0.407	0.534
N	4806	4806	4806	4806
	Operation management	Monitoring	Monitoring 'compliance'	Monitoring 'law'
NA in t=0 x trend	-0.0000422	-0.0000603	-0.000161	0.0000400
	(0.000102)	(0.0000895)	(0.0000984)	(0.000115)
NA designation	0.0000538	0.000412	0.000948*	-0.000124
	(0.000413)	(0.000436)	(0.000511)	(0.000549)
NA implementation	0.000725	0.000260	0.000138	0.000383
	(0.000452)	(0.000442)	(0.000482)	(0.000543)
NA designation + NA implementation	0.0007788	0.000672	0.001086	0.000259
Test: NA design + NA implement=0 (p-value)	0.0868	0.0814	0.0125	0.629
R sq	0.585	0.599	0.515	0.579
N	4806	4806	4806	4806
	RTI	log(training)	log(education)	Share requiring master degree
NA in t=0 x trend	-0.0000973	0.000571	-0.0000443	0.0000730
	(0.000262)	(0.000511)	(0.000120)	(0.000123)
NA designation	0.000828	-0.00217	-0.000280	-0.000964**
	(0.00113)	(0.00226)	(0.000483)	(0.000478)
NA implementation	-0.00172	0.00292	0.000992*	0.000860*
	(0.00118)	(0.00227)	(0.000516)	(0.000467)
NA designation + NA implementation	-0.000892	0.00075	0.000712	-0.000104
Test: NA design + NA implement=0 (p-value)	0.497	0.719	0.179	0.822
R sq	0.591	0.295	0.576	0.611
N	4806	4806	4806	4806

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).

Table 11 - Estimates by state-industry for manufacturing sectors

	Science	Engineering & technical	Engineering 'high'	Engineering 'low'	Operation management	Monitoring
Ozone emission intensity	-0.00324	-0.00210*	-0.00479**	-0.000815	-0.00380***	-0.00216***
	(0.00215)	(0.00113)	(0.00204)	(0.000815)	(0.00127)	(0.000781)
N	2846	2846	2846	2846	2846	2846
	Science	Engineering & technical	Engineering 'high'	Engineering 'low'	Operation management	Monitoring
PM 2.5 emission intensity	-0.00648**	-0.00398***	-0.00707**	-0.00243**	-0.00527***	-0.00302***
	(0.00270)	(0.00152)	(0.00279)	(0.00100)	(0.00154)	(0.000792)
N	2846	2846	2846	2846	2846	2846

State-by-industry (4-digit NAICS) OLS estimates for 2012 weighted by employment for manufacturing industries. Industries: Manufacturing (NAICS 31-33), Mining, Quarrying, and Oil and Gas Extraction (NAICS 21) and Utilities (NAICS 22). Standard errors clustered by NAICS 3-digit and state. Other control variables: State dummies, employment growth rate 2002-2012, log(count facilities in NEI). Emission intensity (per employee) and skill intensity measured as the log of ratios with respect to the national average in the same 4-digit industry.

Appendix A: Green Skills

This appendix provides details of the data source and the procedure for the selection of GGS based on the greenness of green occupations (the full list of green occupations and their level of greenness is reported in Table 12). Table 13 reports the estimated β of equation 2 for all general skills and tasks for which the beta was significant at the 99 percent level or more. Recall that results are based on 921 occupations observed at the 8-digit SOC level for the year 2012 and regressions include 3-digit SOC dummies. Out of 108 general skills and tasks, 16 have been selected as particularly relevant for green occupations.

[Table 12, Table 13 and Table 14 about here]

As discussed in section 2.2, we perform a principal component analysis (PCA) on these 20 general skills and tasks to generate more aggregate measures of GGS. As discussed in section 3.2, we retain five components with respective Eigenvalues (unrotated components) of 5.58, 3.93, 1.34, 0.99 and 0.92, and a cumulative explained variance of 79.72 percent. Table 14 shows the factor loadings of the 5 rotated components (orthogonal VARIMAX rotation) that exceeded a 0.2 threshold. The first component groups together “Engineering & Technical Skills”. The second component, labelled “Operation Management Skills”, includes abilities that are relevant for management practices associated with new technology. The third component is “Monitoring Skills”. Therein we observe that two general skills (Law and Government and Evaluating Information to Determine Compliance with Standards) load much more than the third one (Operating Vehicles, Mechanized Devices, or Equipment) which, instead, loads negatively on the second component. A thorough reading of the description of these skills (from O*NET) reveals that only the first two bear direct relevance for Monitoring activities, while the third one has to do with operating machineries, vehicles and means of transport and thus not only with the use of monitoring devices. We therefore excluded this third item from the construct. The fourth component clearly refers to Science Skills. Finally, the fifth component is characterized by a large factor loading (Geography, 0.84) and a smaller loading one (Law and Government which, however, was already assigned to component 3). Geographic skills capture activities such as urban planning and analysis of emission dynamics (several profession intensive of Geography skills are green, such as Environmental Restoration Planners, Landscape Architects and Atmospheric and Space Scientist). Due to the specificity of this last component, which only refer to one general skill, we left it out of the analysis. Results on the impact of environmental regulation for this GGS and for each single general skill selected here (including "Geography" and "Operating Vehicles, Mechanized Devices, or Equipment", which were excluded from the GGS constructs) are shown in the Appendix D.

[Table 15 and Table 16 about here]

We tried several alternative ways of selecting GGS to assess the robustness of our selection procedure and to identify the GGS that are selected irrespective of the procedure. We present here two of these additional exercises. First, we estimate equation 2 by weighting each occupation by the total of employees in year 2012[23]. Note that this is not our favourite selection method because it assigns undue importance to occupations that are highly present in the service sector and thus are not directly affected by the sustainability issues. Results are reported in Table 15. This second method only retains general skills that enter two of our Engineering & Technical and Science skills constructs, with the addition of Chemistry that was not selected in our preferred approach. Engineering & Technical and Science skills encompass the core technical and scientific know-how that is required in green occupations. Second, we decompose the indicator of *Greenness* into its two components, that is, the count of green specific tasks and the count of total specific tasks. In this specification we allow both components of the *Greenness* indicator to have an independent effect on general skills. Results for the coefficients associated with green specific tasks and total specific tasks are reported in Table 16. We observe a positive and significant (at the 99 percent level) relationship between the number of green specific tasks for 13 general skills. Out of these 13 skills, just one (*Systems Evaluation*) also shows a positive and significant correlation with the total number of specific tasks. These 13 general skills represent a subset of our initial selection of 16 general skills. This second criterion excludes two general skills that entered the Operation Management GGS (System Analysis and Updating and Using Relevant Knowledge) and one Science skills (Biology).

Taking the cue from the polarization of occupations within engineering skills, in Table 4 we take a closer look at the component parts of this construct: Engineering & Technology, Design, Building & Construction, Mechanical, Drafting and Estimating quantifiable characteristics. The descriptions provided by O*NET serve as first point of reference to detect functional commonalities and differences across these items. Engineering & Technology and Design are areas of knowledge associated with the application of scientific principles to practical problems. By contrast, Building & Construction, Mechanical, Drafting and Estimating quantifiable characteristics pertain to areas of practical know-how of e.g. materials, machines, tools as well as of the technical specifications that are necessary to operate them. In short, the first two items of Green Engineering skills are about "Conceiving solutions" while the remaining three are about "Implementing solutions". This functional difference is reflected also in the educational levels

[23] Weights at the 6-digit SOC level for year 2012 are based on the Occupational Employment Statistics prepared by the Bureau of Labor Statistics. It collects, among other things, aggregate employment measures by detailed occupation. No information is available at the 8-digit SOC level. As discussed in Appendix B about state-industry measures, we decide to weight equally each 8-digit occupation within its corresponding 6-digit macro-occupation.

associated with each of these specific skills. The upper portion of Table 4 shows that an average 21% of workers in occupations with the highest (top 10%) value of E&T skills possess a college degree, while only 5% have postgraduate education. At the same time, the high standard deviation for college graduates suggests strong within group variability which is confirmed by the mean values for each individual skill item. In particular, Engineering & Technology and Design look rather similar since for both the average number of top occupations with at least college degree is above 40%. This is not so for the other items, in particular for Mechanical and Drafting skills where average values range between 8% and 18% respectively. Such a polarization in the educational requirements of occupations with the highest intensity of green Engineering skills hints at interesting heterogeneity in the type of knowledge possessed by these workers with vocational and technical degrees more important for "low" engineering skills.

Appendix B: Data

*B1. O*NET and BLS data*

Our set of skill measures is built using occupation-MSA employment levels from BLS Occupational Employment Statistics (BLS-OES) for 2006-2014 to weight O*NET data on occupational skills. We use the release 17.0 (July 2012) of O*NET.

Importance scores of selected skill measures range from 1 (not important) to 5 (very important) and measure how important is the general task for the occupation. Before computing GGS_k, we rescale scores to range between 0 and 1 (we subtract 1 and divide by 4 each item that enters GGS_k). In addition to our GGS indeces, we also build an index of Routine Task Intensity based on the items of O*NET identified by Acemoglu and Autor (2010). The list of items is reported in Table 17.

[Table 17 about here]

BLS-OES data at the metropolitan area level are released yearly since 1999. However, prior to 2006 metropolitan areas boundaries were defined differently and cannot be easily harmonized with the new delineation that has been adopted starting from 2006. Moreover, no information for non-metropolitan areas was available before 2006. Employment by occupation and metropolitan and non-metropolitan areas is reported if it is greater than 30 and if the cell occupation-area was 'sampled'. We filled missing values based on employment observed in the same cell occupation area in adjacent years or, if no information available, split employment in the cell macro-occupation (2-digit SOC) - area to 6-digit occupations based on federal-level employment shares. Finally, we employed a weighted crosswalk between SOC2009 and SOC2010 classification to obtain data in terms of SOC2010 occupations also for the period 2006-2009.

It is worth recalling that the mismatch between the aggregation of the O*NET database and the Occupational Employment Statistics is corrected by assuming that employees are uniformly distributed across 8-digit SOC occupations within each 6-digit SOC occupation. 8-digit and 6-digit occupations coincide for 678 occupations. For the remaining 97 6-digit occupations the average number of 8-digit occupation is 3 and the median is 2, with a maximum of 12. The task constructs at 6-digit SOC are built as the simple mean of the task constructs at 8-digit SOC. This is clearly a limitation of the combination of O*NET with the BLS Occupational Employment Statistics Database but, in the absence of detailed information on employment at the 8-digit SOC level, the aggregation of information of O*NET by means of simple mean remains the most suitable options.

A possible alternative to BLS-OES data to evaluate the labour force composition of US regions would be information from the American Community Survey (ACS) available at IPUMS (Integrated Public Use

Microdata Series). The time coverage of the ACS is 2005-2013 since no information on the PUMA (Public Use Microdata Area) of work of workers is available prior of 2005 with the exception of decennial censuses. However, the advantage of having additional information on some features of the labor force (e.g. industry, earnings, educational attainment) comes at the cost of losing information about the detailed composition of the local labor force. ACS classifies workers into occupations using the SOC (Standard Occupational Classification) system, similarly to BLS data. Furthermore many occupations (including many green occupations and occupations with high intensity of green skills) are classified in aggregate categories (e.g. 5-digit SOC or even 3-digit SOC) compared to the OES-BLS database. This implies that regional variation in employment for the occupations that are relevant to our GGS constructs are measured less precisely. We have computed the GGS by MSA using the ACS Census and find that these data are highly volatile.

[Figure 4 about here]

In Figure 4 we report standard deviation of yearly changes in our GGS measures at the metropolitan and nonmetropolitan level for each year, estimated either using ACS or BLS. The volatility of these changes is substantially larger for ACS than for BLS. Since workforce composition is long-term persistent feature of a region, this large volatility of ACS data may indicate the lack of representativeness of the yearly employment statistics at region-by-occupation level. In addition, this large volatility is worrisome as we use variation within a region to identify the impact of environmental regulation on GGS.

[Figure 5 and Figure 6 about here]

In Figure 5 we also plot the GGS intensity by metropolitan and non-metropolitan areas using BLS and ACS data respectively, using the average value for each area from 2006-2013. The two estimates look rather similar overall, but some large deviations exist. The correlation between the two measures is 0.76 for Science, 0.85 for Engineering and Technical, 0.93 for Operation Management and 0.83 for Monitoring. However, when we look at the long run change in GGS in metropolitan and non-metropolitan areas (2005-2013), reported in Figure 6, differences between the two data source become very relevant. The correlation between the changes in the two estimates is very weak for Engineering and Technical (0.12) and Monitoring (0.01) and even negative in some case (correlation for Science and Operation Management is, respectively, -0.17 and -0.13).

In sum, BLS data seem much more reliable for our purposes than ACS data for at least two reasons. The first regards the fact that the occupational level of aggregation in BLS is finer (6-digit SOC occupation) than the one for ACS (occupations may be aggregated at the 5-digit or even 3-digit SOC level). Secondly, samples of the ACS are not stratified by metropolitan and nonmetropolitan area: this means that they are not necessarily representative of the population of workers in the area and thus displays significantly higher volatility than BLS data.

B2. Environmental Regulation

Information on county-level nonattainment is retrieved from the 'Green Book Nonattainment Areas for Criteria Pollutants' maintained by the Environment Protection Agency (EPA) and available here http://www3.epa.gov/airquality/greenbook/. Attainment status by county is extended to the whole metropolitan and non-metropolitan area sample as discussed in Section 3.1. Moreover, as discussed in Ferris et al. (2014), all counties and areas in the states included in the Ozone Transport Region have to implement regulatory actions equivalent to the ones mandated for nonattainment counties for the Ozone standards, even though they comply with the standard.

B3. Data sources for control variables

Information on the distribution of employment by industry of metropolitan and non-metropolitan areas comes from the BLS Quarterly Census of Employment and Wages (CEW). We aggregated county-level figures to the metropolitan and non-metropolitan area level. Primary industries include NAICS codes 11 and 21, utilities NAICS codes 22 manufacturing industries NAICS codes 31-33. Also information on average establishment size (average employees per establishment) is retrieved from the BLS-CEW.

Data on resident population comes from the US Census Bureau. Also in this case we retrieve information at the county-level and the aggregate it at the metropolitan and non-metropolitan level.

Import penetration is measured as the ratio between import and 'domestic consumption' (import + domestic production - export) at the 4-digit NAICS level for year 2006. Data on total import and export for the US as a whole come from Schott (2009) and are available here http://faculty.som.yale.edu/peterschott/sub_international.htm. Data on total production at the federal level by 4-digit NAICS manufacturing industries come from the NBER-CES database. We compute import penetration at the federal level and attribute it to metropolitan and non-metropolitan areas by multiplying industry-level import penetration by area-level employment share by 4-digit NAICS industry. This latter information, for year 2006, comes from the County Business Patterns database.

B5. State-industry data

Our set of skill measures is built using occupation-industry-state employment levels from BLS (Occupational Employment Statistics, year 2012) weighted by O*NET data on occupational skills. Note that occupation-industry-state cells with less than 30 employees are not reported. Out of 18,942,800 employees in NAICS industries 21, 22, 31, 32 and 33 in year 2012 (Occupational Employment Statistics, BLS), detailed information (6-digit SOC occupation[24] by 4-digit NAICS industry) by state is available for 14,882,610 employees, that is 78.6 percent of the total. Skill measures for state i and industry j are built using equation 3, i.e. $GGS_{ij} = \sum_k GGS_k \times \frac{L_{kij}}{L_{ij}}$.

Emissions of Criteria Pollutants (here Ozone, given by the sum of NO2 and NMVOC, and particulate matter smaller than 2.5 mircon, PM 2.5) by plant are collected once every three years into the National Emission Inventory (NEI) developed by the EPA, which contains detailed geographical and sectoral information to assign emission to 4-digit NAICS industry in each state. However, since obligation to report for point sources depends on a series of minimum emission thresholds for each specific pollutant, several sector-state pairs are characterized by zero emissions (36.4% of the total state-industry pairs that account for 31.5% of employment in 2012).

The main advantage of using emissions as a proxy for environmental regulation is that they capture particularly well within-sector changes affecting the workforce composition particularly well. Indeed, a recent paper by Levinson (2015) shows that around 90% of emission abatement is due to technical improvement within the sector, which in turn can stem from the direct adoption of emission abatement technologies and environmentally-friendly organizational practices.

In particular, environmental regulation (ER_{ij}) is measured as $(1 + emission_{ij;2002-2011})/(1 + employment_{ij;2011})$. Due to lack of data on value added by 4-digit NAICS and state, we cannot exactly follow the approach of Brunel and Levinson (2013) based on scaling emissions by the economic value created by the sector. Our imperfect proxy of value is therefore total employment. Rather, we compute weighted average of emissions over the years 2002, 2005, 2008 and 2011, giving more weights to more recent years o account, at least in part, for regulatory stringency in the recent past. As discussed in Section 4, our indicator of regulatory stringency is built as the (log of the) ratio between emission intensity in industry i and state j and the corresponding emission intensity of industry i at the federal level, as in Brunel and Levinson (2013).

B6. Descriptive statistics for GGS

We report some descriptive statistics about the distribution of GGS across metropolitan and non-metropolitan areas. In particular Table 18 shows the distribution of GGS, weighted by area employment, for 537 metropolitan and non-metropolitan areas and by year. Table 19 reports the cross-sectional

[24] Both O*NET and BLS use the 2010 version of the Standard Occupational Classification.

correlation matrix across GGS at the metropolitan and non-metropolitan area level weighted by area employment (average 2006-2014).

[Table 18 and Table 19 about here]

Finally, for illustrative purposes we report some descriptive statistics. Table 20 shows top 10 industries in terms of emission intensity and GGS intensity by industry for year 2012.

[Table 18 about here]

Appendix C: Brown jobs

As discussed in Section 2.4, we define brown jobs (occupations) as the occupations for which more than 10 percent of the overall workforce is employed in energy intensive industries. These include the 'Mining, Quarrying, and Oil and Gas Extraction' industry (NAICS 21) and 'Electric Power Generation, Transmission and Distribution' (NAICS 2211) industry (for which, however, no direct information share of energy costs over total costs) together with the top decile of manufacturing industries in terms of share of energy costs over total production (source: NBER-CES database, year 2006). This resulted in the selection of the following NAICS codes (4-digit): 3112, 3131, 3133, 3221, 3251, 3252, 3271, 3272, 3272, 3274, 3279, 3311, 3313, 3315 and 3328. As a second step we calculate for each 6-digit SOC occupations the share of total employees of occupations that are employed in any of the brown industries using the BLS-OES estimates of occupational employment by 4-digit NAICS industries for years 2006-2014. The list of 6-digit SOC brown occupations is reported in Table 21.

[Table 21 about here]

Appendix C Robustness

Table 22 reports results on the impact of environmental regulation on the demand for green skills (as described in Section 3.2) for each GGS item.

[Table 22 about here]

Results confirm our baseline results for GGS. However, for the two items that were not assigned to any GGS group, we find a negative result for NA designation for Geography and no effect for implementation. Similarly, we find no effect for Operating Vehicles, Mechanized Devices, or Equipment.

Tables for Appendix A

Table 12 – List of jobs using green skills

SOC 2010	Title	Greenness	Total spec tasks	Green spec tasks
11-1011.03	Chief Sustainability Officers	1.00	18	18
11-1021.00	General and Operations Managers	0.06	18	1
11-2021.00	Marketing Managers	0.20	20	4
11-3051.02	Geothermal Production Managers	1.00	17	17
11-3051.04	Biomass Power Plant Managers	1.00	18	18
11-3071.01	Transportation Managers	0.18	28	5
11-3071.02	Storage and Distribution Managers	0.23	30	7
11-3071.03	Logistics Managers	0.30	30	9
11-9021.00	Construction Managers	0.28	25	7
11-9041.00	Architectural and Engineering Managers	0.19	21	4
11-9121.02	Water Resource Specialists	1.00	21	21
11-9199.01	Regulatory Affairs Managers	0.15	27	4
11-9199.02	Compliance Managers	0.20	30	6
11-9199.04	Supply Chain Managers	0.30	30	9
11-9199.11	Brownfield Redevelopment Specialists and Site Managers	1.00	22	22
13-1022.00	Wholesale and Retail Buyers, Except Farm Products	0.24	21	5
13-1041.07	Regulatory Affairs Specialists	0.19	32	6
13-1081.01	Logistics Engineers	0.37	30	11
13-1081.02	Logistics Analysts	0.19	31	6
13-1151.00	Training and Development Specialists	0.10	21	2
13-1199.01	Energy Auditors	1.00	21	21
13-1199.05	Sustainability Specialists	1.00	14	14
13-2051.00	Financial Analysts	0.33	18	6
13-2052.00	Personal Financial Advisors	0.14	21	3
13-2099.02	Risk Management Specialists	0.17	24	4
15-1199.04	Geospatial Information Scientists and Technologists	0.08	24	2
15-1199.05	Geographic Information Systems Technicians	0.26	19	5
17-1011.00	Architects, Except Landscape and Naval	0.37	19	7
17-1012.00	Landscape Architects	0.26	19	5
17-2011.00	Aerospace Engineers	0.33	18	6
17-2051.00	Civil Engineers	0.47	17	8
17-2051.01	Transportation Engineers	0.23	26	6
17-2071.00	Electrical Engineers	0.14	22	3
17-2072.00	Electronics Engineers, Except Computer	0.22	23	5
17-2081.00	Environmental Engineers	1.00	28	28
17-2081.01	Water/Wastewater Engineers	1.00	27	27
17-2141.00	Mechanical Engineers	0.26	27	7
17-2161.00	Nuclear Engineers	0.35	20	7
17-2199.01	Biochemical Engineers	0.34	35	12
17-2199.02	Validation Engineers	0.09	22	2
17-2199.03	Energy Engineers	0.95	21	20
17-2199.04	Manufacturing Engineers	0.17	24	4
17-2199.05	Mechatronics Engineers	0.13	23	3
17-2199.07	Photonics Engineers	0.19	26	5
17-2199.08	Robotics Engineers	0.08	24	2
17-2199.10	Wind Energy Engineers	1.00	16	16
17-3023.03	Electrical Engineering Technicians	0.21	24	5
17-3024.00	Electro-Mechanical Technicians	0.08	12	1
17-3024.01	Robotics Technicians	0.09	23	2
17-3025.00	Environmental Engineering Technicians	1.00	26	26
17-3026.00	Industrial Engineering Technicians	0.22	18	4
17-3029.02	Electrical Engineering Technologists	0.40	20	8
17-3029.03	Electromechanical Engineering Technologists	0.29	17	5
17-3029.04	Electronics Engineering Technologists	0.17	23	4
17-3029.05	Industrial Engineering Technologists	0.17	23	4
17-3029.06	Manufacturing Engineering Technologists	0.28	29	8
17-3029.07	Mechanical Engineering Technologists	0.14	21	3
17-3029.08	Photonics Technicians	0.20	30	6
17-3029.09	Manufacturing Production Technicians	0.20	30	6
19-1013.00	Soil and Plant Scientists	0.63	27	17
19-1031.01	Soil and Water Conservationists	1.00	33	33
19-2021.00	Atmospheric and Space Scientists	0.50	24	12

SOC 2010	Title	Greenness	Total spec tasks	Green spec tasks
19-2041.01	Climate Change Analysts	1.00	14	14
19-2041.02	Environmental Restoration Planners	1.00	22	22
19-2042.00	Geoscientists, Except Hydrologists and Geographers	0.48	31	15
19-2099.01	Remote Sensing Scientists and Technologists	0.08	24	2
19-3011.01	Environmental Economists	1.00	19	19
19-3051.00	Urban and Regional Planners	0.37	19	7
19-3099.01	Transportation Planners	0.14	22	3
19-4011.01	Agricultural Technicians	0.12	25	3
19-4041.01	Geophysical Data Technicians	0.24	21	5
19-4041.02	Geological Sample Test Technicians	0.19	16	3
19-4051.01	Nuclear Equipment Operation Technicians	0.41	17	7
19-4091.00	Environmental Science and Protection Technicians, Including Health	1.00	25	25
19-4099.02	Precision Agriculture Technicians	0.30	23	7
19-4099.03	Remote Sensing Technicians	0.14	22	3
23-1022.00	Arbitrators, Mediators, and Conciliators	0.05	20	1
27-3022.00	Reporters and Correspondents	0.05	22	1
27-3031.00	Public Relations Specialists	0.24	17	4
29-9012.00	Occupational Health and Safety Technicians	0.35	26	9
41-4011.00	Sales Representatives, Wholesale and Manufacturing, Technical and Scientific Products	0.11	38	4
41-4011.07	Solar Sales Representatives and Assessors	1.00	13	13
43-5071.00	Shipping, Receiving, and Traffic Clerks	0.09	11	1
47-2061.00	Construction Laborers	0.18	33	6
47-2152.01	Pipe Fitters and Steamfitters	0.15	20	3
47-2152.02	Plumbers	0.39	23	9
47-2181.00	Roofers	0.30	30	9
47-2211.00	Sheet Metal Workers	0.24	25	6
47-2231.00	Solar Photovoltaic Installers	1.00	26	26
47-4011.00	Construction and Building Inspectors	0.26	19	5
47-4041.00	Hazardous Materials Removal Workers	0.91	23	21
47-4099.03	Weatherization Installers and Technicians	1.00	18	18
47-5013.00	Service Unit Operators, Oil, Gas, and Mining	0.05	19	1
47-5041.00	Continuous Mining Machine Operators	0.17	12	2
49-3023.02	Automotive Specialty Technicians	0.40	25	10
49-3031.00	Bus and Truck Mechanics and Diesel Engine Specialists	0.16	25	4
49-9021.01	Heating and Air Conditioning Mechanics and Installers	0.23	30	7
49-9071.00	Maintenance and Repair Workers, General	0.13	31	4
49-9081.00	Wind Turbine Service Technicians	1.00	13	13
49-9099.01	Geothermal Technicians	1.00	24	24
51-2011.00	Aircraft Structure, Surfaces, Rigging, and Systems Assemblers	0.13	30	4
51-4041.00	Machinists	0.07	29	2
51-8011.00	Nuclear Power Reactor Operators	0.33	18	6
51-8013.00	Power Plant Operators	0.21	24	5
51-8099.03	Biomass Plant Technicians	1.00	16	16
51-9012.00	Separating, Filtering, Clarifying, Precipitating, and Still Machine Setters, Operators, and Tenders	0.05	20	1
51-9061.00	Inspectors, Testers, Sorters, Samplers, and Weighers	0.06	32	2
51-9199.01	Recycling and Reclamation Workers	1.00	18	18
53-3032.00	Heavy and Tractor-Trailer Truck Drivers	0.09	33	3
53-6051.07	Transportation Vehicle, Equipment and Systems Inspectors, Except Aviation	0.41	22	9
53-7081.00	Refuse and Recyclable Material Collectors	1.00	16	16

Table 13 – Selection of green skills

Item	Description	Beta	S.E.
2B4g	Systems Analysis	0.0589***	(0.0185)
2B4h	Systems Evaluation	0.0603***	(0.0182)
2C3b	Engineering and Technology	0.181***	(0.0518)
2C3c	Design	0.158***	(0.0451)
2C3d	Building and Construction	0.203***	(0.0503)
2C3e	Mechanical	0.135***	(0.0514)
2C4b	Physics	0.182***	(0.0546)
2C4d	Biology	0.0933***	(0.0301)
2C4g	Geography	0.140***	(0.0331)
2C8b	Law and Government	0.0948***	(0.0345)
4A1b3	Estimating the Quantifiable Characteristics of Products, Events, or Information	0.0563***	(0.0196)
4A2a3	Evaluating Information to Determine Compliance with Standards	0.0553***	(0.0185)
4A2b3	Updating and Using Relevant Knowledge	0.0482***	(0.0180)
4A3a4	Operating Vehicles, Mechanized Devices, or Equipment	0.0942***	(0.0310)
4A3b2	Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment	0.124***	(0.0373)
4A4b6	Provide Consultation and Advice to Others	0.0666***	(0.0206)

N=475 occupations (8-digit SOC). 3-digit SOC occupations with no green occupations are excluded. 3-digit SOC dummies included. OLS estimates. Standard errors clustered by 3-digit SOC in parenthesis. Beta and S.E. refer to the variable *Greenness*

Table 14 – Principal component analysis

Item	Description	Component 1	Component 2	Component 3	Component 4	Component 5
2B4g	Systems Analysis		0.4346			
2B4h	Systems Evaluation		0.4245			
2C3b	Engineering and Technology	0.4278				
2C3c	Design	0.4536				
2C3d	Building and Construction	0.3021				0.2204
2C3e	Mechanical	0.3326	-0.2976			
2C4b	Physics	0.3191			0.4405	
2C4d	Biology				0.8000	
2C4g	Geography					0.8432
2C8b	Law and Government			0.4602		0.3856
4A1b3	Estimating the Quantifiable Characteristics of Products, Events, or Information	0.2564				
4A2a3	Evaluating Information to Determine Compliance with Standards			0.6999		-0.2124
4A2b3	Updating and Using Relevant Knowledge		0.3241			
4A3a4	Operating Vehicles, Mechanized Devices, or Equipment		-0.5026	0.3407		
4A3b2	Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment	0.4298				
4A4b6	Provide Consultation and Advice to Others		0.3535	0.2250		

Principal component analysis. VARIMAX rotated components with loadings<0.2 not shown. Cumulative explained variance (5 components): 79.72%. Eigenvalues for the first six unrotated components: 5.58, 3.93, 1.34, 0.99, 0.92, 0.65.

Table 15 – Selection of green skills (with employment weights)

Item	Description	Beta	S.E.
2C3b	Engineering and Technology	0.244***	(0.0496)
2C3c	Design	0.206***	(0.0638)
2C3d	Building and Construction	0.303***	(0.0903)
2C3e	Mechanical	0.221***	(0.0446)
2C4b	Physics	0.246***	(0.0367)
2C4c	Chemistry	0.140***	(0.0427)
2C4d	Biology	0.124***	(0.0275)
2C4g	Geography	0.153***	(0.0306)

N=475 occupations (8-digit SOC). 3-digit SOC occupations with no green occupations are excluded. 3-digit SOC dummies included. OLS estimates weighted by employment share. Standard errors clustered by 3-digit SOC in parenthesis. Beta and S.E. refer to the variable *Greenness*.

Table 16 – Selection of green skills (count of specific tasks)

Item	Description	Green specific tasks		Total specific tasks	
		Beta	S.E.	Beta	S.E.
2B4h	Systems Evaluation	0.00230**	(0.000840)	0.00158**	(0.000716)
2C3b	Engineering and Technology	0.00836***	(0.00240)	-0.000794	(0.00119)
2C3c	Design	0.00718***	(0.00202)	-0.000306	(0.00150)
2C3d	Building and Construction	0.00931***	(0.00221)	-0.00217	(0.00128)
2C3e	Mechanical	0.00637**	(0.00233)	-0.00191	(0.00124)
2C4b	Physics	0.00839***	(0.00244)	-0.00134	(0.000823)
2C4g	Geography	0.00681***	(0.00146)	0.000354	(0.00107)
2C8b	Law and Government	0.00419***	(0.00150)	0.00102	(0.00129)
4A1b3	Estimating the Quantifiable Characteristics of Products, Events, or Information	0.00266**	(0.00103)	-0.000312	(0.000760)
4A2a3	Evaluating Information to Determine Compliance with Standards	0.00260***	(0.000854)	0.000859	(0.000728)
4A3a4	Operating Vehicles, Mechanized Devices, or Equipment	0.00520***	(0.00149)	-0.000908	(0.00124)
4A3b2	Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment	0.00570***	(0.00163)	0.0000792	(0.00117)
4A4b6	Provide Consultation and Advice to Others	0.00291***	(0.000798)	0.000844	(0.00123)

N=475 occupations (8-digit SOC). 3-digit SOC occupations with no green occupations are excluded. 3-digit SOC dummies included. OLS estimates weighted. Standard errors clustered by 3-digit SOC in parenthesis. Beta and S.E. refer to the variables *Count of green specific tasks* and *Count of total specific tasks*.

Tables for Appendix B

Table 17 - Items included in the Routine Task Intensity (RTI) index

Non-routine analytical (NRA)	
4A2a4	Analyzing Data or Information
4A2b2	Thinking Creatively
4A4a1	Interpreting the Meaning of Information for Others
Non-routine interactive (NRI)	
4A4a4	Establishing and Maintaining Interpersonal Relationships
4A4b4	Guiding, Directing, and Motivating Subordinates
4A4b5	Coaching and Developing Others
Routine cognitive (RC)	
4C3b4 (cx)	Importance of Being Exact or Accurate
4C3b7 (cx)	Importance of Repeating Same Tasks
4C3b8 (cx)	Structured versus Unstructured Work (reverse)
Routine manual (RM)	
4A3a3	Controlling Machines and Processes
4C2d1i (cx)	Spend Time Making Repetitive Motions
4C3d3 (cx)	Pace Determined by Speed of Equipment

Figure 4 - Standard deviation of annual growth rate in GGS by metropolitan and nonmetropolitan areas measured with ACS and BLS data

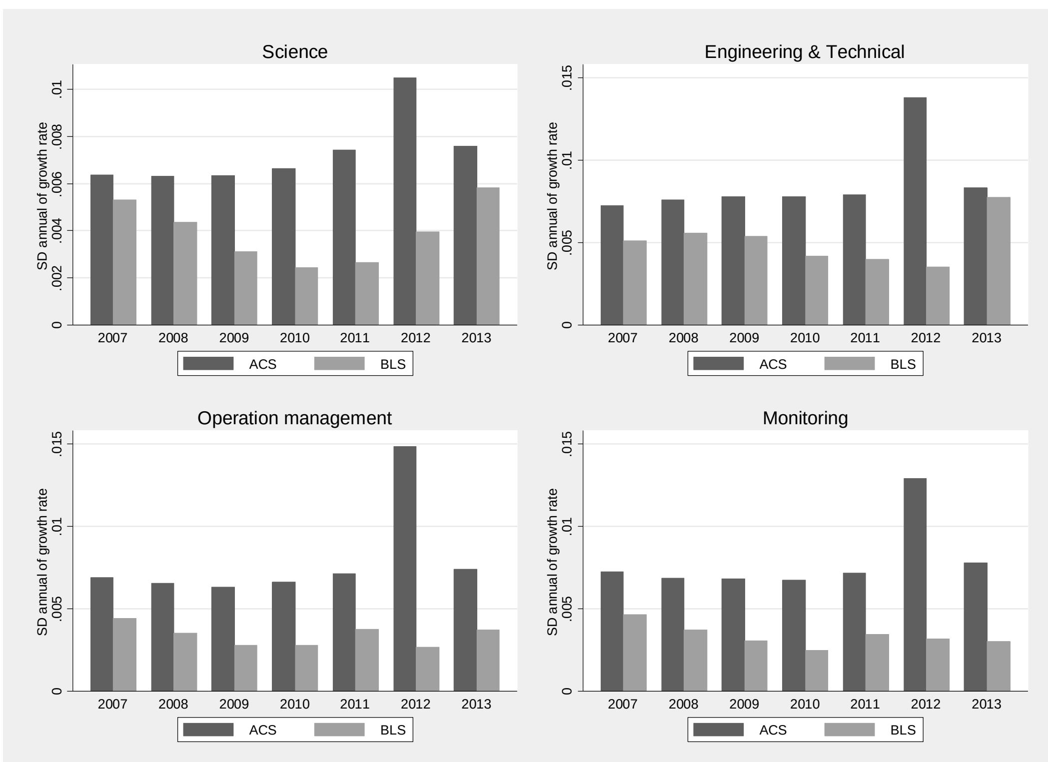

Figure 5 - Comparison of GGS measures by metropolitan and nonmetropolitan area measured with ACS and BLS (average 2006-2013)

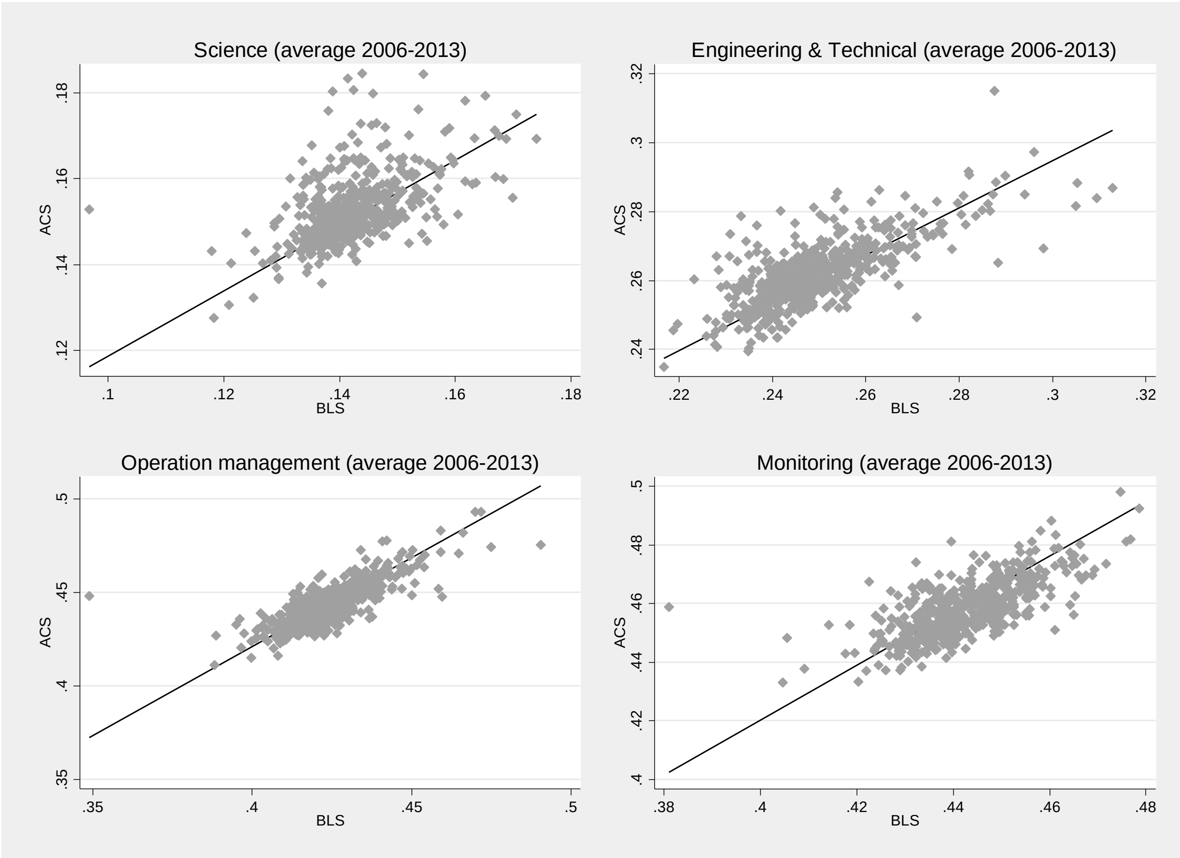

Figure 6 - Comparison of GGS measures by metropolitan and nonmetropolitan area measured with ACS and BLS (change 2006-2013)

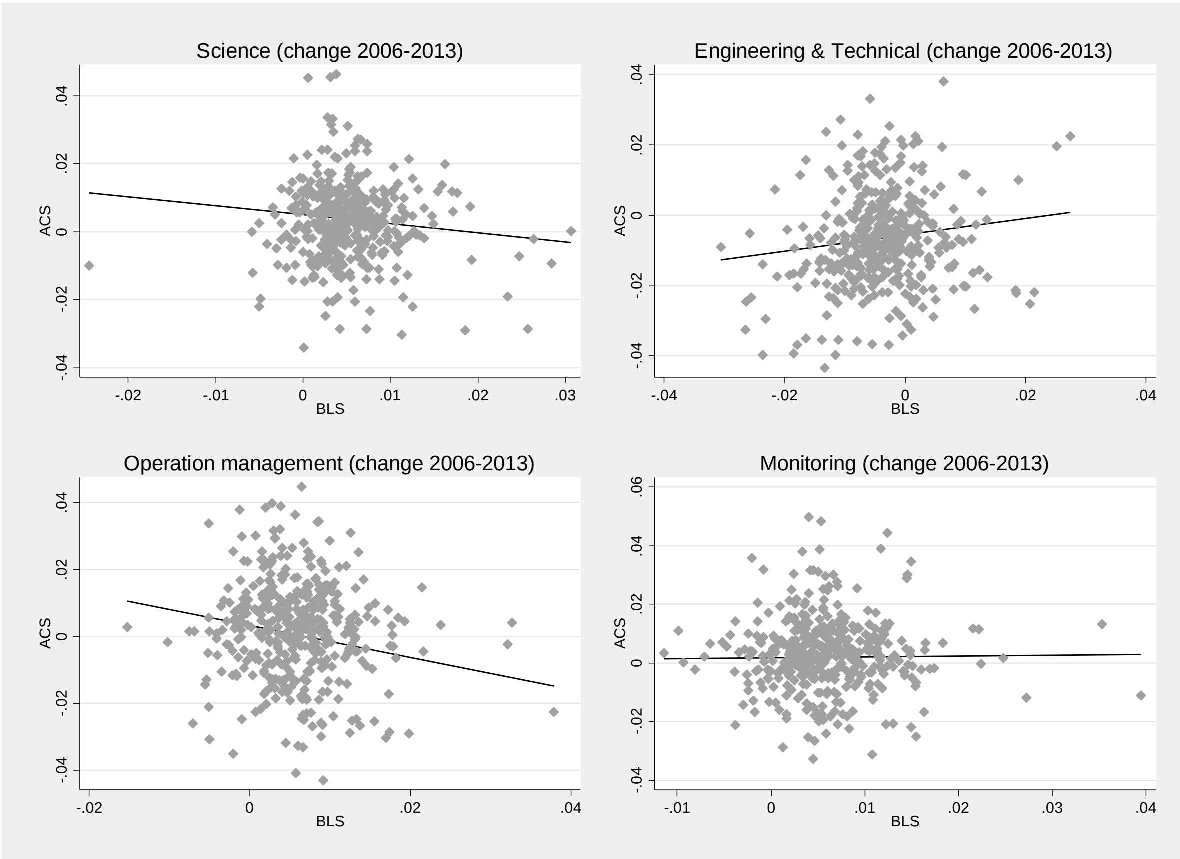

Table 18 – Descriptive statistics of GGS by metropolitan and non-metropolitan area

Year	Min	Q1	Median	Q3	Max	Average	SD	IQR
				Engineering and Technical				
2006	0.221	0.244	0.251	0.257	0.307	0.251	0.011	0.013
2007	0.218	0.245	0.251	0.257	0.308	0.251	0.012	0.012
2008	0.217	0.243	0.250	0.256	0.316	0.250	0.012	0.013
2009	0.215	0.241	0.248	0.254	0.321	0.248	0.012	0.013
2010	0.212	0.239	0.245	0.251	0.320	0.245	0.011	0.012
2011	0.214	0.239	0.245	0.251	0.319	0.245	0.012	0.013
2012	0.214	0.239	0.245	0.252	0.324	0.246	0.012	0.012
2013	0.215	0.240	0.245	0.253	0.378	0.247	0.013	0.013
2014	0.215	0.240	0.246	0.253	0.361	0.247	0.013	0.013
Total	0.212	0.240	0.247	0.254	0.378	0.248	0.012	0.014
				Science				
2006	0.113	0.133	0.136	0.140	0.202	0.137	0.007	0.008
2007	0.101	0.133	0.137	0.141	0.185	0.138	0.007	0.008
2008	0.100	0.133	0.138	0.142	0.185	0.138	0.007	0.009
2009	0.091	0.135	0.140	0.144	0.180	0.140	0.007	0.008
2010	0.091	0.136	0.140	0.144	0.180	0.140	0.007	0.008
2011	0.088	0.137	0.141	0.144	0.179	0.141	0.007	0.007
2012	0.087	0.138	0.141	0.145	0.175	0.141	0.007	0.008
2013	0.092	0.136	0.142	0.145	0.215	0.141	0.008	0.009
2014	0.095	0.137	0.142	0.146	0.206	0.142	0.008	0.010
Total	0.087	0.135	0.139	0.144	0.215	0.140	0.008	0.009
				Operation management				
2006	0.343	0.420	0.429	0.438	0.485	0.429	0.014	0.019
2007	0.347	0.421	0.430	0.439	0.481	0.430	0.014	0.018
2008	0.348	0.422	0.432	0.440	0.480	0.431	0.014	0.018
2009	0.345	0.424	0.433	0.441	0.487	0.434	0.014	0.017
2010	0.352	0.425	0.435	0.441	0.494	0.434	0.015	0.016
2011	0.357	0.425	0.436	0.441	0.498	0.435	0.015	0.016
2012	0.349	0.426	0.438	0.442	0.498	0.435	0.015	0.016
2013	0.349	0.426	0.438	0.442	0.517	0.436	0.015	0.017
2014	0.348	0.426	0.438	0.443	0.506	0.436	0.015	0.016
Total	0.343	0.424	0.434	0.441	0.517	0.433	0.015	0.018
				Monitoring				
2006	0.375	0.439	0.446	0.452	0.477	0.445	0.010	0.013
2007	0.378	0.441	0.447	0.453	0.482	0.446	0.010	0.012
2008	0.379	0.441	0.447	0.454	0.478	0.446	0.010	0.013
2009	0.377	0.444	0.450	0.456	0.478	0.449	0.010	0.012
2010	0.384	0.445	0.451	0.456	0.479	0.450	0.010	0.011
2011	0.393	0.444	0.452	0.456	0.488	0.450	0.010	0.011
2012	0.382	0.445	0.452	0.457	0.497	0.451	0.010	0.012
2013	0.382	0.445	0.452	0.457	0.494	0.451	0.010	0.012
2014	0.372	0.445	0.452	0.458	0.498	0.451	0.010	0.013
Total	0.372	0.443	0.450	0.455	0.498	0.449	0.010	0.013

Statistics weighted by total employment. N=537 metropolitan and nonmetropolitan areas

Table 19 – Correlation between GGS measures at the metropolitan and non-metropolitan area level

	Engineering & Technical	Science	Operation management	Monitoring
Engineering & Technical	1.000			
Science	0.560	1.000		
Operation management	0.065	0.091	1.000	
Monitoring	-0.076	0.091	0.833	1.000

N=537. Correlation on average 2006-2014 values weighted by average employment.

Table 20 - Top 10 industries (4-digit NAICS) in terms of emission intensity and GGS (year 2012)

NAICS	Description	PM2.5/empl	NAICS	Description	Ozone/empl
2211	Electric Power Generation, Transmission and Distribution	0.919	2211	Electric Power Generation, Transmission and Distribution	5.941
3221	Pulp, Paper, and Paperboard Mills	0.592	3221	Pulp, Paper, and Paperboard Mills	2.640
3274	Lime and Gypsum Product Mfg	0.536	3274	Lime and Gypsum Product Mfg	2.387
3241	Petroleum and Coal Products Mfg	0.452	3241	Petroleum and Coal Products Mfg	2.000
3311	Iron and Steel Mills and Ferroalloy Mfg	0.398	2111	Oil and Gas Extraction	1.837
2122	Metal Ore Mining	0.339	3251	Basic Chemical Mfg	1.336
3113	Sugar and Confectionery Product Mfg	0.338	2122	Metal Ore Mining	1.025
3251	Basic Chemical Mfg	0.294	3273	Cement and Concrete Product Mfg	1.016
3212	Veneer, Plywood, and Engineered Wood Product Mfg	0.268	3112	Grain and Oilseed Milling	0.962
3313	Alumina and Aluminum Production and Processing	0.237	3272	Glass and Glass Product Mfg	0.827
NAICS	**Description**	**Engineering & Technical**	**NAICS**	**Description**	**Science**
2382	Building Equipment Contractors	0.528	6221	General Medical and Surgical Hospitals	0.305
5413	Architectural, Engineering, and Related Services	0.519	6215	Medical and Diagnostic Laboratories	0.299
2362	Nonresidential Building Construction	0.518	6223	Specialty (except Psychiatric and Substance Abuse) Hospitals	0.288
2381	Foundation, Structure, and Building Exterior Contractors	0.496	6219	Other Ambulatory Health Care Services	0.288
2373	Highway, Street, and Bridge Construction	0.488	5417	Scientific Research and Development Services	0.288
2379	Other Heavy and Civil Engineering Construction	0.482	4812	Nonscheduled Air Transportation	0.286
2361	Residential Building Construction	0.479	2213	Water, Sewage and Other Systems	0.280
2371	Utility System Construction	0.477	5413	Architectural, Engineering, and Related Services	0.266
2122	Metal Ore Mining	0.467	4879	Scenic and Sightseeing Transportation, Other	0.262
2389	Other Specialty Trade Contractors	0.462	6211	Offices of Physicians	0.255
NAICS	**Description**	**Operation Management**	**NAICS**	**Description**	**Monitoring**
5415	Computer Systems Design and Related Services	0.603	5411	Legal Services	0.731
5112	Software Publishers	0.597	4812	Nonscheduled Air Transportation	0.618
5417	Scientific Research and Development Services	0.571	4879	Scenic and Sightseeing Transportation, Other	0.596
3341	Computer and Peripheral Equipment Manufacturing	0.566	5221	Depository Credit Intermediation	0.591
5239	Other Financial Investment Activities	0.565	5239	Other Financial Investment Activities	0.588
5232	Securities and Commodity Exchanges	0.564	5259	Other Investment Pools and Funds	0.584
5211	Monetary Authorities-Central Bank	0.561	5231	Securities and Commodity Contracts Intermediation and Brokerage	0.581
5231	Securities and Commodity Contracts Intermediation and Brokerage	0.558	5251	Insurance and Employee Benefit Funds	0.570
5182	Data Processing, Hosting, and Related Services	0.557	5241	Insurance Carriers	0.563
5413	Architectural, Engineering, and Related Services	0.555	6219	Other Ambulatory Health Care Services	0.561

Tables for Appendix C

Table 21 - Brown occupations

SOC 2010	Title
11-3051	Industrial Production Managers
17-2041	Chemical Engineers
17-2071	Electrical Engineers
17-2131	Materials Engineers
17-2151	Mining and Geological Engineers, Including Mining Safety Engineers
17-2161	Nuclear Engineers
17-2171	Petroleum Engineers
19-2032	Materials Scientists
19-2042	Geoscientists, Except Hydrologists and Geographers
19-4031	Chemical Technicians
19-4041	Geological and Petroleum Technicians
19-4051	Nuclear Technicians
27-1012	Craft Artists
29-9011	Occupational Health and Safety Specialists
29-9012	Occupational Health and Safety Technicians
43-5041	Meter Readers, Utilities
47-2073	Operating Engineers and Other Construction Equipment Operators
47-5011	Derrick Operators, Oil and Gas
47-5012	Rotary Drill Operators, Oil and Gas
47-5013	Service Unit Operators, Oil, Gas, and Mining
47-5021	Earth Drillers, Except Oil and Gas
47-5031	Explosives Workers, Ordnance Handling Experts, and Blasters
47-5041	Continuous Mining Machine Operators
47-5042	Mine Cutting and Channeling Machine Operators
47-5051	Rock Splitters, Quarry
47-5061	Roof Bolters, Mining
47-5071	Roustabouts, Oil and Gas
47-5081	Helpers--Extraction Workers
49-2095	Electrical and Electronics Repairers, Powerhouse, Substation, and Relay
49-3042	Mobile Heavy Equipment Mechanics, Except Engines
49-9012	Control and Valve Installers and Repairers, Except Mechanical Door
49-9041	Industrial Machinery Mechanics
49-9043	Maintenance Workers, Machinery
49-9044	Millwrights
49-9045	Refractory Materials Repairers, Except Brickmasons
49-9051	Electrical Power-Line Installers and Repairers
49-9081	Wind Turbine Service Technicians
49-9096	Riggers
51-1011	First-Line Supervisors of Production and Operating Workers
51-4021	Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic
51-4023	Rolling Machine Setters, Operators, and Tenders, Metal and Plastic
51-4032	Drilling and Boring Machine Tool Setters, Operators, and Tenders, Metal and Plastic
51-4033	Grinding, Lapping, Polishing, and Buffing Machine Tool Setters, Operators, and Tenders, Metal and Plastic
51-4051	Metal-Refining Furnace Operators and Tenders
51-4052	Pourers and Casters, Metal
51-4062	Patternmakers, Metal and Plastic
51-4071	Foundry Mold and Coremakers
51-4072	Molding, Coremaking, and Casting Machine Setters, Operators, and Tenders, Metal and Plastic
51-4191	Heat Treating Equipment Setters, Operators, and Tenders, Metal and Plastic
51-4193	Plating and Coating Machine Setters, Operators, and Tenders, Metal and Plastic
51-4194	Tool Grinders, Filers, and Sharpeners
51-6061	Textile Bleaching and Dyeing Machine Operators and Tenders
51-6064	Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders
51-6091	Extruding and Forming Machine Setters, Operators, and Tenders, Synthetic and Glass Fibers
51-8011	Nuclear Power Reactor Operators
51-8012	Power Distributors and Dispatchers
51-8013	Power Plant Operators
51-8021	Stationary Engineers and Boiler Operators
51-8091	Chemical Plant and System Operators
51-8092	Gas Plant Operators
51-8093	Petroleum Pump System Operators, Refinery Operators, and Gaugers
51-8099	Plant and System Operators, All Other

SOC 2010	Title
51-9011	Chemical Equipment Operators and Tenders
51-9012	Separating, Filtering, Clarifying, Precipitating, and Still Machine Setters, Operators, and Tenders
51-9021	Crushing, Grinding, and Polishing Machine Setters, Operators, and Tenders
51-9022	Grinding and Polishing Workers, Hand
51-9023	Mixing and Blending Machine Setters, Operators, and Tenders
51-9031	Cutters and Trimmers, Hand
51-9032	Cutting and Slicing Machine Setters, Operators, and Tenders
51-9041	Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders
51-9051	Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders
51-9121	Coating, Painting, and Spraying Machine Setters, Operators, and Tenders
51-9123	Painting, Coating, and Decorating Workers
51-9192	Cleaning, Washing, and Metal Pickling Equipment Operators and Tenders
51-9194	Etchers and Engravers
51-9195	Molders, Shapers, and Casters, Except Metal and Plastic
51-9196	Paper Goods Machine Setters, Operators, and Tenders
53-7011	Conveyor Operators and Tenders
53-7021	Crane and Tower Operators
53-7031	Dredge Operators
53-7032	Excavating and Loading Machine and Dragline Operators
53-7033	Loading Machine Operators, Underground Mining
53-7041	Hoist and Winch Operators
53-7071	Gas Compressor and Gas Pumping Station Operators
53-7072	Pump Operators, Except Wellhead Pumpers
53-7073	Wellhead Pumpers
53-7111	Mine Shuttle Car Operators

Tables for Appendix D

Table 22 – Item-by-item estimates of the impact of environmental regulation on green skills

	NA in t=0 x trend	NA designation	NA implement	Test: NA design+NA implement=0 (p-value)	R sq	N
Science						
Physics (2C4b)	-0.0000908	0.000387	0.000616	0.0232	0.330	4806
	(0.000101)	(0.000433)	(0.000441)			
Biology (2C4d)	0.0000335	-0.00135**	0.000821*	0.262	0.599	4806
	(0.000117)	(0.000541)	(0.000485)			
Engineering and Technical - High						
Engineering and Technology (2C3b)	-0.000225	0.00136**	0.000729	0.00391	0.367	4806
	(0.000156)	(0.000617)	(0.000719)			
Design (2C3c)	-0.000218	0.00125**	0.000926	0.00159	0.455	4806
	(0.000171)	(0.000592)	(0.000666)			
Engineering and Technical - Low						
Building and Construction (2C3d)	-0.0000207	0.000488	0.000623	0.109	0.629	4806
	(0.000169)	(0.000731)	(0.000716)			
Mechanical (2C3e)	-0.000142	0.00126*	0.000505	0.0658	0.515	4806
	(0.000199)	(0.000744)	(0.000848)			
Estimating the Quantifiable Characteristics of Products, Events, or Information (4A1b3)	-0.0000918	0.000798**	0.00000162	0.0435	0.377	4806
	(0.0000992)	(0.000365)	(0.000391)			
Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment (4A3b2)	-0.000140	0.00109**	0.000361	0.0236	0.479	4806
	(0.000140)	(0.000525)	(0.000570)			
Operation Management						
Systems Analysis (2B4g)	-0.000101	0.0000143	0.000781	0.119	0.550	4806
	(0.000112)	(0.000457)	(0.000505)			
Systems Evaluation (2B4h)	-0.0000595	0.000126	0.000557	0.154	0.558	4806
	(0.000105)	(0.000456)	(0.000499)			
Updating and Using Relevant Knowledge (4A2b3)	-0.000102	0.000113	0.000865	0.0687	0.477	4806
	(0.000103)	(0.000491)	(0.000541)			
Provide Consultation and Advice to Others (4A4b6)	0.0000938	-0.0000380	0.000697*	0.129	0.651	4806
	(0.000116)	(0.000399)	(0.000376)			
Monitoring						
Law and Government (2C8b)	0.0000400	-0.000124	0.000383	0.629	0.579	4806
	(0.000115)	(0.000549)	(0.000543)			
Evaluating Information to Determine Compliance with Standards (4A2a3)	-0.000161	0.000948*	0.000138	0.0125	0.515	4806
	(0.0000984)	(0.000511)	(0.000482)			
Other						
Geography (2C4g)	0.0000807	-0.000735**	0.000303	0.210	0.363	4806
	(0.0000978)	(0.000359)	(0.000342)			
Operating Vehicles, Mechanized Devices, or Equipment (4A3a4)	0.0000443	0.000800	-0.000681	0.913	0.529	4806
	(0.000197)	(0.000768)	(0.000923)			

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).