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GREEN SKILLS

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ABSTRACT

The catchword ‘green skills’ has been common parlance in policy circles for a while, yet 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. The present paper proposes a data-driven methodology to identify green skills and to gauge the ways in which the demand for these competences responds to environmental regulation. Accordingly, we find that green skills are high-level analytical and technical know-how related to the design, production, management and monitoring of technology. The empirical analysis reveals that environmental regulation triggers technological and organizational changes that increase the demand for hard technical, engineering and scientific skills. Our analysis suggests also that this is not just a compositional change in skill demand due to job losses in sectors highly exposed to trade and regulation.

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1 Introduction

The catchword ‘green skills’ has been common parlance in policy circles for a while, even more since the Obama stimulus package committed 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.[2] 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 crucial to inform policy. More to the point, the benefits of tailoring training policy to the actual skill needs of the workforce holds the promise of mitigating the negative employment effects that are traditionally associated to environmental regulation (e.g. Becker and Henderson, 2000; Greenstone, 2002). This, however, requires prior identification of the skills that are complementary to green technology and organizational practices.

The present paper addresses this issue by elaborating a two-step data-driven methodology. First, using the occupation-specific information of the Occupational Information Network (O*NET), we identify a set of skills that are used more intensively in green occupations relative to non-green ones. Our data-driven measures build upon prior work on changes in the demand for skills due to structural shocks such as technology (Goldin and Katz, 1998; Autor, Levy and Murnarne, 2003) and trade (Lu and Ng, 2013). Second, we use these Green Skills constructs to assess the effect of environmental regulation (ER henceforth), proxied by emission levels, on the demand for skills. In particular, we use variations in employment shares across states, sectors and occupations to construct aggregate skill measures for each sector-state pair. In so doing, we identify the impact of ER on green skills using environmental

[2] 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

enforcement activities as instrument to address potential endogeneity of regulation under the assumption that enforcement decisions affect the demand for green skills only through emission reductions (Carrion-Flores and Innes, 2010).

This study contributes to the literature in three ways. First, it complements quantitative assessments of the effect of ER on employment (e.g. Greenstone, 2002; Walker, 2013) by highlighting qualitative aspects of the composition of workforce skills. Secondly, it extends the remit of literature on the effect of structural shocks, such as trade and technology (e.g., Autor and Dorn, 2013), on skill demand by focusing on the transition to a sustainable economy. At the same time, since structural shocks are likely to undermine the relevance of existing know-how and create the need for new specific competences, it is important to use suitable measures. Thus, third, our data-driven methodology allows the identification of skills that are important for green occupations and that are amenable to comparison with the standard skill measures of Autor et al. (2003).

The main findings of this paper are two. First, our profiling exercise identifies green skills as a set of competences related to the design, production, management and monitoring of technology. Second, we find that environmental regulation triggers technological and organizational changes that increase the demand of high-level analytical and technical skills. Furthermore, our analysis suggests that this is not just a compositional change in skill demand due to job losses in sectors highly exposed to trade and regulation.

The remainder of the paper is organized as follows. Section 2 provides the conceptual framework on the relation between environmental regulation and green skills. Section 3 presents the methodology for the construction of green skills measures. Section 4 outlines the structure of the data and the empirical strategy, while section 5 presents the main results. Section 6 concludes.

2 Conceptual Framework

The analysis of the relation between environmental regulation and the demand for skills is still at an exploratory stage. By and large previous works focus mostly on the net employment effects of ER, and in the absence of suitable points of reference in the literature we draw insights from two areas of research on structural changes in employment that provide a simple conceptual framework to guide our analysis of the impact of ER on workforce skills.[3]

The composition of employment has undergone significant structural changes over the last three decades, and one of the most widely recognized marks of this transformation is increasing job polarization, that is, higher demand for occupations at the top and at the bottom of the skill distribution relative to middle-skill occupations (e.g. Acemoglu and Autor, 2011). Answers to the question of what drives this phenomenon point to two, not mutually exclusive (Bloom et al. 2014), main determinants: technology and international trade. The seminal work of Autor, Levy and Murnarne (2003) (ALM henceforth) first proposed a heuristic occupational classification based on prior identification of salient task dimensions: 'cognitive' versus 'manual' jobs, and 'routine' versus 'non-routine' jobs. This interpretative framework offers a persuasive explanation of the changes observed in the structure of employment during the 1990s in the US and, in particular, of the role of ICTs diffusion in triggering capital-labour substitution among occupations that consisted mostly of routine, viz. rule-based, tasks.

[3] Empirical evidence on the labour market effects of environmental regulation contemplates a variety of outcomes. Some studies predict job losses driven by redistribution 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). Other studies on the US distinguish plant-level effects depending on the extent to which employment changes consist in 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. Greenstone (2004) gauges the effects of the 1977 Amendments to the Clean Air Act (CAA) on industrial activity by drawing a comparison of within plant effects under the attainment and nonattainment regulation regimes and finds that the latter has a modest negative impact on employment. A more recent paper by Walker (2013) uses worker-level data from the US to estimate the costs associated to reallocation over time and across jobs due to the 1990 Amendments of the CAA. Again, the impact of environmental regulation is negative and the estimated loss of earnings per worker depends on the strength of the local labour market. 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 ER.

Following the same logic, the complementarity between ICTs and non-routine analytical and interactive tasks was identified as a key driver of increased demand for high-skilled professionals (Goldin and Katz, 1998). More recently international trade has been pinpointed as another key driver of changes in the demand for skills. Ng and Lu (2013) find that import competition is a significant driver of worker displacement in US manufacturing and, in particular, that higher exposure to foreign competitors has induced a composition effect in favour of non-routine (cognitive and interactive) skills to the detriment of routine skills. Evidence by Autor et al (2013) indicates that international trade had negative employment effects among workers in routine jobs relative to other occupational categories. On the whole, the contraction of industries more exposed to trade has induced compositional changes and, thus, an overall improvement in the quality of the workforce. By analogy, since the most reliable estimates points to a negative employment effect of ER (Greenstone, 2002; Walker, 2011) we expect that environmental regulation triggers a re-composition in favour of high-level skills.

It should be clear that the main advantage of the task-based model is that it accounts particularly well for changes in workforce skills induced by new technology, in particular the emergence of new work tasks and transformations in the task requirement of occupations. Such a framework is attractive for the goal of the present paper, namely identifying categories of competences that match the emerging green technology paradigm and analysing the effects of an inducement factor like ER. It is worth recalling that innovations tend to originate in specific contexts and, accordingly, to draw on particular bodies of know-how that carry unique peculiarities of the problem-solving process that guides the identification of critical problems and the search for novel solutions (Rosenberg, 1976). For instance, ICTs belong to the well-known family of General-Purpose Technologies (GPTs), that is, a uniquely identified blend of machinery and know-how that can be employed across a wide variety of contexts (Bresnahan and Trajtenberg, 1995). Having said this, even if technology is a crucial driver of emission reductions (Levinson, 2014), comparisons with other large-scale transitions should be made with caution for there is no obvious equivalent to a GPT in the remit of environmental sustainability. A look at well-established taxonomies of environmentally sound technologies, such as the selection of environment-related IPC patent classes done in the WIPO Green Inventory[4] or the ENV-Tech Indicator[5] of the OECD for example, confirms significant heterogeneity across technologies that are closely tailored to the specific needs of the user industries. At the moment 'green technology' is a broad-encompassing label for a variety of sector-specific responses rather than a standardized technology like ICTs in the context of computerization. This calls for caution also in uncritically adopting skill measures that were devised for the study of ICTs and trade, and indeed Section 3 will illustrate a data-driven methodology to identify the skills that are most relevant to environmental issues. With this caveat in mind, we think that prior experiences of large-scale transitions can still offer useful insights to guide our expectations for the empirical analysis.

Recent work shows that the demand for high-level skills due to ICT adoption has decelerated over the last decade possibly because the technology has entered a mature stage of the life-cycle (e.g. Beaudry et al., 2013). This is consistent with theoretical literature showing that at the onset of a new wave of technological change the demand for new skills initially surges and subsequently dissipates inasmuch as codification and standardization facilitate the diffusion of new best practices and of the attendant skills (Aghion et al, 2002; Vona and Consoli, 2014). By analogy since green technology is still at early stages we expect that their adoption will be associated with an increase in the demand of highly skilled workers. Descriptive plant-level evidence by Becker and Shadbegian (2009) shows that for a given level of output and factor usage, plants producing green goods and services employ a lower share of production workers, which lends support to the working hypothesis that green technologies are skill-biased. Another broad similarity with recent large-scale transitions concerns the prominence of organizational changes that enabled significantly the adoption of both information (Bresnahan,

[4] http://www.wipo.int/classifications/ipc/en/est/
[5] http://www.oecd.org/env/consumption-innovation/indicator.htm

Brynjolfsson and Hitt, 2002) and environmental technology (Gillingham and Palmer, 2014). With regards to the latter, a wealth of empirical studies highlights positive effects due to adoption of managerial practices and adaptation of organizational structures aimed at improving both environmental and economic performance.[6] On the other hand some works pinpoint organizational and human capital factors acting as significant barriers that prevent the adoption of profitable energy-saving investments (De Canio, 1998; Sorrell et al, 2011). More in general, the literature on skill-biased organizational change finds a strong complementarity between certain organizational practices and workforce skills (Caroli and van Reenen, 2001). These considerations suggest that technology adoption may not be the sole inducement channel through which firms respond to ER (see Jaffe et al, 2002). To identify a suitable empirical indicator that captures the effects of both technological and organizational change in this context, in section 4 we consider environmental regulation rather than a direct measure of green technology adoption since this is expected to proxy all changes affecting both firm's environmental performance and the demand for skills.

Summing up, the scarcity of literature on the relation between environmental regulation and the skill content of occupations limits the formulation of hypotheses. It is however possible to draw useful insights from other strands of research. The literatures outlined above suggest that since ER induces adoption of green technology and organizational practices and, since these technologies are still in an early phase of the life-cycle, regulation is expected to have stronger effects for high-skilled workers. This should be reinforced by compositional changes following ER. Clearly, insights drawn from laterally relevant literature can shape our expectations only to a limited extent, and a more precise delineation of the framework elaborated here requires an empirical investigation of the main hypotheses and concepts at hand. Let us begin with the identification of green skills.

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[6] Martin et al (2012) find that energy managers have a positive impact on climate friendly innovation. Similarly, Hottenrott and Rexshouser (2013) report productivity improvements due to complementarity between the implementation of organizational practices and environmental technology adoption. Also Boyd and Curtis (2014) show that policies aimed at improving generic management practice trigger positive spillovers on firms' productivity.

3 Identification and Measurement of Green Skills

This section is organized in three parts. The first offers a critical review of previous and current work on green occupations and green skills. The second subsection details a novel data-driven methodology for identifying the core green skills within the US workforce. In the last part we propose a conceptual and empirical validation of our findings.

3.1 Green Jobs vs. Green Skills

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 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). A look at ongoing work by national statistical agencies corroborates this view. In 2010 the US Bureau of Labor Statistics (BLS) launched the Green Jobs Initiative, a scheme aimed at gathering information on the scale, the trends as well as the industrial, occupational, and geographic distributions of green jobs. Drawing on multiple sources, the BLS circulates a mail survey, the Green Goods and Services, among a sample of establishments identified as potentially producing such products and services on the basis on their NAICS classification. Under this approach, the criteria for capturing green jobs are two, namely the output approach ("jobs in businesses that produce goods or provide services that benefit the environment or conserve natural resources") or the process approach ("jobs in which workers' duties involve making their establishment's production processes more environmentally friendly or use fewer natural resources").[7] Although this evidence indicates that green employment in 2011 was just 2.4% of the total US workforce (Deschenes, 2013), several projections forecast significant growth in green

[7] http://www.bls.gov/green/home.htm (Last access: 28 February, 2015)

employment over the next two decades (UNEP, 2008; UNEP, 2012). [8] Arguably, however, these estimates are rather sensitive to where the boundaries of the green economy lie and to what assumption are made regarding its expansion (Deschenes, 2013). In addition, such an approach ignores the heterogeneous nature of know-how and the ways in which it feeds into human labour that were elucidated by task-based model (e.g. ALM).

Another suitable resource is the ‘Green Economy’ program developed by the Occupational Information Network (O*NET) under the auspices of the US Department of Labor. The core of O*NET is a rich database containing occupation-specific information on skill occupational requirements and tasks performed on the job since the early 2000. Therein data encompass multiple aspects of human labour, namely information on tasks performed on the job, on minimal education and experience requirements for each occupation and on characteristics of the attending work context. These categories are organized in detailed descriptors to which expert evaluators and job incumbents assign quantitative ratings on the basis of questionnaire data on a representative sample of US firms. The Green Economy program of O*NET is of interest for the present paper because it facilitates the identification of the skill content of green jobs. These are classified in three groups: (i) existing occupations that are expected to be highly in 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). Arguably, 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’. At the same time while acknowledging the intrinsic value of green job classification of O*NET, we find that this classification may be too coarse and misleading even for the greener occupations within the

[8] A recent study on the US by Elliot and Lindley (2014) finds that the within industry correlation between productivity growth and intensity of green employment is negative and, also, that fast-growing industries featured overall lower intensity of production of green goods and services.

NE and GE groups. Indeed the descriptions of some items within the O*NET catalogue of green occupations raises questions concerning the use of the 'full green' attribute for, among others, Chemical Engineers, Electric Engineers, Financial Analysis, Rail-track Operators or Metal Sheet Workers. Rather than the entire skill set of these and other GE and NE occupations being 'green', we observe that only a fraction can be realistically thought of as attuned to environmental purposes.

3.2 A methodology for the identification of Green Skills

Fortunately O*NET allows for a finer distinction between green and non-green tasks, at least for a sub-set of tasks that are occupation-specific. Thereby, consistent with standard human capital theory (Becker, 1975), O*NET provides information on 'general' tasks, which are common to all occupations, and tasks that are instead specific to each occupation. Different from general tasks, whose importance for any given occupation is defined on a continuous scale, specific tasks are a binary characteristic. The Green Task Development Project of O*NET enriches this distinction for 'New & Emerging' and 'Green-Enhanced' occupations by partitioning the set of specific tasks into green and non-green. By way of example, Metal Sheet 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 metalworking 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.

Using the distinction between green and non-green specific tasks, a first intuitive measure of skill *Greenness* is the ratio between the number of green specific tasks and the total number of specific tasks performed by an occupation *k*:

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

Bearing in mind that the share of green specific tasks over the total number of specific tasks varies considerably within both GE and NE occupations, this indicator can be interpreted as a proxy of the time spent by an occupation in 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. Indeed, the indicator represents pretty well the greenness of an occupation as shown by examples in Table 1.[9] 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, also, with an ample spectrum of non-green tasks have an intermediate score, for example Electrical Engineers, Metal Sheet 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 and Table 2 about here]

At the same time we acknowledge that using the *Greenness* indicator as a pure measure of skills carries limitations to the effect of formulating policy recommendations. First, rather than giving information on the exact types of skills associated with green jobs, the indicator provides no more than a synthetic measure of the importance of green task within an occupation. Second, an indicator based on specific tasks is by definition not suitable to compare the skill profiles of green and non-green occupations and,

[9] The full list of green occupations and their greenness is reported in Table 2.

thus, to understand which non-green skills can be successfully transferred to green activities and which green skills should be targeted by educational programs. But 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). The identification is based on measures of general tasks retrieved from the release 17.0 (July 2012) of the O*NET database. Importance scores for 108 general skills and tasks are reported for 912 SOC 8-digit occupations.[10] In particular, we propose a two-step procedure. First, we regress the importance score[11] of each general task (or skill) *l* in occupation *k* on our greenness indicator plus a set of four-digit occupational dummies:

$$Task\_Imp_k^l = \alpha + \beta^l \times Greenness_k + D_k^{SOC\_3digit} + \varepsilon_k, \qquad (2)$$

where these regressions are weighted by the employment of the occupation. Occupational dummies ($D_k^{SOC\_3digit}$) 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

[10] 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 contained 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 Appendix B.
[11] 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).

Service (see Table 3).[12] Here, a positive (negative) and significant β^l denotes that task *l* is used more (less) intensively in greener occupations. Subsequently we assign the green label to the general task item *l* when the estimated $\hat{\beta}^l$ is statistically significant at 99%. To illustrate, a coefficient of 0.2 implies a 20% difference in importance of task *l* in occupation *k* that has greenness equal to 1 as opposed to similar occupations with greenness equal to zero. 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.[13] We use PCA only to cluster items into coherent macro-groups and build our final General Green Skill (GGS_k) skill index for each occupation *k* 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_k index is computed as the simple average between the importance score of 'Biology' and the importance score of 'Physics' (see Table 4).

As shown in Table 3, occupations with positive Greenness tend to be concentrated in macro-occupational groups (2-digit SOC) that are intensive in abstract skills e.g. Management, Business and Financial Operations, Architects and Engineers and Life, Physical, and Social Scientists. The polarization of green occupations in these high-level occupational groups explains in part the prevalence of high skills in our selection of GGS. This finding 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). Thereby our strategy yields four macro-groups

[12] The *Greenness* of an occupation is positive for 'Green-Enhanced' and 'New & Emerging' green occupations. The polarization of green occupations in 'high-skill' macro occupational groups partly explains the prevalence of high skills in our selection of green skills.
[13] In fact, we chose a slightly lower cut-off of 0.98 to include the GSS Science. Science appear together with engineering a core GGS when using more demanding selection criteria. In Appendix A we present further robustness exercises with different approaches to select our set of green general skills.

of Green General Skills that are high skilled, and are summarized in the first panel of Table 4.[14] In the next sub-section we will describe and validate these constructs in detail.

[Table 3 and Table 4 about here]

3.3 Preliminary validation

This section is devoted to commenting on and assessing the empirical constructs outlined in Table 4. For the goal of grounding our GGS_k index within the existing literature, in the absence of suitable scholarly work specifically focussed on green skills, we take as our main conceptual reference the wealth of empirical evidence elaborated in the context of policy reports produced by various international organizations. At the same time, we find it useful to explore commonalities with standard skill measures developed by the literature on routinization.

The first Green General Skills group, *Engineering & Technical Skills*, emerges consistently from several policy reports on Green jobs, especially for green building construction and wind turbine installations (Ecorys, 2008; UKCES, 2010). These hard skills encompass competences involved with the design, construction and assessment of technology usually mastered by engineers and technicians. Engineering skills are also an essential input for energy-saving R&D projects and programs aimed at reducing the environmental impacts of production activities.

The second item, *Science skills*, is directly related to the first since it also encompasses competences stemming from bodies of knowledge broad in scope and essential to innovation activities, for example Physics and Biology. According to a Cedefop (2009) study, this category of skills is especially in high

[14] The fifth group would only include *Geography*. We therefore excluded it from the main analysis due to the too narrow definition of this last component. Baseline results for Geography (and for all single items) are reported in Table 23 in the Appendix D.

demand at early stages of the value chains and in the utility sector. Although scientific and engineering knowledge can be highly transferable across domains of use, not all occupations that score high in these skills have high specific knowledge applicable to environmental issues. For instance, the occupations with high importance scores in this Green General Skill group are Environmental Scientists, Materials Scientists and Hydrologists, all having clear direct applications to environmental problems, as well as Biochemists, Biophysicists and Biologist, which instead are more general-purpose occupations (Rosenberg, 1998). Similar examples can be made for engineering professions, e.g. environmental engineers vs. civil engineers.

The third GGS set, *Operation Management skills*, includes know-how related to change in organizational structure required to support green activities and an integrated view of the firm through life-cycle management, lean production and cooperation with external actors, including customers. These skills have been observed to be relevant in two domains of influence (UNEP, 2007; Cedefop, 2009). The first involves the capacity to use and disclose information on products' and processes' characteristics that are relevant for the environment, such as energy-saving and emission accounting. Examples of professions intensive in these skills are related to the integration of green knowledge into organizational practices, i.e., sales engineers, climate change analysts and sustainability specialists. The second relates to adaptive management, that is, the capacity to identify environmental needs and to stir the dialogue across different stakeholders' groups, as is the case for Chief Sustainability Officers, supply chain managers and Chief sustainability officers Transportation Planners.

The fourth macro group, *Monitoring skills*, concerns technical and legal aspects of business activities that are fundamentally different way from the remit of Engineering or of Science. Rather than being directly involved in the design of new products and production methods, these skills are employed when assessing the observance of technical criteria and legal standards, i.e. regulatory requirements. The key occupations in this remit are Environmental Compliance Inspectors, Nuclear Monitoring

Technicians, Government Property Inspectors, Emergency Management Directors and Legal Assistants. The prominence of technical monitoring competences is documented in several policy reports, while the capacity of understanding the new environmental laws and regulations is key for firms operating in polluting sectors (UNEP, 2008; OECD/Cedefop, 2014).

A comparison of our green skills constructs with Autor and Dorn's (2013) Routine Task Intensity (RTI henceforth) index is useful to assess the extent to which work tasks can be replaced by computer capital. Such an index is computed as the difference between routine task scores –manual (RM) and cognitive (RC) – and non-routine task scores –interactive (NRI) and abstract (NRA), see Table 4.[15] The index increases together with the importance of routine tasks in each occupation, and declines the higher the importance of interactive and abstract tasks.

[Table 5 about here]

Against the backdrop of the conceptual validation outlined above, Table 5 presents some descriptive evidence of our GGS_k constructs. First, we observe that the employment share of green occupations is 11% in aggregate. Therein occupations with a low Greenness score (between 0 and 0.25) hold the lion share (8%) followed by Medium- and High-Greenness intensity with similar shares (1.5% and 1.8%, respectively). Interestingly the share of green employment weighted by the time spent in green activities (i.e. the greenness indicator) is 2.8%, which is rather close to the estimate reported by Deschens (2013) using the abovementioned approach based on the Green Good and Service survey. Further, as expected the scores of our GGS_k constructs among Green occupations are systematically

[15] The index is defined as $RTI = \log(RM + RC) - \log(NRA + NRI)$, with the single components (RM, RC, NRA and NRI) initially normalized to range between zero and five. We use the O*NET items proposed by Acemoglu and Autor (2011) to build these task constructs. Differently from previous works, we do not include non-routine manual task construct in the index because it displays a very high correlation with our routine manual task construct.

higher than for Non-Green occupations (middle part of Table 5). Looking at individual constructs, the gap is higher for Engineering skills across all occupations (more than 100%) and for Science and Operation Management among Medium- and High-Greenness occupations. Monitoring is the exception in that the gap with non-green occupations is rather homogeneous across occupations with varying degree of Greenness. Thus, the gap between Green and Non-Green occupations emerges as more pronounced for high-level skills.

Descriptive evidence in Table 5 corroborates our earlier remark that Green Occupations are less routine intensive than non-green ones, particularly so Medium-Green and High-Green. Lastly, when grafted onto a standard measure of human capital such as the required years of on-the-job training (O*NET), the bottom part of Table 5 suggests that only Medium-Green occupations have a significantly higher score than both Non-Green and High-Green occupations.

[Table 6 about here]

Table 6 indicates higher correlation of the greenness index with Engineering and Science skills compared to Monitoring and Operation Management skills. This is consistent with the robustness analysis showing that these hard skills are the true core green skills (see Appendix B). The coefficients reveal the highest correlations between Operation Management-Monitoring skills followed by Science-Engineering skills. While the latter reflects the mutual relevance of high-level scientific and technical skills, the former suggests strong complementarity between technical, organizational and legal competences involved in strategies to deal with environmental issues. The second part of Table 6 shows the correlations between our green skills measures and the routinization measures. Operation Management skills exhibit a marked non-routine character because they entail dealing with work environments that demand situational adaptability and communication, general and problem solving skills required by ICT technologies. Engineering and Science exhibit as expected a high positive correlation with NRA since they are all complex cognitive competences to allow the identification of problems and the design of problem-solving strategies. However, it is worth noting that the correlations of NRA with Science and Engineering are significantly lower than the one with Operation Management, and that engineering and technical has a higher correlation with routine manual takss than NRA tasks.[16]

Summing up, this section 3 has proposed a data-driven methodology for the identification of green skills based on occupation-specific data on the US workforce. The four core competences that emerge from this exercise are for the most part high-level analytical and technical skills markedly related to the design, production, management and monitoring of technology. In the next section these constructs will be put to assess the effects of environmental regulation on the demand for green skills.

4 Testing the relationship between Environmental Regulation and Green Skills

This section describes the data and the methodology used to validate our green skills measures. We propose a simple empirical strategy to disentangle the impact of a more stringent environmental regulation on the demand of Green Skills.

4.1 Data

Our analysis of the effect of ER on workforce skills is at the sector-by-state level. This level of regional aggregation is the most appropriate to preserve fine-grained information of the workforce skills at 4-digit NAICS industry level. Since the scale of green jobs and skills is still relatively small in US employment, preserving the maximum level of sectoral and occupation details is necessary for a correct

[16] The low correlation between NRA and Engineering & Technical and Science skills may be due to the fact that NRA is particularly important for *Computer and Mathematical occupations* (SOC code 15) for which no green occupation is observed.

measure of our variables of interest. This comes at the cost of not being able to exploit the time dimension in the data because detailed information on the distribution of the workforce by occupation, industry and state is only available for the years 2012 and 2013.

Our primary dependent variables are the four measures of GGS_k plus the greenness indicator built by weighting occupational skill measures by employment using the 2012 BLS 'Occupational Employment Statistics (OES) Research Estimates by State and Industry'. These data provide information on the number of employees by occupation (SOC 2010 6-digit), industry (4-digit NAICS) and state. We limit our analysis to industries effectively exposed to environmental regulation: utilities, manufacturing and construction.[17] We aggregate these average values of green skills for each 6-digit occupation, *k,* to compute the following index by industry *i* and state *j* as follows:

$$GGS_{ij} = \sum_k GGS_k \times \frac{L_{kij}}{L_{ij}}. \tag{3}$$

Here L_{kij} represents the employment in occupation *k*, industry *j* and state *i*, while L_{ij} is the employment in sector j and state i. Recall that GGS_k measures are normalized to vary between 0 and 1. Note that differences in our measures across industries and states depend exclusively on differences in the composition of the labour force (share of employees in occupation *k* in industry *i* and state *j*) whereas the green skills content of occupations (GGS_k) is defined at the occupational level and so it is not state-specific. Likewise, we can use equation (3) to construct sector-state skill measures based on the Greenness indicator, the routine intensity index or standard human capital measures such as training. When using the share of green specific skills as proxy of green skills, the effect should be taken with caution because this variable was constructed under the assumptions concerning the

[17] Taken together these three sectors account for more than 90% of air emissions from point sources for all the pollutants that we consider in our empirical analysis.

distribution of employment within 8-digit SOC category. Further details on the database construction are contained in the data Appendix B.

Our main explanatory variable is stringency of environmental regulation at the state-by-sector level proxied by air emission intensity of toxic substances and pollutants covered by the Clean Air Act (CAA), the most important federal piece of legislation aimed at reducing air pollution concentrations in the US.[18] Accordingly, our favourite regulatory measures are emissions of the six criteria pollutants identified by the EPA and subject to the CAA.[19] First introduced in the 1963, the CAA has been amended several times, the last major amendment dating back to 1990. The legislation sets county-specific attainment standards on concentration of pollutants and hazardous substances (NAAQS and NESHAPS, respectively).[20] Counties that fail to meet concentration levels for one or more substances (toxic substances or one or more of the six criteria pollutants) are designated as nonattainment areas, and the corresponding states are required to put in place implementation plans to meet federal concentration standards within 5 years.[21] Emissions of Criteria Pollutants 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).

[18] Brunel and Levinson (2015) review various approaches to proxy the stringency of environmental regulation and conclude that when the sectoral breakdown is sufficiently narrow emissions are the best proxies of environmental regulatory stringency because they reflect, by means of a continuous measure, the actual enforcement of regulation rather than purely legislative acts.
[19] Ozone-formation (sum of nitrogen oxides – NOx – and volatile organic compounds – VOC), particulate matter (PM) smaller than 2.5 micron, carbon monoxide, nitrogen oxides (NOx), sulphur dioxide (SO2) and lead. In the appendix, we show also results for the emissions of toxic substances retrieved from the Toxic Release Inventory (TRI) developed by the Environmental Protection Agency (EPA), a proxy of regulation used by related study of Carrion-Flores and Innes (2010).
[20] National Ambient Air Quality Standards (NAAQS) set maximum levels of concentration for the six criteria pollutants and National Emissions Standards for Hazardous Air Pollutants (NESHAP) set maximum levels of concentration of hazardous air pollutants.
[21] States may use a variety of policy tools to comply with concentration standards, such as creating a system of pollution permits or mandating the adoption of specific technologies.

The main advantage of using emissions as a proxy for ER 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.

[Table 7 about here]

shows basic descriptive evidence for the skill and regulatory measures by 3-digit NAICS industry. Briefly notice that the sectors where the share of engineering and science skills is highest are construction (NAICS 23) and Utilities (NAICS 22) respectively. These two sectors are exactly those indicated by the policy reports discussed in Section 3. In turn, Operation Management skills are higher in Oil and Gas extraction (NAICS 211), Utilities (NAICS 22) and Petroleum and Coal Products Manufacturing (NAICS 324) while Monitoring skills are most important in Utilities (NAICS 22) and Petroleum and Coal Products Manufacturing (NAICS 324). The Utilities sector, which includes the power generation sector, exhibits the greatest concentration of all categories of green skills as well as the highest level of emission intensity. This is closely followed by the Petroleum and Coal Products Manufacturing (NAICS 324), which is also a large employer of green skills intensive occupations. As expected, GGS are particularly important in few very emission intensive sectors.

4.2 Estimating equation

To explore the relationship between environmental regulation and green skills, we estimate the following equation for each of our four GGS_{ij} indices:

$$GGS_{ij} = \beta ER_{ij} + \boldsymbol{\gamma}\mathbf{X}_{\mathrm{ij}} + d_i + d_j + \varepsilon_{\mathrm{ij}}. \quad (4)$$

where i indexes sector and j indexes states; d_j are state effects absorbing unobservable factors that affect both skill demand and ER, such as the demand for sustainable products; d_i are three-digit NAICS industry dummies that intend to capture unobservable sectorial characteristics potentially affecting the demand of skills, i.e. technology; $\mathbf{X}_{ij}$ is a set of controls varying at the sector-by-state level; ε_{ij} is a conventional error term. Since our dependent variables adjust slowly to structural shocks, all explanatory variables are lagged by one or more years. In particular, environmental regulation (ER_{ij}) is measured as: $\log\left(1 + emission_{ij;2002-2011}\right) - \log\left(1 + employment_{ij;2011}\right)$.[22] We compute weighted average of emissions over the years 2002, 2005, 2008 and 2011 (see Appendix B), giving more weights to more recent years o account, at least in part, for regulatory stringency in the recent past. In addition, we use the logarithm to mitigate the influence of outliers in emissions, while expressing ER in per-employee terms to depurate the effect of sector size within the state.[23] For comparison, we also estimate versions of equation (4) that use other common measures of skills used in the literature, including the importance of routine and non-routine tasks and the years of training required. Further details on the data sources and the measurement of the variables included in the econometric analysis are given in the Appendix B.

The set of state-by-industry controls is included to separate the estimated effect of ER on workforce skills from structural factors likely to affect both variables. First, we include the log of the average plant size in year 2011 (employees per establishment, BLS), which is likely to be positively correlated

[22] Due to the absence of data on value added by 4-digit NAICS and state, we cannot follow the approach proposed by 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.

[23] It is worth remarking that these assumptions have no qualitative effects on our results, which remain qualitatively unchanged if, for instance, we allow the log in the number of employees to have an autonomous effect on the skill composition.

with both environmental regulation (Becker and Henderson, 2000; Becker et al, 2013) and the employment share of high skilled workers such as engineers or scientists (Doms et al, 1997; Berman and Bui, 2001). Second, we include 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 compositional effects. For example, workforce skills may be higher simply because under-performing firms relocate in countries or states with milder regulations and thus overall employment declines. Third, we include the log of the number of monitored facilities to control for the extent to which industrial and other mobile sources not included in the National Emission Inventory contribute to local emissions and consequently to the local concentration of toxic substances. States and industries with larger point sources are more easily targeted by emissions standards as opposed to those with more diffuse emission sources.

[Table 8 about here]

Table 8 shows that industry-by-state controls tend to be highly correlated with our measures of ER and hence should be included. In line with previous evidence (Becker and Henderson, 2000; Becker et al., 2013), the average size of a plant is significantly larger in sectors with higher emissions, while emissions per employee tend to be higher where more plants are subject to monitoring. Quite surprisingly, the sign of the correlation between different types of emissions and the past 10-years change in employment is negative but close to zero. Finally, polluting sectors tend to be slightly more exposed to import penetration. Since import penetration is a significant driver of changes in workforce skills, the interaction of ER and import shocks will be investigated in greater detail in what follows.

Two final remarks are in order. First, using state-level data may appear a limitation compared to recent studies using exogenous change in county level attainment status in terms of ER as research design

(Walker, 2011; 2013). However, county-level data do not contain the fine-grained occupational and sector details essential to distil all the possible information on a relatively small phenomenon such as green employment. Second, the effect of ER is identified within 3-digit sectors, thus it may be driven by sectoral differences across 4-digit sectors in each three digit block. We opted for the 3-digit sector specification with dummies to capture the effect of import penetration and of its interaction with ER. At the same time, as shown in Section 5, results are unaffected in a specification with 4-digit sector dummies.

4.3 Endogeneity

A causal interpretation of the estimated coefficient of ER in Equation 3 should rest on the assumption that, conditional to the set of controls, the correlation between ER and the error term is zero.[24] This assumption is likely to be violated in our empirical framework for at least two reasons. First, even in the favourite specification with three-digit industry dummies, sectors with a higher share of green workforce may be better equipped to reduce emission irrespective of the level of ER. Second, emissions are just a proxy of ER, which is likely to be affected by measurement errors. In particular, we cannot directly observe state policies in sector *i*, but only the effect of these policies on emissions. To comply with federal standards, which are based on local air concentrations of pollutants and toxic substances, states intervene by regulating point sources and other sources.[25] Moreover, air concentrations depend on other factors such as geographical features of the area and winds. However, the National Emission Inventory provides detailed information on industry and location of emissions only for point sources. The exclusion of non-point sources and the failure to account for other factors

[24] Controlling for the average plant size and the number of establishments monitored under the NEI, as we do, is clearly not enough to solve endogeneity problems because non-point sources and other local features affecting concentration of pollutants and hazardous substances can display huge variations within and between states.
[25] As observed by Shapiro and Walker (2015), the intervention of states and local authorities to reduce emissions are not limited to non-attainment counties, that are forced to reduce their pollution concentration, but also on attainment counties that need to keep their emissions low in order to avoid the risk of passing the pollution concentration thresholds and become non-attainment counties.

affecting emission concentrations create a gap between latent environmental regulatory stringency and actual emission intensities of point sources that may generate measurement errors in our proxies. The latent level of environmental regulatory stringency enacted by states depends on the presence of nonattainment areas within the state and on the risk that attainment areas may switch to the status of nonattainment areas.

Taken together these two sources of endogeneity make it difficult to predict the direction of gap between OLS and IV estimates. OLS are likely to underestimate the effect of ER in presence of measurement error but the direction of the omitted variable bias crucially depends on initial conditions which are hard to capture with cross sectional data. On the one hand, if green skills are essential to abate pollution, sectors that are initially better equipped with these skills have a comparative advantage in reducing emissions. On the other hand, stringent ER should disproportionally hit sectors that underperform in terms of emissions and lag behind in terms of technological competences required to reduce emissions, including green skills. Overall, endogeneity should be addressed to correctly identify the effect of ER on green skills, but it is difficult to make a reliable guess on the direction of the bias without resorting to panel data.

To address these concerns, we use the instrument of Carrion-Flores and Innes (2010) to address endogeneity in the effect of ER. Recall that Carrion-Flores and Innes (2010) estimate the effect of ER, measured using emission levels, on adoption of green technologies at the sector level.[26] The analogy with the present paper is that both technology and skills are complements in a hypothetical production, and thus emission, function. Thereby a successful empirical strategy should identify an instrument that is highly correlated with regulation but uncorrelated with skill or technology measures. Environmental enforcement activity is a valid candidate. On the one hand the instrument is likely to be a strong predictor of regulatory stringency given the support of a vast empirical literature showing that

[26] In their setting, the main source of endogeneity is reverse causality going from innovation to environmental regulation.

enforcement activities are a stimulus to abate emissions (Gray and Deily, 1996; Magat and Viscusi, 1990; Decker and Pope, 2006; Gray and Shimshack, 2011). On the other hand the instrument is likely to be uncorrelated with our skill measure other than through their effect on regulation. For the case of patents, Carrion-Flores and Innes (2010) claim that with the exception of effects due to "effective" environmental standards (i.e. emission levels) enforcement activity does not affect the adoption of environmental technologies. A similar argument applies to green skills since, different from environmental patents, GGS are sets of competences of a general character and are not exclusively employed to improve environmental performance and abate emissions.

Following on the above we account for endogeneity by instrumenting ER with the number of inspections and violations at sector-state level over the period 2000-2009 (Enforcement and Compliance History Online – ECHO, managed by the EPA, see Appendix B). Just as for the measure of ER, the instruments are expressed in per-employee terms (the Appendix C shows that the first-stage results corroborate our choice). We report in the regressions Tables that the excluded instruments display a partial F statistics well above the usual cut-off of 10 (Staiger and Stock, 1997). This result is not surprisingly and confirms the one obtained by Carrion-Flores and Innes (2010) exploiting the time variation of the data rather than the state variation. The next section illustrates the main results and presents a series of robustness checks.

5 Estimation Results

This section provides evidence on the positive effect of stringent ER on the demand for green skills. Recall that a higher emission level implies a weaker regulation, thus we expect a negative coefficient of ER on green skills. The main results are reported in Table 9. The top panel presents results for our measures of green skills, including the overall greenness indicator of an industry (column 1), or four green general skill importance scores (columns 2-5), and an average count of green specific tasks (column 6). For comparison, the bottom panel of Table 9 includes regression results using several standard measures of skills proposed by previous literature.

We focus on Instrumental Variable results only since endogeneity affects the reliability of OLS estimates of the effect of ER on workforce skills. As seen in the notes to Table 9, our instruments are strong, with a partial F-statistic for the excluded instruments of 112. Full first stages are reported in Table 24 the Appendix C. For the sake of space and since estimation results appear very similar across the six criteria pollutants, we report results for SO2 only and leave to Appendix C (Table 19 and Table 20) the results for other pollutants, including those in the complementary pollution data contained in Toxic Release Inventory. We focus on SO2 emissions since they are the criteria pollutant experiencing the greatest reduction over the period 2002-2011, and because a revision of the NAAQS for SO2 occurred in 2010.[27]

[Table 9 and Table 10 about here]

Our most important finding is that a lower level of SO2 emissions per capita (and hence stricter environmental regulation) increases demand for each of our general green skills.[28] To quantify the effect of environmental regulation on green skills, note that SO2 emissions decreased by more 50% between 2005 and 2011. In the absence of a clear target for criteria pollutant, we use this amount as a reasonable point of reference for the assessment of a long-term emissions reduction scenario. While the resulting magnitude appears quite small, since halving emissions would just increase the industry greenness by 0.002, note from Table 10 that the effective range of variation of our skill indicators is

[27] SO2 emissions shrunk by about 54 percent over the period 2002-2011, the reduction for CO emissions was 9 percent, for NOx emissions was 46 percent, for ozone emissions was 41 percent and for PM2.5 emissions was 34 percent. As already discussed, no information about emissions of lead was available in the NEI before 2011.

[28] It is also worth noting that the effect of ER is conditional to the average plant size and to the share of monitored plants. As expected and shown in the Tables, the latter variable has a positive and statistically significant effect on GGS. Results for these control variables are shown in Appendix C.

significantly smaller than the theoretical one (i.e. 0-1).[29] The inter-quartile range (IQR) between the 25th and 75th percentile of our various green skills indicators ranges from 0.05 for the greenness indicator to 0.133 for engineering skills. Since our dependent variable is essentially the mean of a qualitative index, we use inter-quartile changes to gauge the effective magnitude of the influence of environmental regulation on green skills and find that a 50% decrease in emissions increase industry greenness by 4.2% of a full inter-quartile range. It is worth noting that this result is fully driven by a positive and large effect of ER on green specific tasks, which see an increase equivalent to 8.2% of the inter-quartile range, rather than on the average count of non-green specific tasks (see columns 6 in the top Panel and 1 in the bottom Panel). Interestingly, environmental regulation increases demand for both hard technical skills and organization management skills. The largest increase in demand for green general skills occurs for operations management and science. A 50 percent reduction in emissions increases the importance of operations management by 12.6 percent of the inter-quartile range, and the importance of science skills by 9.5 percent of the inter-quartile range. Operations management skills are important for coordinating different aspects of the production processes to achieve sustainability goals, such as technical information, strategic problem-solving and marketing strategies.

Our results also indicate that the complexity of work increases with more stringent environmental regulation. The bottom Panel of Table 9 shows that more stringent ER increases demand for non-routine skills relative to routine skills as illustrated by the effect on the Autor and Dorn's (2013) Routine Task Intensity. This effect is the result of a positive effect of ER on the demand of non-routine (NR) skills and a negative one on the demand of routine manual (RM) skills. A 50 percent reduction in emissions increases the importance of NR skills, such as "thinking creatively", by almost 7.1% of the

[29] Throughout this section, we refer to a per-employee reduction in emissions, as used in the regressions. For ease of exposition, we omit the reference to per-employee in most cases. To calculate the emissions reductions, we compute the weighted average of emissions and employment for each sector/state observation, weighted by employment in 2012. We then calculate the change in our green skills indices from a given emissions abatement target $\bar{e}$ are calculated as: $\Delta GGS_{ij} = \hat{\beta} \times \log\left(\frac{aveEmis+1}{aveEmpl+1}\right) - \log\left(\frac{(1-\bar{e})aveEmis+1}{aveEmpl+1}\right)$.

inter-quartile range. In contrast, a 50 percent reduction in emissions reduces the importance of routine manual (RM) skills by 10.7 percent of the inter-quartile range. Notably, a more stringent ER does increase the demand of Routine Cognitive tasks, a category highly affected by the diffusion of information technologies and that experienced a considerable decline during the 1980s and the 1990s particularly in clerical occupations of the service industry (e.g., Acemoglu and Autor, 2011). This result is explained by the relatively high importance of RC skills for technical occupations, especially in the nuclear power sector (i.e. Nuclear Equipment Operation Technicians), and thus tends to disappear when we consider manufacturing sectors only.[30] Finally, the importance of training also increases as emissions fall, but the magnitude is small, with an elasticity of just -0.05, i.e. only one and half week in response to a 50 percent emission reduction.

In combination, these results support the conceptual framework outlined in Section 2, which suggests that, in the wake of a structural shock, firms rely on high-level competences to navigate the impending technological uncertainty. They are also consistent with previous literature on the effects of ICT technology on the task content of occupations, since skills associated with abstract reasoning and problem-solving are strong candidates for the successful implementation of technological and organizational changes necessary to deal with the opportunities and the challenges of emission abatement.

[Table 11 about here]

Table 11 shows that our results are generally robust to including 4-digit, rather than 3-digit, sector dummies with the exception of engineering skills and routine cognitive tasks. As expected, the magnitudes of the effects of ER on green general skills declines slightly when including 4-digit sector

[30] Table 21 in the Appendix C shows results of our baseline specification when considering manufacturing sectors only.

dummies. One exception is the effect of ER on engineering and technical skills, which is no longer statistically significant. However, the effect remains significant when considering only manufacturing, as seen in Table 21 and Table 22 in Appendix C.

5.1 Environmental Regulation and the Decline in Manufacturing Employment

To further explore the consequences of environmental regulation on the composition of employment, in this section we consider two additional specifications that allow us to frame our results in the broader picture of considerable decline in US manufacturing employment over the last two decades, which coincidences with the massive increase of China's presence in international trade (Pierce and Schott, 2012; Acemoglu at al., 2014). This contraction in employment has recently been touted as a possible source of improvement in workforce quality. The argument is that, as unskilled-intensive processes are relocated to labour-abundant countries such as China, the remaining US firms offset price competition by increasing output quality which, in turn, requires high-level skills.[31] By analogy, more stringent ER likely adds to the ongoing trade effect and induces further shrinking of high-emission sectors. However, it is a matter of debate whether the combination of high exposure to trade and regulatory shocks amplify the compositional effects found for trade by previous studies (e.g., Ng and Li, 2013).

[Table 12 about here]

First, we re-run our regressions while splitting our sample into expanding and contracting sectors in Table 12. If the bulk of the ER effect is concentrated in contracting sectors, the technical effect of needing new labour skills to reduce emissions would be fully dominated by the compositional effect of

[31] See in particular Bloom et al (2014) on this.

high polluting tasks moving to countries with weaker regulation and thus green technologies and management practices are not the true drivers of the observed shift in skill demand. Although as expected the effects of ER on our various green skills indicators are stronger in sectors where employment has decreased over the last 10-years, this effect remains positive and, with the exception of the overall Greenness index, statistically significant also in expanding sectors. Similarly, the bottom Panel of Table 12 shows that compositional effects influence the RTI index and the demand of NR tasks, but still do not completely cancel out the technical effect.

Our second additional specification adds import penetration, a standard measure of exposure to international competition, to our main specification in equation (4).[32] Import penetration is available only at the 4-digit NAICS sectors, thus trade effects are identified exploiting variation within 3-digit NAICS sectors. We use only manufacturing sectors in Table 13, since trade exposure is absent in utilities and construction. These results are presented in the odd columns of Table 13.

In the even columns of Table 13, we also include an interaction term between ER and import penetration. This interaction allows us to test whether the effect of ER on demand for skills is stronger in sectors facing greater import competition. This would be the case if, for example, greater import competition makes it easier for dirty industries to relocate to countries with weaker environmental standards. Finally, note that import penetration can also be endogenous to workforce skills. Sectors with high levels of productivity employ a larger share of high skilled workers and, at the same time, are able to escape international competition. Thus, we instrument import penetration using its lagged values (Autor and Dorn, 2013).

[Table 13 about here]

[32] We use data on bilateral trade by NAICS industry (Schott, 2008) combined with the NBER-CES Manufacturing Industry Database. Import penetration by NAICS industry is measured as the ratio between the value of import and the value of output consumed domestically (value of shipment plus import minus export), calculated using data from 2009.

The most important result, presented in odd Columns of Table 13, is that the qualitative effect of ER is not affected by the inclusion of import penetration. The one exception is years of training, which becomes insignificant. In line with previous research (Ng and Li, 2013), import penetration tends to increase the demand of high skilled workers, but the effect is significant only for the Greenness indicator and NR skills, including both RTI and the closely related GGS Operation Management. In the even Columns of Table 13, we present results for the interaction between import penetration and ER. Since stricter ER results in lower emissions, a negative sign indicates that ER has a stronger effect when import penetration is higher. As expected, the joint compositional effects of ER and import penetration reinforce each other for two GGS, Monitoring and Operation Management, as well as for more general non-routine tasks. Interestingly, the effect of ER on Monitoring skills is observed only in sectors with high exposure also to import competition. Conversely, high exposure to both regulatory and trade shocks decrease the demand of Engineering and Science skills relative to sectors with lower levels of exposure to import competition. However, the cut-off point at which the positive effect of reducing emissions becomes insignificant is reached occurs at the 75th percentile of import penetration. Overall, these results indicate that the compositional changes brought about by trade and ER reinforce each other for classical non-routine skills, but at the same time being over-exposed to trade and regulatory shocks may put an excessive burden on the firm and slightly reduce its capacity to attract scientific talents. These conclusions are admittedly preliminary and indicate a promising avenue for future research.

6 Conclusions

This paper takes a first step in filling a gap in our understanding of the incidence of environmental regulation in the labour market. To this end it has, first, identified a set of skills that define more closely green occupations and, secondly, has gauged 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). Of the four competences that emerge from this exercise all have a strong analytic and technical content, but only Operation Management has considerable overlap with the Non-routine skills that complement ICTs. In turn, the other green skills are more related to specific applications of Science and Engineering disciplines that require heavy investments in formal education.

Second, our findings concerning quantitative effects bear relevance for the design of policy. If a target of a 50% emission reduction entails a 9.5% increase of demand for scientists and a 4.5% of demand of engineering professions, education emerges as a critical ingredient in the policy mix to promote sustainable economic growth. Note that an increase in the supply of these skills would pin down the wages of engineers and scientists thus reducing the cost of adopting clean production methods and thus the harmful economic consequences of regulation.

Finally, our analysis suggests that compositional changes due to employment contraction among sectors that are highly exposed to trade and regulation drive only partially the positive effect of environmental regulation. The positive effect observed for expanding sectors can be more safely attributed to technological and organizational changes affecting the demand of skills. The interplay of compositional effects and pure technological effects requires, however, further investigations using panel data that allow decomposing the relative magnitude of the two effects.

Appendix A: Green Skills

This appendix discusses in detail the results of the selection of GGS. Table 14 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 4-digit SOC dummies. Out of 108 general skills and tasks, 16 have been selected as particularly relevant for green occupations.

[Table 14 and Table 15 about here]

As anticipated in section 3.2, 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 15 shows the factor loadings of the 5 rotated components (orthogonal VARIMAX rotation) that exceeded a 0.2 threshold. The first component groups together what we define Engineering & Technical Skills. The second component, that we label Operation Management Skills, is composed by a group of skills relevant to coordinate management practices with new technical devices. In the third component we observe three general skills that we label Monitoring Skills. In this component we observe, however, that two of the 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, in turns, loads negatively on the second component. Moreover, from careful reading of the description of these skills, we noted that while the first two clearly define different aspects of Monitoring Skills, the third one does not relate directly to monitoring skills. We thus decided to exclude this variable from the monitoring skills construct. The fourth component clearly refers to Science Skills. Finally, the fifth components is characterized by a big factor loading from Geography (0.84) and a smaller loading from Law and Government (that was, however, already assigned to component 3). 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 refer to one general skill, we do not include it in the main analysis. Results on the impact of ER for this GGS and for each single

general skill selected here (including “Operating Vehicles, Mechanized Devices, or Equipment” and “Geography”, that were excluded from the GGS constructs) are discussed in the Appendix D.
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 for its number of employees in year 2012[33]. Note that this is not our favourite selection method because it assigns excessive 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 16. This second method only retain 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 appear to be the set of core technical and scientific skills that are 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 component 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 17. 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).

Appendix B: Data

*O*NET and BLS data*

Our set of skill measures is built using occupation-industry-state employment levels from BLS to weight O*NET data of occupational skills. We use the release 17.0 (July 2012) of O*NET and employment figures for the year 2012. 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

[33] 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.

year 2012 (Occupational Employment Statistics, BLS), detailed information (6-digit SOC occupation[34] by 4-digit NAICS industry) by state is available for 14,882,610 employees, that is 78.6 percent of the total.

It is also worth recalling that the mismatch between the aggregation of the O*NET database and the Occupational Employment Statistics has been addressed 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 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 only viable option.

Construction of the skill measures

Skill measures at the industry-state level are built using equation 3, i.e. $GGS_{ij} = \sum_k GGS_k \times \frac{L_{kij}}{L_{ij}}$.

Importance scores 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, potentially, between 0 and 1 (we subtract 1 and divide by 4 each item that enters GGS_k). Some of the items that are needed for the construction of the RC indicators suggested by Acemoglu and Autor (2010) are ‘Work context’ (labelled as ‘cx’ in Table 4). Scores for ‘Work context’ items refer, depending on the specific item, on the importance, frequency or other dimensions of the work context analysed. Scores, that range from 1 to 5, have been rescaled to vary between 0 and 1 in the same way as importance scores.

Emissions

We retrieve information on the six criteria pollutants regulated by the Clean Air Act (SO2, NOx, VOC, lead, ozone and PM 2.5) and on the hazardous substances subject to the National Emissions Standards for Hazardous Air Pollutants (NESHAPS). Emissions for criteria pollutants from point sources are collected by the EPA every third year and published in the National Emission Inventory (NEI) database at the facility level while releases of hazardous substances from point sources are collected every year by the EPA and published in the Toxic Release Inventory (TRI). For both NEI and TRI, the obligation to report emissions concerns facilities above certain size and emission thresholds. While the thresholds

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

for TRI are set at the federal level[35], thresholds for the NEI are set at the state level. For what concerns hazardous substances in the TRI, from the initial list of chemical substances we selected 148 subject to concentration standards under the 1990 CAA Amendments for which we have information on the toxicity potential and weight toxic emissions accordingly.[36]

For both criteria pollutants and emissions of hazardous substances, we assigned emissions to the main 4-digit NAICS industry and state in which the polluting facility operates. We employ weighted average of emissions in the years 2002, 2005, 2008 and 2011. The weights are such that emissions at t are weighted half as much as emissions at t+3. The weights for 2002, 2005, 2008 and 2011 are, respectively, 0.0667, 0.1333, 0.2667 and 0.5333. Lead emissions are available for 2011 only. Results remain unaffected when choosing different weighting. Trends in total emissions of criteria pollutants for point sources in the US are reported in Table 18. We divide emissions by the number or employees by industry and state in year 2011 (Quarterly Census of Employment and Wages, BLS).

[Table 18 about here]

Instrumental variables

We instrument our proxy of regulatory stringency, that is emissions per employee, with the number of violations and the number of (full) inspections by industry (main NAICS 4-digit code of the facility) and state. Information on violations and inspections is retrieved from the Enforcement and Compliance History Online (ECHO) database maintained by the EPA. We count full inspections[37] and violations[38] per employee (2009) registered in the period 2000-2009.

[35] The obligation to submit a TRI report concerns facilities employing 10 or more full-time equivalent employees and manufacturing, processing or using TRI-listed chemicals above certain thresholds. More specifically, facilities should manufacture or process more than 25,000 lbs. of a TRI-listed chemical or use more than 10,000 lbs. of a listed chemical in a given year.

[36] We use average toxicity weights for inhalation unit risk and oral slope factors from the EPA's Risk-Screening Environmental Indicators (RSEI) (EPA, 2013).

[37] As suggested in the guidelines of ECHO (http://echo.epa.gov/files/echodownloads/AFS_Data_Download.pdf), full inspections correspond to the following codes of the field 'NATIONAL_ACTION_TYPE': FF (STATE CONDUCTED FCE/OFF-SITE), FS (STATE CONDUCTED FCE/ON-SITE), FE (EPA FCE/ON-SITE - FCE = Full Compliance Evaluation), FZ (EPA CONDUCTED FCE/OFF-SITE), 1A (EPA INSPECTION - LEVEL 2 OR GREATER), and 5C (STATE INSPECTION - LEVEL 2 OR GREATER).

[38] We record violations of any of the pollutants regulated by the EPO.

Appendix C: Additional information and robustness checks for results discussed in Section 5

[Table 19, Table 20 Table 23 about here]

Appendix D: Results for single items of skills

In this appendix we briefly discuss results of our baseline specification when using each single general skill that results to be a ‘green skill’ according to our selection procedure (see Appendix). We have a total of 16 green general skills that have been selected as described in Section 3.2 and Appendix A. Results for our baseline specification (see Section 4.2) for these general skills are reported in Table 27.

[Table 27 about here]

First, we observe a positive and significant relationship between environmental regulatory stringency and the demand for skills (negative sign for our proxy of regulatory stringency), both with 3-digit and 4 digit NAICS dummies, for 8 out of 16 general skill measures while for other 3 general skill measures the relationship holds only for one of the two specifications while it is not statistically significant for the other. For the remaining 5 measures (including Geography), a positive sign is observed for Operating Vehicles, Mechanized Devices, or Equipment (that did not enter any GGS measure), no significant relationship is found for Building and Construction, Estimating the Quantifiable Characteristics of Products, Events, or Information and Evaluating Information to Determine Compliance with Standards while we observe a change in the sign, from negative to positive when moving from 3-digit NAICS dummies to 4-digit NAICS dummies, for Mechanical skills. All in all, results for our GGS measures are confirmed for most of the items that enter the GGS construct themselves.

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Main tables

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 – 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

SOC 2010	Title	Greenness	Total spec tasks	Green spec tasks
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
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

SOC 2010	Title	Greenness	Total spec tasks	Green spec tasks
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 3 - Distribution of occupations and green occupations (8-digit SOC) across macro-occupations

SOC 2-digit	Tot N of occupations	Green occupations (greenness>0)
11 - Management	47	15
13 - Business and Financial Operations	46	10
15 - Computer and Mathematical	29	2
17 - Architecture and Engineering	61	32
19 - Life, Physical, and Social Science	58	17
21 - Community and Social Service	14	0
23 - Legal	8	1
25 - Education, Training, and Library	58	0
27 - Arts, Design, Entertainment, Sports, and Media	43	2
29 - Healthcare Practitioners and Technical	83	1
31 - Healthcare Support	17	0
33 - Protective Service	28	0
35 - Food Preparation and Serving Related	16	0
37 - Building and Grounds Cleaning and Maintenance	8	0
39 - Personal Care and Service	32	0
41 - Sales and Related	22	2
43 - Office and Administrative Support	61	1
45 - Farming, Fishing, and Forestry	16	0
47 - Construction and Extraction	59	11
49 - Installation, Maintenance, and Repair	54	6
51 - Production	109	8
53 - Transportation and Material Moving	52	3
Total	921	111

Table 4 –Skills measures from O*NET: Green and Classic

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

Table 5 - Descriptive statistics by level of *Greenness*

	Non-green 0	Low greenness (0,0.25]	Medium greennes (0.25,0.5]	High greennes (0.5,1]	Total
N occupations	810	56	28	27	921
Empl share	0.8895	0.0819	0.0159	0.0127	1
Empl share (weighted with greenness)	-	0.0098	0.0054	0.0126	0.0278
Engineering & Technical	0.176	0.409	0.546	0.493	0.205
Science	0.428	0.472	0.584	0.552	0.436
Operation Management	0.132	0.185	0.276	0.340	0.142
Monitoring	0.444	0.489	0.559	0.551	0.451
Routine task intensity	-0.112	-0.188	-0.388	-0.362	-0.126
Years of training	1.63	1.347	2.148	1.451	1.613

N=921 occupations (8-digit SOC). Averages weighted by employment in 2012 at the 6-digit occupation level.

Table 6 – Correlation between skill measures

	Engineering & Technical	Science	Operation Management	Monitoring	Greenness	Routine task intensity	Routine cognitive tasks	Routine manual tasks	Non-routine analytical tasks	Non-routine interactive tasks	Log(Years of training)
Engineering & Technical	1.00	0.45	0.26	0.14	0.38	0.01	-0.21	0.30	0.20	0.05	0.10
Science		1.00	0.42	0.34	0.24	-0.23	-0.19	0.02	0.38	0.31	0.15
Operation Management			1.00	0.65	0.16	-0.75	-0.20	-0.48	0.90	0.75	0.14
Monitoring				1.00	0.13	-0.50	-0.02	-0.35	0.64	0.53	0.05
Greenness					1.00	-0.09	-0.14	-0.01	0.14	0.01	0.02
Routine task intensity						1.00	0.57	0.83	-0.79	-0.75	-0.23
Routine cognitive tasks							1.00	0.29	-0.21	-0.30	-0.34
Routine manual tasks								1.00	-0.52	-0.43	-0.08
Non-routine analytical tasks									1.00	0.67	0.14
Non-routine interactive tasks										1.00	0.22
Log(Years of training)											1.00

N=921 occupations (8-digit SOC). Pairwise correlations weighted by employment in 2012 at the 6-digit occupation level.

Table 7 – Descriptive statistics by industry

NAICS	Engineering & Technical	Science	Operation Management	Monitoring	Greenness	RTI	Non-routine tasks	Years of training	Log(SO2/L)	Import penetration
211	0.388	0.236	0.514	0.520	0.070	-0.310	0.5650	1.815	9.638	-
212	0.454	0.210	0.414	0.491	0.040	0.106	0.4710	1.451	7.834	-
213	0.406	0.209	0.415	0.469	0.037	0.070	0.4875	1.748	2.119	-
221	0.400	0.256	0.491	0.527	0.046	-0.225	0.5620	1.861	11.511	-
236	0.506	0.188	0.416	0.491	0.066	-0.160	0.5185	1.783	2.129	-
237	0.485	0.206	0.397	0.479	0.075	-0.038	0.4995	1.729	2.827	-
238	0.502	0.198	0.421	0.477	0.072	-0.090	0.5010	2.257	1.642	-
311	0.296	0.131	0.347	0.379	0.024	0.195	0.4380	1.388	5.235	0.038
312	0.284	0.102	0.393	0.380	0.023	0.024	0.4680	1.088	6.651	0.086
313	0.302	0.118	0.379	0.354	0.015	0.205	0.4575	1.030	6.901	0.036
314	0.266	0.072	0.351	0.328	0.013	0.255	0.4195	1.709	5.706	0.109
315	0.252	0.066	0.349	0.325	0.011	0.240	0.4150	1.830	2.994	0.253
316	0.270	0.061	0.316	0.324	0.010	0.236	0.3980	1.295	5.012	0.509
321	0.354	0.102	0.357	0.363	0.021	0.177	0.4470	1.401	6.019	0.096
322	0.349	0.121	0.428	0.386	0.039	0.049	0.5080	1.663	7.378	0.115
323	0.311	0.089	0.406	0.360	0.016	0.050	0.4770	1.205	3.122	0.014
324	0.397	0.195	0.490	0.478	0.057	-0.130	0.5390	1.231	11.922	0.031
325	0.357	0.190	0.466	0.460	0.044	-0.076	0.5210	1.134	7.102	0.083
326	0.329	0.119	0.387	0.389	0.035	0.131	0.4660	1.365	4.560	0.024
327	0.360	0.133	0.405	0.430	0.056	0.056	0.4735	1.209	9.745	0.109
331	0.378	0.138	0.399	0.388	0.029	0.133	0.4665	1.340	8.529	0.140
332	0.381	0.131	0.402	0.391	0.036	0.079	0.4755	1.505	3.755	0.041
333	0.394	0.143	0.432	0.414	0.047	-0.021	0.5000	1.531	3.799	0.075
334	0.384	0.169	0.494	0.458	0.064	-0.271	0.5520	1.331	3.004	0.091
335	0.354	0.136	0.411	0.426	0.042	-0.010	0.4945	1.376	4.791	0.112
336	0.398	0.150	0.437	0.436	0.057	-0.024	0.5045	1.608	4.245	0.138
337	0.369	0.095	0.368	0.370	0.016	0.150	0.4515	1.412	4.423	0.103
339	0.331	0.133	0.425	0.416	0.043	-0.059	0.5055	1.496	3.404	0.130
Total	0.404	0.163	0.418	0.437	0.050	-0.021	0.4955	1.646	4.244	0.051

N=3328 industry-state pairs. Averages weighted by employment in 2012 at the state and NAICS 4-digit level.

Table 8 – Correlation between covariates

	Log(SO2/L)	Log(ozone/L)	Log(CO/L)	Log(NOx/L)	Log(PM2.5/L)	Log(lead/L)	Log(TRI/L)	Log(count NEI plants)	Empl growth 2002-2011	Log(empl/N estab)	Import penetration
Log(SO2/L)	1.00	0.79	0.88	0.90	0.87	0.78	0.52	0.38	-0.03	0.37	0.11
Log(ozone/L)		1.00	0.92	0.94	0.91	0.69	0.59	0.66	-0.06	0.52	0.06
Log(CO/L)			1.00	0.97	0.94	0.77	0.59	0.57	-0.03	0.49	0.14
Log(NOx/L)				1.00	0.94	0.75	0.59	0.59	-0.03	0.50	0.11
Log(PM2.5/L)					1.00	0.79	0.58	0.54	-0.05	0.44	0.08
Log(lead/L)						1.00	0.54	0.26	-0.07	0.34	0.16
Log(TRI/L)							1.00	0.35	-0.05	0.48	0.07
Log(count NEI facilities)								1.00	-0.08	0.38	-0.14
Empl growth 2002-2011									1.00	0.11	-0.05
Log(empl/N estab)										1.00	0.18
Import penetration											1.00

N=3328 industry-state pairs. Pairwise correlation weighted by employment in 2012 at the state and NAICS 4-digit level. * p<0.05.

Table 9 – Impact of environmental regulation on skills (with 3-digit NAICS dummies)

	Greenness	Engineering & Technical	Science	Operation Management	Monitoring	Green specific tasks
log(SO2/L)	-0.00303***	-0.00878***	-0.0110***	-0.0134***	-0.00466***	-0.211***
	(0.000974)	(0.00193)	(0.00155)	(0.00271)	(0.00118)	(0.0461)
Hansen test (p-value)	0.241	0.699	0.250	0.648	0.849	0.251
	Non-green specific tasks	RTI	NR tasks	R manual	R cognitive	Log(Years of training)
log(SO2/L)	-0.0557	0.0268***	-0.00479***	0.0192***	-0.00259***	-0.0504***
	(0.121)	(0.00578)	(0.00143)	(0.00278)	(0.000814)	(0.0126)
Hansen test (p-value)	0.878	0.815	0.526	0.889	0.996	0.875

N=3328 industry-state pairs. Standard errors clustered by state and 3-digit NAICS in parenthesis. * p<0.10, ** p<0.05, *** p<0.01. Regressions weighted by employment in 2012 at the state and NAICS 4-digit level. Controls not shown: growth rate of employees 2002-2012; log average establishment size (employees per establishment) in 2012; log of the count of facilities reporting to the NEI; NAICS 3-digit dummies, state dummies. IVs: log of violation (2000-2009) per employee (2009); log of full inspection (2000-2009) per employee (2012). Partial F of excluded IVs: 112.

Table 10 – Descriptive statistics of our main dependent variables

Variable	Average	S.D.	Min	25th percentile	Median	75th percentile	Max	IQR
Greenness	0.050	0.036	0.000	0.023	0.044	0.073	1.000	0.050
Engineering & Technical	0.404	0.081	0.062	0.339	0.396	0.471	0.716	0.133
Science	0.163	0.054	0.011	0.122	0.159	0.202	0.621	0.080
Operation Management	0.418	0.055	0.177	0.381	0.409	0.455	0.718	0.074
Monitoring	0.437	0.054	0.210	0.392	0.441	0.479	0.678	0.087
Green specific tasks	1.881	1.356	0.000	0.903	1.666	2.668	35.000	1.765
Non-green spec tasks	25.796	4.474	8.000	23.129	25.897	28.296	219.000	5.167
RTI	-0.021	0.174	-1.109	-0.155	-0.010	0.096	0.726	0.251
NR tasks	0.496	0.043	0.278	0.472	0.493	0.518	0.764	0.047
R manual	0.518	0.081	0.104	0.453	0.528	0.578	0.837	0.124
R cognitive	0.459	0.025	0.280	0.440	0.460	0.477	0.611	0.037
log(Years of training)	0.458	0.287	-1.556	0.302	0.440	0.604	1.465	0.302

N=3328 industry-state pairs. Statistics weighted by employment in 2012.

Table 11 – Impact of environmental regulation on skills (with 4-digit NAICS dummies)

	Greenness	Engineering & Technical	Science	Operation Management	Monitoring	Green specific tasks
log(SO2/L)	-0.00251*	-0.00171	-0.00305**	-0.00855***	-0.00258**	-0.0941
	(0.00138)	(0.00209)	(0.00148)	(0.00183)	(0.00126)	(0.0641)
Hansen test (p-value)	0.746	0.536	0.227	0.641	0.498	0.768
	Non-green specific tasks	RTI	NR tasks	R manual	R cognitive	Log(Years of training)
log(SO2/L)	-0.149	0.0319***	-0.00654***	0.0158***	0.00152**	0.00571
	(0.173)	(0.00563)	(0.00137)	(0.00261)	(0.000759)	(0.00778)
Hansen test (p-value)	0.209	0.470	0.435	0.386	0.554	0.117

N=3328 industry-state pairs. Standard errors clustered by state and 3-digit NAICS in parenthesis. * p<0.10, ** p<0.05, *** p<0.01. Regressions weighted by employment in 2012 at the state and NAICS 4-digit level. Controls not shown: growth rate of employees 2002-2012; log average establishment size (employees per establishment) in 2012; log of the count of facilities reporting to the NEI; NAICS 4-digit dummies, state dummies. IVs: log of violation (2000-2009) per employee (2009); log of full inspection (2000-2009) per employee (2009). Partial F of excluded IVs: 42.35.

Table 12 - Impact of environmental regulation on skills: contracting vs growing industries

	Greenness		Engineering & Technical		Science		Operation Management	
	Contracting	Growing	Contracting	Growing	Contracting	Growing	Contracting	Growing
log(SO2/L)	-0.00345**	-0.00205	-0.0115***	-0.00597*	-0.0127***	-0.0109***	-0.0178***	-0.00971**
	(0.00137)	(0.00197)	(0.00255)	(0.00358)	(0.00213)	(0.00291)	(0.00376)	(0.00413)
Hansen test (p-value)	0.792	0.0263	0.978	0.370	0.928	0.310	0.482	0.532
	Monitoring		RTI		Non-routine tasks		Log(Years of training)	
	Contracting	Growing	Contracting	Growing	Contracting	Growing	Contracting	Growing
log(SO2/L)	-0.00568***	-0.00450**	0.0345***	0.0174*	-0.00661***	-0.00311	-0.0645***	-0.0751***
	(0.00164)	(0.00192)	(0.00811)	(0.00956)	(0.00204)	(0.00221)	(0.0174)	(0.0259)
Hansen test (p-value)	0.625	0.897	0.542	0.310	0.323	0.361	0.563	0.286

Contracting state-industy pairs: N=2381; growing state-industry pairs: N=945. Standard errors clustered by state and 3-digit NAICS in parenthesis. * p<0.10, ** p<0.05, *** p<0.01. Regressions weighted by employment in 2012 at the state and NAICS 4-digit level. Controls not shown: growth rate of employees 2002-2012; log average establishment size (employees per establishment) in 2012; log of the count of facilities reporting to the NEI; NAICS 3-digit dummies, state dummies. IVs: log of violation (2000-2009) per employee (2009); log of full inspection (2000-2009) per employee (2009). Partial F of excluded IVs in 'contracting sectors': 76.69. Partial F of excluded IVs in 'growing sectors': 24.16.

Table 13 - Impact of environmental regulation on skills: import penetration

	Greenness		Engineering & Technical		Science		Operation Management	
log(SO2/L)	-0.00360***	-0.00279**	-0.00543***	-0.00797***	-0.00655***	-0.00841***	-0.00931***	-0.00771***
	(0.00110)	(0.00128)	(0.00208)	(0.00274)	(0.00132)	(0.00167)	(0.00256)	(0.00289)
Imp. penetr 2009	0.0704***	0.143**	0.0145	-0.207***	0.0172	-0.142**	0.121***	0.262***
	(0.0186)	(0.0691)	(0.0211)	(0.0774)	(0.0196)	(0.0718)	(0.0252)	(0.0914)
log(SO2/L) x Imp. penetr 2009		-0.0106		0.0326***		0.0234**		-0.0208*
		(0.00934)		(0.0108)		(0.00936)		(0.0121)
Hansen test (p-value)	0.476	0.681	0.927	0.798	0.346	0.796	0.512	0.710
	Monitoring		RTI		NR tasks		Log(Years of training)	
log(SO2/L)	-0.00203**	0.000185	0.0271***	0.0183**	-0.00439***	-0.00244	-0.00432	-0.00640
	(0.00102)	(0.00118)	(0.00632)	(0.00713)	(0.00160)	(0.00184)	(0.00719)	(0.00824)
Imp. penetr 2009	0.0632***	0.256***	-0.402***	-1.182***	0.0730***	0.245***	-0.101	-0.245
	(0.0142)	(0.0777)	(0.0734)	(0.300)	(0.0165)	(0.0653)	(0.0980)	(0.366)
log(SO2/L) x Imp penetr 2009		-0.0284***		0.115***		-0.0253***		0.0219
		(0.00982)		(0.0384)		(0.00864)		(0.0481)
Hansen test (p-value)	0.302	0.300	0.232	0.321	0.371	0.499	0.0644	0.187

N=2603 industry-state pairs (only manufacturing sectors). Standard errors clustered by state and 3-digit NAICS in parenthesis. * p<0.10, ** p<0.05, *** p<0.01. Regressions weighted by employment in 2012 at the state and NAICS 4-digit level. Controls not shown: growth rate of employees 2002-2012; log average establishment size (employees per establishment) in 2012; log of the count of facilities reporting to the NEI; NAICS 3-digit dummies, state dummies. IVs: log of violation (2000-2009) per employee (2009); log of full inspection (2000-2009) per employee (2009), import penetration (2005). Additional IVs for specifications with the interaction between log(SO2/L) and import penetration: interactions between log of violation (2000-2009) per employee (2009) and log of full inspection (2000-2009) per employee (2009) with import penetration (2005). Partial F of excluded IVs in the specification without the interaction: 68.38. Partial F of excluded IVs in in the specification with the interaction: 41.57.

Tables for Appendix A

Table 14 – 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 15 – 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 16 – 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 17 – 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 18 – Trends in total criteria pollutants emissions (2002=100)

	SO2	CO	NOx	Ozone	PM2.5
2002	1.00	1.00	1.00	1.00	1.00
2005	0.99	1.04	0.87	0.88	0.98
2008	0.75	0.97	0.75	0.75	0.82
2011	0.46	0.91	0.56	0.59	0.66

Tables for Appendix C

Table 19 - Impact of environmental regulation on skills: alternative regulation measures (I)

	Greenness	Engineering & Technical	Science	Operation Management	Monitoring	Green spec tasks
Log(ozone/L)	-0.00273***	-0.00784***	-0.00988***	-0.0120***	-0.00417***	-0.189***
	(0.000845)	(0.00161)	(0.00127)	(0.00227)	(0.000996)	(0.0383)
Hansen test (p-value)	0.262	0.640	0.296	0.722	0.910	0.285
	Greenness	Engineering & Technical	Science	Operation Management	Monitoring	Green spec tasks
Log(CO/L)	-0.00299***	-0.00880***	-0.0110***	-0.0134***	-0.00465***	-0.209***
	(0.000948)	(0.00181)	(0.00146)	(0.00265)	(0.00114)	(0.0442)
Hansen test (p-value)	0.214	0.889	0.146	0.487	0.702	0.206
	Greenness	Engineering & Technical	Science	Operation Management	Monitoring	Green spec tasks
Log(NOx/L)	-0.00295***	-0.00874***	-0.0109***	-0.0133***	-0.00462***	-0.207***
	(0.000940)	(0.00178)	(0.00143)	(0.00259)	(0.00114)	(0.0433)
Hansen test (p-value)	0.198	0.948	0.115	0.438	0.659	0.177
	Greenness	Engineering & Technical	Science	Operation Management	Monitoring	Green spec tasks
Log(PM2.5/L)	-0.00314***	-0.00885***	-0.0112***	-0.0136***	-0.00472***	-0.216***
	(0.000947)	(0.00177)	(0.00137)	(0.00243)	(0.00107)	(0.0435)
Hansen test (p-value)	0.325	0.464	0.517	0.969	0.916	0.409
	Greenness	Engineering & Technical	Science	Operation Management	Monitoring	Green spec tasks
Log(lead/L)	-0.00378***	-0.0110***	-0.0137***	-0.0167***	-0.00581***	-0.263***
	(0.00121)	(0.00237)	(0.00190)	(0.00357)	(0.00147)	(0.0582)
Hansen test (p-value)	0.245	0.722	0.225	0.601	0.817	0.261
	Greenness	Engineering & Technical	Science	Operation Management	Monitoring	Green spec tasks
Log(TRI/L)	-0.00321***	-0.00978***	-0.0120***	-0.0147***	-0.00513***	-0.227***
	(0.00111)	(0.00207)	(0.00188)	(0.00303)	(0.00137)	(0.0543)
Hansen test (p-value)	0.141	0.755	0.0717	0.193	0.435	0.105

N=3328 industry-state pairs. Standard errors clustered by state and 3-digit NAICS in parenthesis. * p<0.10, **p<0.05, *** p<0.01. Regressions weighted by employment in 2012 at the state and NAICS 4-digit level. Controls not shown: growth rate of employees 2002-2012; log average establishment size (employees per establishment) in 2012; log of the count of facilities reporting to the NEI; NAICS 3-digit dummies, state dummies. IVs: log of violation (2000-2009) per employee (2009); log of full inspection (2000-2009) per employee (2009). Partial F for excluded IVs: ozone 234; CO 133.6; NOx 160; PM2.5 145.2; lead 81.15; TRI 47.97.

Table 20 - Impact of environmental regulation on skills: alternative regulation measures (II)

	Non-green spec tasks	RTI	NR tasks	R manual	R cognitive	Log(Years of training)
Log(ozone/L)	-0.0500	0.0239***	-0.00430***	0.0172***	-0.00231***	-0.0450***
	(0.108)	(0.00496)	(0.00123)	(0.00230)	(0.000694)	(0.0107)
Hansen test (p-value)	0.886	0.878	0.557	0.775	0.938	0.945
	Non-green spec tasks	RTI	NR tasks	R manual	R cognitive	Log(Years of training)
Log(CO/L)	-0.0551	0.0267***	-0.00476***	0.0192***	-0.00259***	-0.0503***
	(0.121)	(0.00584)	(0.00141)	(0.00284)	(0.000762)	(0.0120)
Hansen test (p-value)	0.861	0.661	0.436	0.865	0.830	0.694
	Non-green spec tasks	RTI	NR tasks	R manual	R cognitive	Log(Years of training)
Log(NOx/L)	-0.0546	0.0265***	-0.00472***	0.0191***	-0.00257***	-0.0499***
	(0.120)	(0.00572)	(0.00139)	(0.00277)	(0.000766)	(0.0121)
Hansen test (p-value)	0.856	0.620	0.413	0.797	0.780	0.648
	Non-green spec tasks	RTI	NR tasks	R manual	R cognitive	Log(Years of training)
Log(PM2.5/L)	-0.0572	0.0271***	-0.00489***	0.0194***	-0.00262***	-0.0510***
	(0.123)	(0.00549)	(0.00134)	(0.00254)	(0.000758)	(0.0111)
Hansen test (p-value)	0.904	0.936	0.689	0.538	0.753	0.864
	Non-green spec tasks	RTI	NR tasks	R manual	R cognitive	Log(Years of training)
Log(lead/L)	-0.0694	0.0334***	-0.00598***	0.0240***	-0.00323***	-0.0628***
	(0.151)	(0.00774)	(0.00186)	(0.00378)	(0.000969)	(0.0158)
Hansen test (p-value)	0.876	0.776	0.494	0.930	0.966	0.844
	Non-green spec tasks	RTI	NR tasks	R manual	R cognitive	Log(Years of training)
Log(TRI/L)	-0.0597	0.0294***	-0.00521***	0.0213***	-0.00286***	-0.0555***
	(0.134)	(0.00652)	(0.00154)	(0.00356)	(0.000936)	(0.0149)
Hansen test (p-value)	0.831	0.343	0.221	0.454	0.589	0.412

N=3328 industry-state pairs. Standard errors clustered by state and 3-digit NAICS in parenthesis. * p<0.10, ** p<0.05, *** p<0.01. Regressions weighted by employment in 2012 at the state and NAICS 4-digit level. Controls not shown: growth rate of employees 2002-2012; log average establishment size (employees per establishment) in 2012; log of the count of facilities reporting to the NEI; NAICS 3-digit dummies, state dummies. IVs: log of violation (2000-2009) per employee (2009); log of full inspection (2000-2009) per employee (2009). Partial F for excluded IVs: ozone 234; CO 133.6; NOx 160; PM2.5 145.2; lead 81.15; TRI 47.97.

Table 21 – Impact of environmental regulation on skills – manufacturing industries only (with 3-digit NAICS dummies)

	Greenness	Engineering & Technical	Science	Operation Management	Monitoring	Green specific tasks
log(SO2/L)	-0.00237**	-0.00518***	-0.00625***	-0.00719***	-0.000924	-0.152***
	(0.00102)	(0.00196)	(0.00122)	(0.00237)	(0.000847)	(0.0392)
Hansen test (p-value)	0.560	0.912	0.353	0.571	0.350	0.979
	Non-green specific tasks	RTI	NR tasks	R manual	R cognitive	Log(Years of training)
log(SO2/L)	0.158	0.0201***	-0.00311**	0.0154***	-0.00155	-0.00616
	(0.149)	(0.00586)	(0.00149)	(0.00228)	(0.000974)	(0.00659)
Hansen test (p-value)	0.972	0.269	0.411	0.346	0.0581	0.0595

N=2603 industry-state pairs (only manufacturing sectors). Standard errors clustered by state and 3-digit NAICS in parenthesis. * p<0.10, ** p<0.05, *** p<0.01. Regressions weighted by employment in 2012 at the state and NAICS 4-digit level. Controls not shown: growth rate of employees 2002-2012; log average establishment size (employees per establishment) in 2012; log of the count of facilities reporting to the NEI; NAICS 3-digit dummies, state dummies. IVs: log of violation (2000-2009) per employee (2009); log of full inspection (2000-2009) per employee (2009). Partial F of excluded IVs: 99.39.

Table 22 – Impact of environmental regulation on skills – manufacturing industries only (with 4-digit NAICS dummies)

	Greenness	Engineering & Technical	Science	Operation Management	Monitoring	Green specific tasks
log(SO2/L)	-0.000910	-0.00506*	-0.00420**	-0.0113***	-0.00413***	-0.0870
	(0.00144)	(0.00259)	(0.00165)	(0.00239)	(0.00160)	(0.0696)
Hansen test (p-value)	0.879	0.185	0.732	0.900	0.643	0.525
	Non-green specific tasks	RTI	NR tasks	R manual	R cognitive	Log(Years of training)
log(SO2/L)	-0.0394	0.0424***	-0.00852***	0.0200***	0.00278***	-0.00361
	(0.226)	(0.00739)	(0.00163)	(0.00353)	(0.000899)	(0.0106)
Hansen test (p-value)	0.742	0.740	0.746	0.871	0.573	0.0295

N=2603 industry-state pairs (only manufacturing sectors). Standard errors clustered by state and 3-digit NAICS in parenthesis. * p<0.10, ** p<0.05, *** p<0.01. Regressions weighted by employment in 2012 at the state and NAICS 4-digit level. Controls not shown: growth rate of employees 2002-2012; log average establishment size (employees per establishment) in 2012; log of the count of facilities reporting to the NEI; NAICS 4-digit dummies, state dummies. IVs: log of violation (2000-2009) per employee (2009); log of full inspection (2000-2009) per employee (2009). Partial F of excluded IVs: 38.59.

Table 23 – Effect of control variables for baseline estimates

	Greenness	Engineering & Technical	Science	Operation Management	Monitoring	Green specific tasks
log(SO2/L)	-0.00303***	-0.00878***	-0.0110***	-0.0134***	-0.00466***	-0.211***
	(0.000974)	(0.00193)	(0.00155)	(0.00271)	(0.00118)	(0.0461)
log(count NEI facilities)	0.00258**	0.00455**	0.00617***	0.00400*	0.00260**	0.154***
	(0.00108)	(0.00195)	(0.00170)	(0.00241)	(0.00118)	(0.0484)
Growth log(Empl) 2002-2011	-0.00136	-0.00146	-0.00188	-0.00194	-0.0000210	-0.0596
	(0.000840)	(0.00145)	(0.00126)	(0.00157)	(0.000742)	(0.0368)
log(empl/N establ, 2011)	0.0103***	0.0111***	0.0126***	0.0130***	0.00859***	0.466***
	(0.00133)	(0.00198)	(0.00203)	(0.00272)	(0.00122)	(0.0500)
Hansen test (p-value)	0.241	0.699	0.250	0.648	0.849	0.251
	Non-green specific tasks	RTI	NR tasks	R manual	R cognitive	Log(Years of training)
log(SO2/L)	-0.0557	0.0268***	-0.00479***	0.0192***	-0.00259***	-0.0504***
	(0.121)	(0.00578)	(0.00143)	(0.00278)	(0.000814)	(0.0126)
log(count NEI facilities)	0.261**	-0.0148***	0.00158	-0.0123***	-0.00114	0.0382***
	(0.132)	(0.00524)	(0.00133)	(0.00267)	(0.000724)	(0.00997)
Growth log(Empl) 2002-2011	0.0166	0.00562	-0.000721	0.00574***	-0.000609	-0.0152*
	(0.110)	(0.00430)	(0.00105)	(0.00217)	(0.000555)	(0.00921)
log(empl/N establ, 2011)	-0.219	-0.0158**	0.00701***	-0.00675*	0.00214**	0.0545***
	(0.163)	(0.00764)	(0.00184)	(0.00355)	(0.00100)	(0.0126)
Hansen test (p-value)	0.878	0.815	0.526	0.889	0.996	0.875

N=3328 industry-state pairs. Standard errors clustered by state and 3-digit NAICS in parenthesis. * p<0.10, ** p<0.05, *** p<0.01. Regressions weighted by employment in 2012 at the state and NAICS 4-digit level. Controls not shown: NAICS 3-digit dummies, state dummies. IVs: log of violation (2000-2009) per employee (2009); log of full inspection (2000-2009) per employee (2009). Partial F of excluded IVs: 112.

Table 24 – First stages for baseline estimates

IV:	log(SO2/L)	log(ozone/L)	log(CO/L)	log(NOx/L)	log(PM2.5/L)	log(lead)	log(TRI/L)
log(violations/L)	0.420***	0.438***	0.492***	0.516***	0.314***	0.347***	0.559***
	(0.112)	(0.118)	(0.131)	(0.128)	(0.121)	(0.0945)	(0.159)
log(full_inspections/L)	0.354***	0.428***	0.278**	0.258**	0.451***	0.273***	0.124
	(0.108)	(0.111)	(0.118)	(0.119)	(0.108)	(0.0927)	(0.159)
N	3328	3328	3328	3328	3328	3328	3328

Standard errors clustered by state and 3-digit NAICS in parenthesis. * p<0.10, ** p<0.05, *** p<0.01. Regressions weighted by employment in 2012 at the state and NAICS 4-digit level.

Table 25 – First stages alternative specifications

	4-digit NAICS	Contracting	Expanding	3-digit NAICS (only manuf)	4-digit NAICS (only manuf)
IV:	log(SO2/L)	log(SO2/L)	log(SO2/L)	log(SO2/L)	log(SO2/L)
log(violations/L)	0.370***	0.391***	0.393*	0.671***	0.448***
	(0.101)	(0.115)	(0.238)	(0.185)	(0.153)
log(full_inspections/L)	0.142	0.307***	0.235	0.237	0.184
	(0.0993)	(0.107)	(0.240)	(0.171)	(0.156)
N	3328	2381	945	2603	2603

Standard errors clustered by state and 3-digit NAICS in parenthesis. * p<0.10, ** p<0.05, *** p<0.01. Regressions weighted by employment in 2012 at the state and NAICS 4-digit level.

Table 26 – First stages for specifications that include import

	Specification without the interaction between import penetration and regulation		Specification with the interaction between import penetration and regulation		
IV:	log(SO2/L)	Imp pen 2009	log(SO2/L)	Imp pen 2009	log(SO2/L) x Imp pen 2009
Imp pen 2005	3.687***	0.992***	12.43***	0.664***	13.64***
	(1.045)	(0.0136)	(3.472)	(0.0595)	(0.924)
log(violations/L)	0.636***	-0.00191	0.519**	0.00168	-0.0406
	(0.182)	(0.00200)	(0.204)	(0.00203)	(0.0382)
log(full_inspections/L)	0.216	0.00265	0.224	0.00311	0.0289
	(0.168)	(0.00199)	(0.197)	(0.00214)	(0.0374)
log(violations/L) x			0.207	-0.0182	-0.170
Imp pen 2005			(1.638)	(0.0233)	(0.499)
log(full_inspections/L) x			1.386	-0.0415	1.381***
Imp pen 2005			(1.736)	(0.0270)	(0.512)
N	2603	2603	2603	2603	2603

Standard errors clustered by state and 3-digit NAICS in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.
Regressions weighted by employment in 2012 at the state and NAICS 4-digit level.

Tables for Appendix D

Table 27 - Impact of environmental regulation on single green skills items

		3-digit NAICS dummies		4-digit NAICS dummies	
Item	Description	log(SO2/L)	Hansen test (p-value)	log(SO2/L)	Hansen test (p-value)
2B4g	Systems Analysis	-0.0170*** (0.00330)	0.815	-0.0101*** (0.00232)	0.314
2B4h	Systems Evaluation	-0.0162*** (0.00302)	0.743	-0.00829*** (0.00208)	0.443
2C3b	Engineering and Technology	-0.0174*** (0.00350)	0.616	-0.00829** (0.00350)	0.814
2C3c	Design	-0.0179*** (0.00299)	0.540	-0.00669** (0.00337)	0.948
2C3d	Building and Construction	0.00148 (0.00161)	0.608	0.000193 (0.00236)	0.692
2C3e	Mechanical	-0.0141*** (0.00397)	0.805	0.00649** (0.00270)	0.111
2C4b	Physics	-0.0181*** (0.00337)	0.877	-0.00320 (0.00225)	0.307
2C4d	Biology	-0.00396*** (0.00126)	0.013	-0.00289** (0.00117)	0.210
2C4g	Geography	-0.000722 (0.00129)	0.0268	-0.00704*** (0.00135)	0.739
2C8b	Law and Government	-0.00919*** (0.00134)	0.565	-0.00810*** (0.00210)	0.522
4A1b3	Estimating the Quantifiable Characteristics of Products, Events, or Information	0.000718 (0.000801)	0.990	0.000139 (0.00112)	0.482
4A2a3	Evaluating Information to Determine Compliance with Standards	-0.000129 (0.00211)	0.635	0.00295* (0.00166)	0.865
4A2b3	Updating and Using Relevant Knowledge	-0.0121*** (0.00263)	0.567	-0.00830*** (0.00153)	0.571
4A3a4	Operating Vehicles, Mechanized Devices, or Equipment	0.0201*** (0.00221)	0.900	0.0110*** (0.00279)	0.0962
4A3b2	Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment	-0.00547*** (0.00182)	0.315	-0.00208 (0.00223)	0.618
4A4b6	Provide Consultation and Advice to Others	-0.00833*** (0.00211)	0.491	-0.00756*** (0.00199)	0.618

N=3328 industry-state pairs. Standard errors clustered by state and 3-digit NAICS in parenthesis. * p<0.10, ** p<0.05, *** p<0.01. Regressions weighted by employment in 2012 at the state and NAICS 3-digit level (left panel) or NAICS 4-digit level (right panel). Controls not shown: growth rate of employees 2002-2012; log average establishment size (employees per establishment) in 2012; log of the count of facilities reporting to the NEI; NAICS 3-digit dummies, state dummies. IVs: log of violation (2000-2009) per employee (2009); log of full inspection (2000-2009) per employee (2009). Partial F for excluded IVs (3-digit NAICS dummies): 112. Partial F for excluded IVs (4-digit NAICS dummies): 42.35.