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from US Local Labor Markets,
2006-2014**

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Summary

This paper explores the nature and the key empirical regularities of green employment in US local labor markets between 2006 and 2014. We construct a new measure of green employment based on the task content of occupations. Descriptive analysis reveals the following: 1. the share of green employment oscillates between 2 and 3 percent, and its trend is strongly pro-cyclical; 2. green jobs yield a 4 percent wage premium; 3. despite moderate catching-up across areas, green jobs remain more geographically concentrated than similar non-green jobs; and 4. the top green areas are mostly high-tech. As regards the drivers, changes in environmental regulation are a secondary force compared to the local endowment of green knowledge and resilience in the face of the great recession. To assess the impact of moving to greener activities, we estimate that one additional green job is associated with 4.2 (2.4 in the crisis period) new jobs in non-tradable activities in the local economies.

Keywords: Green Employment, Local Labor Markets, Environmental Regulation, Environmental Technologies, Local Multipliers

JEL Classification: J23, O33, Q52, R23

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Measures, Drivers and Effects of Green Employment: Evidence from US Local Labor Markets, 2006-2014*

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Abstract

This paper explores the nature and the key empirical regularities of green employment in US local labor markets between 2006 and 2014. We construct a new measure of green employment based on the task content of occupations. Descriptive analysis reveals the following: 1. the share of green employment oscillates between 2 and 3 percent, and its trend is strongly pro-cyclical; 2. green jobs yield a 4 percent wage premium; 3. despite moderate catching-up across areas, green jobs remain more geographically concentrated than similar non-green jobs; and 4. the top green areas are mostly high-tech. As regards the drivers, changes in environmental regulation are a secondary force compared to the local endowment of green knowledge and resilience in the face of the great recession. To assess the impact of moving to greener activities, we estimate that one additional green job is associated with 4.2 (2.4 in the crisis period) new jobs in non-tradable activities in the local economies.

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1 Introduction

A growing wealth of quantitative and qualitative evidence explores the labor market effects of environmental sustainability and spurs debates about whether the transition towards a ‘green economy’ will create or destroy jobs. On the one hand, the jobless recovery in the aftermath of the great recession adds to the concerns of policy-makers that environmental regulations could entail higher compliance costs and prolong, or even exacerbate, the slump in the labor market. On the other hand, optimists argue that the demand for green goods and services can provide new impetus to sluggish growth in OECD countries, especially after the approval of a comprehensive international agreement on climate change like COP21. Much in the spirit of the Porter Hypothesis (Porter and Van der Linde, 1995), environmental policy is portrayed as an instrument that, by spurring comparative advantage in emerging green activities, can also be a driver for economic growth. However, these optimistic expectations remain conjectural and have been partially refuted by cross-sectional evidence on the green industry (e.g., Becker and Shadbegian, 2009). At the same time, policy evaluations point to a modest and negative impact of environmental regulation on employment, especially in energy-intensive industries (Greenstone, 2002; Walker, 2011; Kahn and Mansur, 2014). Clearly, more empirical work is needed to assess the claims of the optimists and, in particular, to understand whether and to what extent environmental policies and large-scale investments in green technologies can effectively contribute to the post-recession employment recovery.

Using data on local labor markets in the United States (US), this paper provides a comprehensive overview of green employment in search of a preliminary answer to the question of whether moving towards environmentally friendly production can spur job creation. The first step is to build an appropriate measure. To do so, we overcome well-known data limitations that characterize prior studies, and we construct a novel measure of green employment (Section 2) based on literature in labor economics that characterizes occupations with the set of tasks required in the workplace (Autor et al, 2003). This is operationalized by pairing data on job task requirements from the Occupational Information Network (O*NET) with Occupational Employment Statistics (OES) of the Bureau of Labor Statistics (BLS) on 826 6-digit SOC occupations across 537 metropolitan and nonmetropolitan areas over the period 2006-2014. The value added of this method is that the ‘greenness’ of an occupation is defined based on job-specific characteristics – namely, engagement with environmental tasks – rather than being inferred from the portion of the workforce that is employed in the production of green goods or that uses particular green production processes. Different from prior studies, our task-based measure captures both the within-sector component of green employment and green job creation in industries that are not directly affected by regulations, such as engineering services, consulting and machinery production. In so doing, we provide empirical validation to the claim that green growth is a widespread phenomenon that extends beyond flagship sectors such as renewable energy and electric vehicle production. Lastly, our approach carries the benefit of being time-varying and thus amenable to capturing the dynamics and the key drivers at work.

Reassuringly, the aggregate employment figures generated by our approach resonate with previous cross-sectional estimates that situate the US green workforce in the region of 2-3 percent employment share (e.g., Deschnes, 2013).

Building on this, in Section 3, we establish four stylized facts: (1) the green employment share has been recovering from the contraction of the great recession; (2) relative to similar occupations, green jobs pay a 4 percent wage premium, which increases to almost 8 percent among low-skilled manual workers; (3) despite moderate catching-up on the part of areas that lagged behind at the beginning of the period, green jobs remain more geographically concentrated than similar non-green jobs; and (4) leading green employment areas exhibit a strong presence of high-tech activities, as signified by a rate of resident green inventors that is three times higher than the national average. On the whole, our analysis shows that the great recession represented a structural break for the growth and distribution of green employment.

Importantly, the crisis coincided with the implementation of policies that put in place new emission standards (National Ambient Air Quality Standards) for four criteria pollutants (PM2.5, Lead, SO2 and Ozone). Exogenous change in environmental regulation across different jurisdictions offers a suitable opportunity to search for causal effects in the observed dynamics of green employment. Accordingly, Section 4 analyses the drivers of green employment and contrasts the effect of new environmental regulations with other structural forces, such as resilience to the financial crisis and local exposure to trade and technology. Differentiating the local effects of these factors is important for at least two reasons. First, recent analyses point to substantial heterogeneity in the response to changes in these factors across local labor markets. Autor and Dorn (2013) document that the extent of job polarization depends the local share of routine cognitive jobs that can be more easily replaced by ICT technologies. Autor et al (2015) find a threefold decline in manufacturing employment following China's accession to the World Trade Organization. However, different from technology, the impact of trade competition on local labor markets is not limited to routine task-intensive manufacturing jobs and extends to manual and abstract task-oriented jobs. Regarding the crisis, Mian and Sufi (2014) show that local labor markets more exposed to the financial crash also experienced a larger decline in non-tradable employment between 2007 and 2009.

The second reason is that we expect these drivers to have a significant impact on green employment. Several green products such as storage technologies, smart houses and electric cars are still at early stages of their life-cycle and are awaiting related innovations for further development. From this, it follows that the local endowment of green knowledge is likely a key discriminant for the attractiveness of a specific location. Openness to trade can also affect the local composition of manufacturing productions, including the production of green equipment such as wind turbines or solar PV cells (Sawhney and Kahn, 2012). Finally, the great recession may have triggered strong and persistent effects on local green production if the budget outlay for environmental products of both households and policy makers were highly elastic to negative income shocks. Clearly, a persistent effect of the great recession on green activities carries relevant implications both for policy design and for the elaboration of green growth models, where non-homotheticity should be properly taken into account (Brock and Taylor, 2010).

The joint empirical identification of these phenomena can be problematic given that the variables of interest are numerous. To reduce endogeneity concerns, we measure exposure to trade, green technology and the great recession in the initial period, and we interact them with a time trend. Still, the identifi-

cation of the effect of new environmental standards may remain problematic in a simple difference-in-differences setting if the areas designed as non-attainment (and thus face a more stringent regulation) under the new standards are systematically different from attainment areas. We address this by using a DID semi-parametric matching estimator (Heckman et al., 1997). The crude DID and the semi-parametric matching estimators deliver similar results on the effect of new emission standards. The overall effect is modest and ranges between 1.7-2.2 percent change in the share of green employment. To put matters in perspective, one inter-quartile range difference in the initial exposure to the great recession is associated with a 3.8-5.3 percent long-term difference in the share of green employment and it is up to 6.1 percent among low-skilled green jobs, while the impact of having a greater (one inter-quartile range difference) green technology base is up to 3.2-3.5 percent and mostly affects high-skilled green jobs. Also of importance for validating our measure of green employment is that all drivers have a stronger effect on our task-based measure compared to industry-based measures. The small effect of environmental regulation on green employment growth is of interest for the literature on the labor market effects of environmental policies, which so far has arguably emphasized the job-destruction side to the detriment of potentially constructive outcomes, for example, the emergence of new occupations.¹ We ascribe the modest effect on job creation in new green activities to the well-known lack of incentives to innovate associated with such command and control forms of regulation.

Section 5 of the paper assesses the impact of green jobs on local labor markets. To this end, we estimate the green local multiplier instrumenting the change in local green employment using a standard shift-share approach, as in Moretti (2010). We find that one additional green job generates 4.2 new jobs in the non-tradable sector. Interestingly, the green local multiplier is quite close to that of high-tech jobs in manufacturing (upper bound), is well above the multiplier for mining, and hangs on around a remarkable 2.5 during the recessionary phase, 2006-2010. Our analysis also indicates that green employment tends to cluster together with high-tech activities. Although we are cautious in interpreting this as a causal effect, our finding resonates with the profiling of green areas as strongly embedded in high-tech production activities. It has to be appreciated that the timing of these results coincides with the expansionary fiscal policy put in place by the Obama administration, which included a dedicated green stimulus package. This is to say that the size of the multiplier effect reflects both circumstances, namely, the effects of the recession and the policy context.

Our contribution to the literature on the local multiplier is, however, limited by data constraints, as local green employment cannot be partitioned into tradable and non-tradable components. Although our results are very robust to different measures of local non-tradable employment that try to account for this, further analysis at different levels of geographical aggregation based on data on

¹The literature on the labor market outcomes of environmental regulation is ample, but the evidence is decidedly mixed. Some studies find no significant employment effects, for example, Berman and Bui (2001) and Morgenstern et al (2002) for the US and Elliott (2007) for the UK. Other works report negative labor market outcomes due to strengthening of the emission standards of the US Clean Air Act, namely, employment reduction (Greenstone, 2002; Walker, 2011; Curtis 2014) and earnings loss due to reallocation across jobs (Walker, 2013).

the export of green products is certainly called for. This and other promising avenues for future research are briefly outlined in Section 6, together with the summary of the key findings.

2 Measuring green employment

Section 2.1 provides a brief critical review of existing measures of green employment. Section 2.2 illustrates the O*NET data and the method used to elaborate a task-based measure of green employment. In Section 2.3, we match occupation-specific data on tasks with data on regional employment to construct green employment measures that vary over time and across geographical locations.

2.1 Approaches to measuring green employment

The empirical identification of green employment represents a challenge for two reasons. First, it is not easy to define what a green job is. Is it an activity devoted to reducing the harmful consequences of pollution and resource exploitation? Or is it an activity devoted to the design of new solutions to prevent pollution by reducing the use of energy and materials? Second, and partly as a reflection of these blurry boundaries, uncoordinated data collection efforts by national statistical offices have given way to incoherent empirical accounts of this phenomenon.

The existing surveys for quantifying employment associated with environmental sustainability follow three main approaches. The first consists in selecting employees of green processes, that is, specialized activities for the protection of the environment, such as active waste management, treatment, and recycling (U.S. Department of Commerce, 2010). If, on the one hand, this method carries the benefit of a sharp identification due to the specificity of these activities, on the other hand, it disregards activities devoted to the whole re-design of products that are often carried out by specialized suppliers of machinery (especially for renewable energy) and engineering and architecture solutions (for insulation, transportation equipment and building).

A second method relies on selecting industries with large fractions of firms that are active in the production of green goods, such as the manufacturing of energy-efficient appliances, filters or wind turbines (OECD, 2012; Peters et al, 2011). While this approach captures green employment at the industry level and is therefore amenable to comparative analysis, it neglects the role of green processes and rests on the strong assumption of inferring the share of green employment of an industry from the share of green products.

A third avenue is a synthesis of the two outlined above in that it relies on employment data of activities dedicated to green products and services, such as hybrid or electric automobiles, insulation products or energy monitoring systems (BLS, 2012; Deschenes, 2013). Although the blending of product- and process-based definitions may compensate for some of the shortcomings of either approach used in isolation, the downside is that this method may overlook green activities that are not directly associated with the production of a particular product or service, such as energy conservation within a firm. Moreover, a sector may not produce green goods per se but may still contribute to en-

vironmental sustainability through other routes, for example, by demanding specialized activities (such as monitoring, consultancy and legal support) to other sectors.

In our view, the approaches detailed above are ill-suited to carrying out a rigorous empirical analysis of the drivers of green employment. The fact that green jobs are inferred only indirectly from industry or product characteristics does not allow an exact quantification of the time spent by workers in performing green activities. The alternative proposed here is to focus on the tasks performed within an occupation as the main unit of analysis to capture directly the environmental activities that are actually carried out in the workplace, and to what extent. Furthermore, environmental issues are pervasive in several industries, leading to the expectation that much of the variation in the share of green employment will be observed within rather than between industries. Environmental issues influence both industries that are directly responsible for environmental degradation (e.g., electricity power plants) and industries that provide polluting industries with equipment (e.g., wind turbines) and consulting activities (e.g., architectural services) to address environmental issues. An occupation-based approach is better suited to capturing, in a flexible way, this within-sector component and the indirect creation of green jobs in industries that do not need to reduce emissions and the use of primary resources.

2.2 Measuring green employment with O*NET

The ‘Green Economy’ program developed by the Occupational Information Network (O*NET) under the auspices of the US Department of Labor focuses on a broad range of work activities aimed at “reducing the use of fossil fuels, decreasing pollution and greenhouse gas emissions, increasing the efficiency of energy usage, recycling materials, and developing and adopting renewable sources of energy” (Dierdorff et al., 2009, p. 3). Using expert interviews with and surveys of representative samples of workers, the Green Economy program has developed a broad definition of green jobs that is fully integrated within the US Standard Occupational Classification (SOC) system and, thus, is amenable to matching with employment data.² Even more important for the goals of the present paper, this resource provides detailed information about the work tasks that are carried out by green occupations, with a clear distinction between green and non-green occupation-specific tasks. Our proposed measure of green employment exploits this distinction to refine the O*NET’s broad definition of green jobs and to quantify the portion of work time that each occupation dedicates to green activities.

[Table 1 about here]

Before detailing the construction of our measure, it is informative to look at the structure of the O*NET data on green jobs. Table 1 shows the distribution of 128 8-digit SOC green jobs across the traditional 2-digit macro-categories of the Standard Occupational Classification (SOC). Green occupations are more prevalent among high-skilled managers and professionals (especially Architecture & Engineering, SOC 17) and low-medium technical jobs (especially Construction

²See Consoli et al. (2016) and the Appendix A and B for further details on the O*NET classification of Green Jobs.

& Extraction, SOC 47; Maintenance & Repair, SOC 49; Production, SOC 51). Note that green jobs are virtually absent within service occupations, reflecting the low relevance of environment-related issues for the tasks performed by these occupations. A closer look reveals that, within O*NET, jobs such as Chemical Engineers or Sheet Metal Workers are labeled ‘green’ even though they are not fully engaged in green activities. This raises the concern that imposing a sharp dualism between green and non-green occupations conflicts with an intuitive set of observations offered by the scholarly and policy literature about greening of the economy as a gradual, widely distributed process that affects a large number of industries and occupations (Henderson and Newell, 2011).

We address this shortcoming by constructing a continuous measure of occupational greenness that is similar to that proposed by Vona et al. (2015). For each occupation i , our measure is the weighted average of the green-specific and non-green tasks:

$$Greenness_i = \sum_{j=1}^n w_{ij} \times (1_{\{j \in green\}} + 1_{\{j \in non-green\}}) \quad (1)$$

where $1_{\{j \in green\}}$ and $1_{\{j \in non-green\}}$ are indicator dummies for, respectively, green and non-green tasks. The weights w_{ij} are given by the relative importance scores attributed to each of the n occupation-specific tasks and are normalized to sum up to 1. Weighting tasks by their importance is crucial to approximate the time spent by each occupation in green activities. While occupations without green tasks (845 out of 974) have greenness equal to zero, those with green tasks (129 out of 974) display substantial heterogeneity in the importance of green tasks. In particular, green tasks are usually less important than non-green tasks in occupations that are marginally green, such as “Maintenance and Repair Workers” (49-9071.00) and “Electronics Engineering Technologists” (SOC 17-3029.04). This is evident by comparing the weighted and unweighted (obtained replacing $1/n$ with w_{ij} in (1)) greenness for the 8-digit green occupations. Figure 1 illustrates that the unweighted greenness systematically over-estimates the greenness of an occupation compared to the weighted greenness.

[Figure 1 about here]

Weighting tasks by their importance allows us to interpret the greenness indicator as an accurate proxy of the time that is devoted to environmental activities within an occupation. Table 2 shows the occupational ranking by greenness. Jobs that are unquestionably green (e.g., Environmental Engineers, Solar Photovoltaic Installers or Biomass Plant Technicians) have a greenness equal to 1, while other occupations have a mixed profile, meaning that environmental tasks are engaged within a broader spectrum of other activities (e.g., Electrical Engineers, Metal Sheet Workers or Roofers). Importantly, the greenness indicator singles out occupations that engage environmental tasks only occasionally and that cannot therefore be considered as green as those at the top end of the scale. This is the case of traditional Engineering occupations, Marketing Managers and Construction Workers.

[Table 2 about here]

To qualify the greenness of an occupation using the O*NET dataset, it is useful to further distinguish between core and supplemental tasks. The former are critical to the occupation, with a relatively higher importance rating, while the latter are less relevant. For example, “Electrical Engineering Technologists” includes 20 specific tasks, 7 of which are green, but not all are core tasks.³ This implies that the estimated greenness for this occupation (i.e., 0.14) represents an upper bound. In general, green tasks are relatively more concentrated among supplemental activities, which is to be expected considering the novel nature of green employment (Lin, 2014). To account for this potential bias, we compute a lower-bound measure of “core greenness” based only on core tasks:

$$\text{Core Greenness} = \sum_{j=1}^n \tilde{w}_{ij} \times 1_{\{j \in \text{core}\}} \times (1_{\{j \in \text{green}\}} + 1_{\{j \in \text{non-green}\}}) \quad (2)$$

where $1_{\{j \in \text{core}\}}$ is one for core tasks and zero otherwise and \tilde{w}_{ij} are renormalized to sum to one for core tasks. We can now present our measures of green employment for local labor markets.

2.3 Measures of green employment in local labor markets

Using greenness to re-weight employment data on 822 6-digit SOC occupations, we construct time-varying measures of green employment for metropolitan and nonmetropolitan areas (537 areas) during the period 2006-2014. The main data source is the Occupational Employment Statistics (OES) of the Bureau of Labor Statistics (BLS), containing detailed information on the composition of the workforce by occupational titles (6-digit Standard Occupational Classification, SOC) across various mutually exclusive dimensions: by state, by metropolitan and nonmetropolitan areas, and by industry (4-digit NAICS).

The main challenge in the matching of O*NET and BLS data is the attribution of the greenness of an 8-digit SOC occupation to the 6-digit SOC level. 8-digit and 6-digit levels coincide for 715 out of 822 6-digit occupations, so the greenness of these occupations is clearly defined. On average, these occupations represent 81.2 percent of total employment. For the remaining occupations, we construct 6-digit greenness using the rule-of-thumb of weighting uniformly the greenness of 8-digit occupations within a 6-digit occupation. However, because certain green occupations represent a thin share of employment within a 6-digit group, using uniform weights for green and non-green jobs would likely over-estimate 6-digit greenness. While the aggregate bias should be small given the accurate mapping between 8- and 6-digit occupations, in these problematic cases, we simply take the greenness of the most general occupation to avoid over-estimation of green employment. Table A1 in the Appendix A reports these cases in detail and discusses them extensively.

With these caveats in mind, our benchmark measure of green employment share is:

³Two examples of green tasks for this occupation are “Test sustainable materials for their applicability to electrical engineering systems or system designs” and “Conduct statistical studies to analyze or compare production costs for sustainable or nonsustainable designs”. See <http://www.onetonline.org/link/details/17-3029.02>. Note that in the O*NET dataset, a small fraction of tasks have not yet been assigned an importance score. We replace these missing scores with the minimum importance score attributed to all other tasks.

$$GE_{jt} = \sum_{i=1}^I Greenness_i \times \frac{L_{ijt}}{L_{jt}} \quad (3)$$

where $\frac{L_{ijt}}{L_{jt}}$ is the employment share of occupation i in area j at time t . The lower bound for this favorite measure uses the greenness built using only core tasks:

$$CGE_{jt} = \sum_{i=1}^I Core\ Greenness_i \times \frac{L_{ijt}}{L_{jt}} \quad (4)$$

Comparing task-based and industry-based measures of green employment is important to gauge the extent to which this phenomenon is occurring mostly within-industry rather than being driven by compositional changes in industry structure. However, due to data limitations, we are unable to construct a measure of green employment that varies across regions, occupations and industries (see the Appendix B for a discussion). To construct an industry-based measure instead, we assume that the national share of green employment for a given industry is a good predictor of the share of green employment for that industry in the local labor market. That is:

$$GIE_{jt} = \sum_{k=1}^K Greenness_{kt} \times \frac{L_{kjt}}{L_{jt}} \quad (5)$$

where $\frac{L_{kjt}}{L_{jt}}$ represents the employment share of industry (4-digit NAICS) k in area j at time t and $Greenness_{kt}$ is the time-varying national greenness for industry k in year t .⁴ We use the County Business Patterns Database, available for the years 2006-2013, to obtain very detailed data on the employment shares of industry k at the county level and subsequently aggregate it at the metropolitan and nonmetropolitan area level. This industry-based measure is the counterfactual share of green employment if all industries in area j had, on average, the same greenness across the country.

The next section presents basic descriptive evidence on the evolution of green employment over time and across geographical space.

3 Facts about green employment

This section presents descriptive evidence on green employment and is organized around four questions: 1. What is the size and the trend of green employment? 2. What is the return to green jobs compared to similar jobs, and how has the green wage premium changed over time? 3. Do green jobs exhibit higher geographical concentration compared to similar jobs, and how has the concentration changed over time? 4. What is the profile of fast-growing and leading green areas? With regard to question 1, we report the dynamics of both measures to give upper (GE) and lower (CGE) bounds to our estimates of green employment. For questions 2, 3 and 4, the descriptive evidence for CGE is in

⁴ $Greenness_{kt} = \sum_{i=1}^I Greenness_i \times \frac{L_{ikt}}{L_{kt}}$, where k indexes industries, i occupations and t time.

the Appendix C, as the results are very similar for GE and CGE. The Appendix B also contains information on the relevant data sources.

Size and aggregate dynamics

Figure 2 shows the evolution of our two main measures of green employment in the US between 2006 and 2014.⁵ The first panel of the figure shows the trend in the GE and CGE employment share of the total workforce: our preferred GE measure oscillates around a 3 percent employment share, while the trend for the share of CGE is around a lower level of 2 percent, consistent with the fact that this measure is built with stricter criteria. Reassuringly, the employment shares reported here for CGE and GE are not dissimilar from estimates of the size of the 'green' economy provided by previous literature on the basis of different sources. A study by the US Department of Commerce (2010) calculated the share of shipments of selected green products and estimated an employment share of approximately 2 percent in 2007. More recent estimates based on the BLS Green Goods and Services Survey (GGS) indicate that the share of green jobs was between 2.4 percent in 2010 (Deschenes, 2013) and 2.6 percent in 2011 (Elliot and Lindley, 2014).

[Figure 2 about here]

The trends in GE and CGE share a common feature, namely, a contraction during the peak of the great recession that continued until 2010 and a recovery afterwards. This is even more evident in the second panel of Figure 2, in which we plot the trends (normalized to 1 in 2006) of GE, CGE and total employment. The decline during the great recession suggests that green employment was more elastic to lower household disposable incomes compared with total employment. By 2012, GE had fully recovered and grown to its peak level of 3.1 percent in the last year of our analysis, approximately 7.3 percent higher than in 2006, while total employment grew by 1.5 percent over the same period. Interestingly, the bulk of the post-crisis growth in GE is driven by the growth of CGE, which was 10.2 percent over the period 2006-2014.

[Table 3 about here]

In Table 3, we report the initial share of green employment and the growth of green employment for the SOC 2-digit occupations with non-zero green employment. To better characterize green employment, we also report the average years of education required by green and non-green jobs within each 2-digit group. The Table shows that the bulk of the increase in green employment took place in high-skilled jobs (i.e., 'Architecture and Engineering' and 'Management'), while low-skilled green jobs, especially those more directly exposed to the crisis, such as construction (SOC-47), experienced a sharp contraction. To put this in context, green low-skilled occupations are part of a broader group of routine manual jobs that experienced jobless recovery during the recession (Jaimovich and Siu, 2014). Among other fast-growing occupations are 'sales green jobs', a sub-group of highly educated sales occupations involved in selling

⁵The aggregate trend for GIE is equal by construction to one of GE.

technical products and in commodity trading.⁶ Indeed, comparing columns (4) and (5) of Table 3, green sales jobs are the only ones for which we observe a large educational gap between green and non-green jobs.

In sum, green employment represents 2 to 3 percent of total employment, displays a stronger pro-cyclical behavior and shows a 6 to 8 percent faster growth than total employment. High-skilled green jobs account for the lion’s share of the increase in green employment, which is consistent with the idea that new technologies, including environmental ones, are skill-biased.

Green wage premium

Because green activities receive various forms of public support, like subsidies and tax credits, it is important to assess whether such expenditures provide diffused benefits such as well-paid jobs and whether the greening of economies creates ‘winners and losers’. To explore these themes, we estimate the green wage premium both in aggregate and split between skilled and unskilled workers. We use average hourly wage estimates by occupation (6-digit SOC) and area aggregated up to the macro level from the Occupational Employment Statistics of BLS, and we tighten the comparison of hourly wages in green and non-green jobs by considering only a sub-sample of macro-occupations (3-digit SOC) that contain at least one green occupation. We first compute the unconditional wage gap between green and non-green jobs at the 3-digit SOC level by allocating the wage of an occupation with greenness in (0,1) proportionally to its greenness.⁷ Then, we compute the green wage premia for all workers and for high- and low-skilled workers weighting by employment shares at the 3-digit SOC level.⁸

[Figure 3 about here]

Figure 3 shows that the green wage premium is positive at approximately 0.04 log points and experiences a slight decline after its peak in 2008. Working in a low-skilled green occupation yields a significantly higher wage premium than working in high-skilled green occupations, i.e., 8 rather than 2 percent. Interestingly, while the green wage premium for high-skilled jobs steadily declined from 2008 onwards, the green wage premium for low-skilled jobs remained stable over the period and experienced a slight increase from 2011 onwards. It is important to note here that although comparing green and non-green jobs within 3-digit SOC occupations improves the reliability of our results, the unobservable sorting of workers to jobs does not allow us to retrieve precise estimates of the returns to greenness. Our estimates should hence be interpreted as merely indicative patterns. With this caveat in mind, we can conclude that green jobs

⁶Sales green jobs include three green jobs: “Securities and Commodities Traders” (SOC 41-3031.03), “Sales Representatives, all others” (SOC 41-3099) and “Sales Representatives of Technical and Scientific Products” (SOC 41-4011.00).

⁷The wage gap for each three-digit occupation is computed as:
 $Green\ wage\ gap_k = \sum_i [\phi_{ki}Greenness_iWage_i - \phi_{ki}(1 - Greenness_i)Wage_i]$
 where ϕ_{ki} is the employment share of occupation i within the three-digit category k . For occupations with greenness between 0 and 1, we thus allocate the wage proportionally to the greenness.

⁸Descriptive evidence on educational requirements in Table 3 indicates that the high-skilled group should include sales besides the usual high-skilled occupations. The high-skilled group is thus composed of all occupations contained in SOC 2-digit 11-13-15-17-19-23-27-29-41; the low-skilled group is composed of all occupations in SOC 2-digit 43, 47, 49, 51, 53.

pay slightly more than similar non-green jobs and that the green wage premium is higher and more sensitive to the economic cycle for low-skilled green workers than for high-skilled ones.

Spatial dynamics

The aggregate trends illustrated above may arguably conceal substantial differences in the capacity of local labor markets to seize the opportunities of new and emerging green activities. The first issue of interest is whether the distribution of green employment across regions converged or not. The top panel of Figure 4 plots the long-term (2006-2014) growth rate in the share of green employment against the initial share of green employment and reports the estimated β -convergence coefficient. Clearly, areas with initially lower shares of green jobs did catch up. Interestingly, splitting the sample between the beginning of the crisis (2006-2010⁹) and the post-crisis period (2010-2014) shows that catching-up is uniform across the two periods, with no significant differences in the estimated β -convergence.

[Figure 4 about here]

Catching-up in the diffusion of green activities can either reflect a true decline in the geographical concentration of green jobs or it can hide structural differences in occupational characteristics, notably in terms of intrinsic scope for clustering together green and non-green activities. To explore this issue, we compare the evolution of geographical concentration for green and matched non-green 3-digit SOC occupations.¹⁰ This allows us to control for occupational similarity and, thus, to track the genuine differential pattern in the concentration of green jobs. The catching-up trend also emerges in Figure 5: green jobs exhibit a decline in concentration that contrasts with the flat movement of matched non-green jobs. Importantly, despite a decrease in concentration, green jobs remain approximately 10 percent more spatially concentrated than comparable non-green jobs. Moreover, an increase in the concentration of green employment from 2011 onwards partially offsets the initial decline that occurred during the great recession.

[Figure 5 about here]

Taken together, these results point to moderate leveling in the geographical distribution of green employment, which, however, remains more concentrated compared to jobs with similar characteristics. Our descriptive result suggests that catching-up may have only been temporarily related to the economic downturn.

⁹We include 2010 as the last year of the crisis, as unemployment keeps increasing until 2010.

¹⁰Following Krugman (1991), the concentration coefficient of occupation i in year t is computed as a location Gini coefficient:

$$Conc.coef_{it} = \sum_{i=1}^I \left| \frac{L_{ijt}}{\sum_{j=1}^J L_{ijt}} - \frac{\sum_{j=1}^J L_{ijt}}{\sum_{i=1}^I \sum_{j=1}^J L_{ijt}} \right|$$

where L_{ijt} is employment in occupation i , area j and year t .

Profiling fast-growing and top areas

Table 4 shows a synthetic profile of geographical areas ranked by quintiles of initial green employment share. The Table characterizes the average area in each quintile of the initial distribution of green employment by various structural characteristics and the growth rate of green employment.

[Table 4 about here]

The higher growth of green employment in the bottom two quintiles confirms the suggestion of catching-up illustrated before. These two groups are, however, quite heterogeneous: while fast-growing areas in the first quintile of GE exhibit, on average, a higher initial share of manufacturing employment as well as a lower population density, fast-growing areas in the second quintile are densely populated and relatively more similar to other areas in terms of industry structure. In addition, fast growing areas in the bottom two quintiles do not differ from other areas in terms of three important drivers that are likely to influence both green and non-green employment dynamics: resilience to the great recession¹¹, innovativeness¹² and trade exposure.¹³

Note that areas with a higher initial GE have a disproportionately higher probability of hosting public R&D labs, a significantly larger stock of green patents per capita and a higher-than-average share of employment in high-tech manufacturing and knowledge-intensive services. These insights relate directly to the policy-sensible issue of profiling the leading areas in the transition towards environmental sustainability. Table 5 lists the top 20 areas by mean GE in 2006 and 2014. In contrast to the observed catching-up, the table highlights limited fluidity, with 12 out of 20 staying in the top tier through the entire period. Column (3) shows that six out of eight new leading areas host a federally funded R&D lab, while Columns (4) to (6) confirm that these areas are high-tech, especially in green technologies, with a presence of green inventors almost three times higher than the national average.

[Table 5 about here]

Three new leaders are highly innovative in green technologies. The Metropolitan Area of Denver (CO) hosts the largest research facility in Wind Energy Technology (the National Wind Technology Center), while Boulder (CO) has a

¹¹The ideal measure of exposure to the great recession is that of Mian and Sufi (2014), but this measure is not available for nonmetropolitan areas. We build a measure of resilience to the great financial crisis as the counterfactual change in local employment given the initial industrial structure of the area. That is:

$$Resilience\ crisis_j = \sum_k Growth_k^{07-10} \times Share_{kj}^{2005}$$

where j indexes the area and k the industry (4-digit NAICS), $Growth_k^{07-10}$ is the growth in employment between 2007 and 2010 for industry k observed for the US as a whole and $Share_{kj}^{2005}$ is the share of employment in industry k in area j in 2005. Employment by 4-digit NAICS for counties is retrieved from the County Business Patterns database.

¹²See Autor et al. (2003), Acemoglu and Autor (2011) and Beaudry et al. (2016). We proxy the innovativeness of the area with the stock of triadic total and green patents assigned to local inventors per inhabitant and, given the importance of public R&D for energy research, the number of areas hosting a federally funded R&D lab. Using triadic patents imposes a high quality threshold on the innovation assigned to each area. Further details on the construction of these measures can be found in the Appendix B.

¹³See Autor et al. (2013) and Acemoglu et al. (2016). We measure trade exposure using import penetration.

long-standing history of commitment to environmental issues and is the home of an important facility, the US National Center for Atmospheric Research. Conversely, while Columbus (IN) does not host any environmentally specific industrial or research activity, it does enjoy a consolidated tradition in equipment manufacturing and in specialized labor forces, particularly production occupations and mechanical engineers (the highest concentration of any metro area in the US). Likewise, renowned manufacturing hubs such as Cleveland (TN) and San Jose (CA) emerge as areas with high shares of green employment (see Muro et al, 2011). Finally, Los Alamos (NM) is a nonmetropolitan area with a long-standing tradition in science and technology due to the presence of one of the country’s largest research facilities, which includes renewable energy and material science among its many specialties.

Overall, despite the observed catching-up, few persistent leading areas emerge with a distinct profile. These areas are home to high-tech manufacturing and knowledge-intensive service activities.

Summary

Our evidence indicates that green employment is strongly tied to the innovativeness of the local labor market, especially in relation to green innovations. The mild observed catching-up did not prevent the consolidation of a group of high-tech green leaders. While the great recession did represent an important structural break in the growth and spatial concentration of green employment, simple growth regressions show no clear association between the reduction in the concentration of green employment and the great recession. A plausible alternative is that, by setting common emission standards at the federal level, recent changes in environmental regulation may have induced green convergence in local labor markets. Because important activities related to pollution abatement, monitoring and enforcement are provided locally, new federal standards have the potential to level the demand for green jobs across areas and may thus be a plausible explanation for the mild convergence documented earlier. Building on this descriptive evidence, the next section focuses on the determinants of growth of green employment.

4 Drivers of green employment

In this section, we contrast the effects of changes in the stringency of emission standards with those of the structural drivers of employment dynamics in local labor markets, with particular emphasis on local exposure to trade, technology and the great financial crisis. Section 4.1 details the regulatory background, Section 4.2 presents the empirical strategy and the baseline results on the main drivers, and Section 4.3 refines the estimates of the effect of environmental regulation combining difference-in-differences and propensity score matching.

4.1 Background on environmental regulation

The Clean Air Act (CAA) sets federal attainment standards for the six criteria pollutants (National Ambient Air Quality Standards, NAAQS) in the US. Counties that fail to meet these concentration levels for one or more of these

pollutants are designated as non-attainment areas. During the timespan under analysis, the EPA issued new standards for four criteria pollutants: particulate matter smaller than 2.5 microns (PM 2.5) in 2006, lead and ozone in 2008, and sulfur dioxide (SO₂) in 2010. Effective designation of non-attainment areas for the new standards occurred with lags: in 2009 for PM 2.5, in 2010 for lead, in 2011 for SO₂, and in 2012 for ozone. We leverage the fact that non-attainment (NA) counties experience a more stringent regulation and are thus a suitable treatment group for a quasi-experiment compared to the control group of attainment counties.¹⁴ The treatment group (156 areas) represents a large share of the 537 metropolitan and nonmetropolitan areas (156/537=29 percent) and an even larger share of the total US population (56 percent). Figure 6 shows that newly designated nonattainment areas (in black) include regions that are intensive in low-tech manufacturing (e.g., Utah), machinery (Mid-West states), high-tech industries (parts of California, Colorado and the North-East states) and traditionally high-density areas in the Ozone Transport Region, which includes 12 states in the North-East of the US.¹⁵ Note also the low incidence of new emission standards in South-Eastern and South-Central regions home to labor-intensive manufacturing (e.g., furniture, toys, apparel, leather goods) that are highly exposed to international competition, mostly from China (see Autor et al, 2013). Put another way, exposure to import penetration and to environmental regulation have little overlap.

[Figure 6 about here]

The key issue for our proposed strategy is capturing effectively the regulatory status of each region, mapping county nonattainment status to larger metro and non-metro areas.¹⁶ With respect to this strategy, it is important to note a few things. First, for ozone, the EPA designs as nonattainment the entire metropolitan area rather than the county (see Sheriff et al., 2015). Second, the share of population affected by the new nonattainment designation in metro and non-metro areas is highly skewed toward 1. Especially for metropolitan areas, only 1/10 of nonattainment areas have an exposed population lower than 50 percent, and only 1/5 of nonattainment areas have an exposed population lower than 92 percent. For non-metro areas, the skewness in the exposed population is also high, with roughly 60 percent of the areas having an exposed population of more than 90 percent.

Based on this evidence, we categorize a metropolitan area j as nonattainment for a particular pollutant in year t if the area includes at least 1/3 of the population affected by the new non-attainment designation. The main advantage of treating nonattainment designation as a binary variable is that it enables rigorous pairwise comparisons between treated and non-treated areas.

¹⁴Non-attainment designation results in compulsory command-and-control regulations to reduce emissions of facilities within the counties, including the need to adopt technologies with the 'lowest achievable emission rates' (LAER) and a compulsory offset of emissions from new plants from other sources within the non-attainment area. See Walker (2011) for further details.

¹⁵Due to persistent transboundary flows of ozone precursors due to geographical features in the North-East, the EPA designates all counties in the Ozone Transport Region as non-attainment for the Ozone 8h NAAQS. See Ferris et al (2014) for further details.

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

This assumption, however, does not change the qualitative texture of our results, as shown in Tables D1 of the Appendix D, where we replicate our analysis using the share of the population affected by nonattainment designation as our continuous treatment. Finally, although an area can be nonattainment for more than one pollutant, this happens only for 53 (46 for 2 pollutants, 7 for more than 2) of the 137 nonattainment areas. In Table D2 of the Appendix D, we show that the impact of environmental regulation on green employment does not differ between areas experiencing a different number of regulatory shocks. This corroborates our choice of treating nonattainment designation as a binary variable.

4.2 Environmental regulation versus other drivers of green employment

Empirical strategy

Our empirical strategy closely follows previous work on the labor market effects of environmental policies (e.g., Greenstone, 2002; Walker, 2011). In particular, we use a quasi-experimental research design to cope with endogeneity in environmental regulation, and we exploit variation in regulatory stringency at the local level due to the approval of new emission standards at the federal level. The identification of the effect of environmental regulation on green employment may be problematic in the absence of an exogenous policy change. In fact, greener regions are more likely to lobby in favor of stringent environmental regulations and policies. Furthermore, if green employment is positively correlated with local consumer preferences for sustainable products, we cannot infer a causal effect in the absence of a clear sequence of events. Finally, the effective cost of compliance with regulation may vary depending on the initial share of green employment. Taken together, these remarks lead us to exploit exogenous policy change to mitigate concerns of reverse causality in a classical difference-in-differences setup.

The first goal of our analysis of the drivers of green employment is to compare the effect of environmental regulation with that of technology, trade and the great recession. Some of these variables may themselves be influenced by regulation. Green innovations (Carrion-Flores and Innes, 2010) and compositional changes away from polluting industries (Kahn and Mansur, 2013) are particularly affected by regulation. To reduce concerns of endogeneity, we keep the area's resilience to the great recession (see footnote 12), the levels of green patent stock per capita and trade exposure (that is, highly correlated with industry composition) fixed at the level of 2006, and we interact these with a time trend. There are good reasons to favor a causal interpretation of the effects captured by these variables. Trade and technology exposure are measured in the initial period and are unlikely to be correlated with future growth of green employment conditional on an area's fixed effects. In turn, our measure of resilience to the financial crisis depends on national changes in the employment of sectors that, like construction, have been highly affected by the great recession. Because we compute these national changes net of local ones, we are confident that our measure of resilience is uncorrelated with unobservable shocks in the local labor market.

More formally, we estimate variants of the following equation for 537 metropoli-

tan and nonmetropolitan areas over the period 2006-2014:

$$y_{jt} = \alpha NA New_{jt_{NA}} + \phi NA Old_{j0} trend_t + \gamma X_{j0} trend_t + \mu_j + \eta_{st} + \tau_{nt} + \varepsilon_{jt} \quad (6)$$

where y_{jt} is one of the green employment measures defined in Section 2; μ_j are area fixed effects; η_{st} a full set of interactions between time and state fixed effects to capture unobservable state-level shocks (especially other environmental policies); τ_{nt} is a full set of interactions between time effects and a dummy equal to one for nonmetropolitan areas; and ε_{jt} is a standard error term. In addition to import penetration, green patent stock per capita and our measure of resilience to the financial crisis, the vector of other drivers X_{j0} includes a dummy equal to 1 for an area hosting a federally funded R&D lab and the total stock of triadic patent per capita in 2006. To put our estimates in perspective, Table 6 provides descriptive statistics for the green employment drivers.

[Table 6 about here]

The variable capturing environmental regulation, $NA New_{jt_{NA}}$, is a dummy defined along the lines detailed above. Because the timing of designation differs for each pollutant, the year in which non-attainment status first takes effect, t_{NA} , varies across regions, depending on the pollutant that is responsible for the switch. To facilitate a *ceteris paribus* comparison between the treated and control groups, we include a differential trend for areas already exposed that had non-attainment status for at least one of the old standards in 2006, $NA Old_{j0}$. This variable is relevant to distinguish between the persistent effect of an old nonattainment designation and the effect of the new emission standard. However, the inclusion of $NA Old_{j0}$ and of area fixed effects may not suffice in retrieving unbiased estimates of the average treatment effect on the treated ($\hat{\alpha}$) due to systematic pre-treatment differences between treated and control areas. To refine our estimates, we should narrow the focus to environmental regulation combining difference-in-differences and propensity score matching in a semi-parametric setting. This analysis is left for the next section.

Estimation results

Table 7 illustrates the main results for i) our three measures of the share of green employment and ii) the log of total employment, to rule out the possibility that our results are driven by strong effects on the denominator of our three measures. We report standard errors clustered by both area (metro and non-metro) and state to allow for unrestricted spatial correlation across regions within each state. Using state as a cluster unit accounts for the fact that states are key actors in US environmental policy and that they draft the plans to respond to county nonattainment designations (the so-called State Implementation Plans). Finally, the estimated coefficients are obtained by weighting each area for the initial level of employment, but the results are unchanged using population weights.

[Table 7 about here]

The first main finding emerging from Table 7 is that the effect of environmental regulation is positive for all three measures of green employment but is

not statistically significant for the industry-based measure GIE. This resonates with previous literature on the decomposition of emission reductions for the US, pointing to a key role of the technique within-industry effect over a compositional between-industry effect (Levinson, 2015; Shapiro and Walker, 2015). Consistently, the effect of new standards is to increase the effort to reduce emissions and, thus, workforce greenness, mainly through a within-industry channel. However, this effect is modest across the board. The coefficient of our favorite measure, GE, indicates that switching to nonattainment yields a 1.7 percent increase in the green employment share to treated areas, while the effect increases up to 2.2 percent when only core-green occupations are considered.¹⁷ Interestingly, old nonattainment designations also have a positive effect on the share of green employment. Although this is not estimated precisely with state-clustered standard errors, the size of the effect is larger than that of new nonattainment designations and amounts to a long-term 3 percent increase in GE.

Second, environmental regulation is a secondary driver of green employment compared to green patents and to local resilience to the great recession. To be more precise, an increase in resilience equivalent to one inter-quartile range (i.e., 1.6 percent) is associated with a 3.8 percent growth in the share of green employment and a 5.3 percent growth in the share of core green employment.¹⁸ Taken at face value, the effects of initial advantage in green technologies is slightly smaller: increasing the green patent stock per capita by one interquartile range yields 3.2 percent growth in GE and 3.5 percent growth in CGE. However, this effect is conditional on the presence of a federally funded R&D lab, which accounts for another 2.8 percent increase in GE. Note also that while all drivers have a stronger effect on task-based measures than on the alternative industry-based measures, green patents and the resilience to the financial crisis both significantly contribute to the structural change towards greener industries.

The last driver, local exposure to international trade, has no significant effect on the share of green employment, while, consistent with the literature (Acemoglu et al., 2016), higher import penetration has a negative and significant effect on total employment. This implies that international competition has, at best, a compositional impact on green employment. However, looking at Column 4, it is important to stress that these compositional effects are not the main drivers of our results on the effect of environmental regulation on local green activities. Indeed, the effect of new nonattainment designation on total employment is negative but not statistically significant at the conventional level.

[Table 8 about here]

Before investigating the effect of policy in greater detail, we conclude by replicating our analysis for i) the crisis and post-crisis periods to capture the structural break in the effect of drivers and ii) skilled and unskilled workers to detect heterogeneous effects across workers. To estimate equation (6) for the two periods, we take the respective long-differences of our dependent variable (2006-2010 and 2010-2014). The results in Table 8 indicate that areas that are more resilient to the crisis experienced a positive differential growth of green employment, especially in the crisis period. Conversely, areas with higher endowment of green knowledge experienced faster growth of GE only during the

¹⁷We obtain these figures by dividing the estimated coefficients for the average share of green employment in the treated group in 2008, the first year before the shock.

¹⁸To put this figure in context, see Table 6.

recovery. Notice, however, that areas that host federally funded R&D labs exhibit above-average GE growth during the recession, which suggests that the downturn gave high-tech areas dependent on public funding the opportunity to increase their comparative advantage in environmental activities. The effect of regulation is not precisely estimated splitting our sample into two periods, but the fact that it occurs only in the post-crisis period excludes pre-trend differences between the treated and control groups (see the next section for a formal test). Overall, being resilient to the great recession ensures a positive and significant differential growth of green employment in the hardest times of the great recession, while the other drivers are particularly active in the recovery phase.

[Table 9 about here]

Table 9 reports separate estimates for high- and low-skilled green employment. The striking finding is that, while the local endowment of green knowledge and the presence of a federally funded R&D lab affect only high-skilled green employment, the permanent effect of the great recession on green employment is considerably larger on low-skilled green workers. The size of the estimated coefficients confirm these differences: during the great recession, an inter-quartile increase in resilience to the crisis is associated with a 6.1 percent (resp. 1.8 percent) increase in the local share of low-skilled (resp. high-skilled) green jobs. The effect of an inter-quartile increase in green patents per capita leads to a remarkable 5.1 percent increase in the local demand of high-skilled green workers, while the effect of a federally funded R&D is only marginally smaller (i.e., 4.9 percent). Finally, the effect of new nonattainment designation is weakened both in terms of size (especially for high-skilled workers, 1.5 percent rather than 1.7 percent) and of statistical significance (especially for low-skilled green jobs). While this may corroborate the claim that the main US environmental regulation does not favor workers' reallocation towards greener activities, the next section tests the validity of this conclusion using an estimation strategy designed to capture in a more precise way the effect of nonattainment designation.

4.3 Focus on the effect of environmental regulation

The new nonattainment designation cannot be considered randomly assigned if systematic differences in the factors that influence the concentration of pollutants (population density, old nonattainment designation, etc.) are correlated with the level and dynamics of green employment. The violation of the random assignment condition leads to a biased estimate of the average treatment effect on the treated (ATET) with a difference-in-differences estimator (Abadie, 2005). To account for these systematic differences, we build a proper counterfactual of attainment areas that mirrors the observable features of treated areas using the difference-in-differences semi-parametric matching estimator proposed by Heckman et al. (1997) and Heckman et al. (1998).

We compute the treatment effect for each N_T treated area j at year t ($\hat{\alpha}_{jt}$) as the difference between in the change in the outcome variable Y (with respect to the base year t^0) between the treated area j and the untreated area k that is matched to area j .¹⁹ The average treatment effect in year t is thus the average

¹⁹ $\hat{\alpha}_{tj} = (Y_t^{Tj} - Y_{t^0}^{Tj}) - (Y_t^{Ukj} - Y_{t^0}^{Ukj})$, where Y is GE, CGE or GIE. Recall that 2008 is t^0 , i.e., the last pre-treatment year; thus, the post-treatment changes are 2008-2009, 2008-2010, etc., and the pre-treatment changes are 2007-2008 and 2006-2008.

of the $\hat{\alpha}_{tj}$:

$$\hat{\alpha}_t = \frac{1}{N_T \sum_{j \in T} L_j^{t^0}} \sum_{j \in T} (\hat{\alpha}_{jt} \times L_j^{t^0}) \quad (7)$$

where the treatment effect for each treated area is weighted by its total employment in 2008 ($L_j^{t^0}$). We estimate the probability of being treated using a set of covariates that are likely to influence the selection into treatment: average establishment size, a dummy for nonmetropolitan areas, population density, share of employment in the utility sector (NAICS 21) and share of population that resides in counties that were non-attainment for at least one of the 'old' standards.²⁰ Another important choice concerns the matching algorithm. The nearest neighbor matching is the one that, in principle, optimizes the balancing of variables for treated and non-treated areas so that only the best matches are retained. However, as discussed in detail in Appendix E, the relatively small pool of potential untreated matches makes it difficult to balance pre-treatment characteristics between treated and control group. Balancing appears slightly easier with a kernel matching algorithm rather than with the ideal nearest neighbor matching and thus we report results for both matching algorithms in the main text.²¹ It is worth noting, however, that also the kernel matching fails in balancing the share of metropolitan areas between treated and control group (see Table E2 in the Appendix). This implies that our results should be interpreted with caution and be mostly considered as a qualitative validation of the findings of previous section.

[Figure 9 about here]

The results for GE are plotted in Figure 9.²² First, as a formal test for the existence of pre-treatment differential trends between the treated and matched untreated groups, it is important to stress that GE exhibits similar dynamics in the two groups before the policy shock (change 2006-2008 and 2007-2008) and that we do not detect any statistically significant pre-treatment difference. This indicates that matching successfully eliminates pre-treatment trend differences between treated and control areas. Second, we find no significant treatment effect in the first three years after the nonattainment designation (2009-2011). Indeed, the treatment effect becomes statistically significant in 2012 (i.e., the year of nonattainment designation for the Ozone 8h standard) and continues to grow until 2014. For the whole 2008-2014 period, the magnitude of the estimated average treatment effect on the treated for GE is between 4 and 5.6 percent, which is substantially larger than that found in the previous section and in line with that of other drivers. This different result may be ascribed

²⁰In Table E4 of the Appendix E, we show that the results are virtually unchanged using a richer PSM specification that includes the share of employment in the manufacturing (NAICS 31-33) and mining (NAICS 21) sectors, the initial GE and our measure of resilience to the crisis.

²¹ $Y_t^{U_{kj}}$ is defined, in the simple case of nearest neighbour matching, as the outcome variable of the untreated area k that is matched to the treated area j . In the kernel matching case, however, $Y_t^{U_{kj}}$ represents the weighted average of the outcome variable for the untreated areas matched to treated area j with weights that decrease (according to the kernel function) with the propensity score distance between treated and untreated areas.

²²To ease interpretation, we already plotted the ATET in terms of relative change in the share of GE, that is, the ration between ATET and the average share of GE in 2008.

either to a heterogeneous effect depending on the regulated pollutant or to the time profile of the labor market adjustment. On the one hand, while only a few (69) of all treated areas (156) were designed nonattainment before 2011 (for PM2.5, SO2 or Lead), the tightening of Ozone standards has been identified as considerably more costly for businesses (Curtis, 2015), thus implying a larger expected impact on the demand of GE to cope with the regulation. On the other hand, if regulation takes time to influence the structure of the workforce, we should not expect large treatment effect in the first years after nonattainment designation. To test these alternative explanations, in Table F4 of the Appendix F, we assess the effect of the Ozone nonattainment designation in isolation. The results lend support to the hypothesis that Ozone shock drives the results of regulation, with the caveat that, also in this case, propensity score matching does not allow to fully balance the characteristics of treated and control group areas (see Tables F2 and F3).

[Figures 10, 11, 12 and 13 about here]

We test the robustness of our results for CGE, GIE and high- and low-skilled green jobs. The results are qualitatively in line with those discussed in the previous section for CGE (positive and significant effect, Figure 10) and for GIE (negligible effect, Figure 11). When splitting green employment into high-skilled (Figure 12) and low-skilled (Figure 13), we observe that regulation increases mostly the employment of high-skilled green workers, while the impact on green low-skilled workers is not statistically significant at conventional levels. Overall, our results point to a modest effect of environmental regulation on green employment that is driven by recent Ozone regulation and thus still needs to be fully evaluated. This modest effect of a command-and-control regulation should not be surprising for environmental policy experts. Instead of providing sufficient incentives to undergo ambitious redesigning of products and processes, command-and-control policies tend to re-orient firms production towards end-of-pipe solutions. If (as seems plausible) easy-to-use end-of-pipe technologies are swiftly adopted by incumbents while redesigning the production process requires new competences and new professional profiles, command-and-control policies are an unlikely instrument to spur comparative advantage in environmental activities.

5 Green job local multiplier

A natural extension of our analysis would consist in the evaluation of welfare effects associated with the greening of our economies. This, in turn, would require a theoretical model that provides structure to the underlying causal mechanisms and, ultimately, to the criteria for such an evaluation. While this is beyond the scope of our exploratory paper, we take an initial step in this direction by estimating the employment effects that can be ascribed to active green policies akin to the stimulus package implemented as part of the American Recovery and Reinvestment Act in 2009.²³ If the expansion of a novel group of

²³For instance, as part of this policy measure, the Energy Department invested more than \$31 billion to support a wide range of clean energy projects across the board, such as the expansion of smart grids, the development of alternative fuel vehicles, the creation of new power sources, and the conservation of natural resources.

economic activities were found to generate positive employment effects in the local economy, well-designed green policies would act as effective place-based policies beyond the remit of environmental sustainability.

According to Moretti (2010), the idea of a multiplier effect responds to a simple and yet highly relevant economic question: how many local jobs are created in response to a positive demand shock in the tradable part of the economy? The aggregate effect is a combination of the effects on the non-tradable sector and on the part of the tradable sector that is not affected by the shock. On the one hand, the non-tradable sector benefits from increased demand for local goods and services (a pecuniary externality). On the other hand, the rest of the tradable sector can become either less competitive due to an increase in local labor costs (a general equilibrium effect) or more competitive by virtue of agglomeration externalities and localized supply chain effects (broadly defined as technological externalities). Recent papers have shown that the size of the local multiplier varies depending on the type of tradable activities that are affected by the positive demand shock (e.g., Marchand, 2012; Moretti and Thulin, 2013). High-tech manufacturing generates larger multipliers than oil and mining because it is a source of stronger agglomeration and pecuniary (via higher wages) externalities. The issue of interest is thus to position green activities in this ranking. To answer this question, we estimate the following model:

$$\Delta \ln(L_j^k) = \alpha + \beta \Delta \ln(\text{Green}_j) + \mu_s + \eta_n + \varepsilon_j \quad (8)$$

where the long-term change in the log of employment in industry k (non-tradable, NT, or, alternatively, manufacturing) is regressed on the long-term change in the log of green employment,²⁴ a constant, and state μ_s and non-metro area η_n dummies. These dummies deparure the green local multiplier from, respectively, state-specific and non-metro area trends. We construct L_{jt}^{NT} net of the employment in the sector “Professional, Scientific, and Technical Services– (NAICS 54) that is both tradable (Jensen and Kletzer, 2005) and one of the largest in terms of green employment.

To estimate equation 8, we face a major data constraint because we cannot measure the number of green jobs in the local tradable sector. This is because our data can be divided either at the industry-by-region level or at occupation-by-region level, thus generating a mechanical correlation between $\Delta \ln(L_j^k)$ and $\Delta \ln(\text{Green}_j)$. Although this correlation should be very small because green jobs represent a rather small fraction of NT jobs and we exclude professional service jobs in computing NT employment, we minimize these concerns by testing the robustness of our results to a different definition of NT non-green employment. This alternative measure identifies NT green employment in local labor markets. As for the Green Industry Employment measure, we compute NT green employment by attributing to local industries the national share of green employment and then subtracting it from total employment in NT industries. We argue that finding similar job multipliers across these two measures would strongly validate our policy conclusions.²⁵

The second identification issue regards endogeneity due to the correlation between changes in green employment and unobservable local shocks. To iso-

²⁴That is: $\text{Green}_{jt} = \sum_{i=1}^I \text{Greenness}_i \times L_{ijt}$.

²⁵Our results are very robust to the use of alternative definitions of NT employment, such as those proposed by Jensen and Kletzer (2005).

late the share of green employment attributed to aggregate shocks, such as subsidies to clean energy or the green stimulus package, as opposed to that due to local shocks, we use the standard shift-share instrumental variable strategy proposed by Moretti (2010). Specifically, we instrument the local change in green employment with the weighted average of nationwide employment growth of 6-digit green occupations, where the weights are the initial employment share of these occupations in area j multiplied by the occupational greenness. To partial out the influence of local conditions, we calculate a nationwide change in green employment specific to the area by subtracting the local change in green employment.

[Table 10 about here]

The main results are presented in Table 10, which contains two panels, one for each of the different measures of non-tradable employment. We report both the elasticity of NT to green employment and the implied local multiplier, which is the product between this elasticity and the weighted median number of NT jobs for each green job in 2014. Our results point to a large green job multiplier irrespective of NT employment and to the estimation technique. Our favorite IV estimates reveal only a small bias in the OLS coefficients. We find that each new green job creates 4.2 new NT jobs in the local economy (Panel 1). The local multiplier increases up to 5.1 new NT jobs when we deplete NT employment from the predicted number of green jobs in NT industries (Panel 2). Because the elasticity of NT employment to green employment ranges between 0.223 and 0.308, these figures are driven by a ratio of approximately 1:18 between green jobs and NT jobs. Ranking multipliers by type of tradable activity, we observe that green jobs are at the top of the list, just below the highest value (5) for high-tech manufacturing (Moretti, 2010). Remarkably, to assess the economic implications of investing in green rather than brown activities, the green job multiplier appears significantly larger than the multipliers found by Marchand (2012) for mining and by Weber (2012) for shale gas. The finding that the local green multiplier is closer to the multiplier effect of high-tech activities rather than mining is not surprising given the high average quality of green employment in terms of both educational requirement and average wages.

Two issues naturally arise from this estimate of the green job multiplier. First, the large green multiplier may be associated with the concentration of tradable activities around a green cluster, or it could just be the result of large pecuniary externalities associated with high (unconditional) green wage premia. Second, the Recovery Act is a plausible candidate to explain the magnitude of the green multiplier.

[Table 11 about here]

To address the first issue, Table 11 illustrates the impact of a new green job on manufacturing employment broken down into total manufacturing, high-tech manufacturing and low-tech manufacturing. We compute manufacturing employment net of the predicted green employment in each sector. For this set of estimates, instrumenting the change in green jobs happens to be particularly important: while an additional green job has a positive and significant effect on both high-tech and low-tech manufacturing employment in OLS, the effect vanishes in our favorite IV estimates. However, the non-significant IV estimate

for high-tech manufacturing is mostly driven by a substantial decrease in the precision of the estimates, as is evident if one looks at the change in the standard errors from Columns (3) to (4). Although this is not a conclusive result regarding the formation of green high-tech clusters, the sign and magnitude of the coefficients resonate with the claim that green employment is associated with high-tech and innovative activities.

[Table 12 about here]

We analyze the extent of structural breaks in the green job multiplier by separating the crisis (2006-2010) and the post-crisis (2010-2014) periods. Table 12 presents the results of this exercise, wherein we modified the instruments to account for the growth rate in national green employment and initial occupational composition in each sub-period. Our estimates provide bounds to the green job multiplier: a lower bound in deep recession and an upper bound during recovery. Remarkably, while the green local multiplier is significantly larger in the expansionary phase, it remains positive, large and significant (or nearly significant for the canonical measure of NT employment) even during the peak of the great recession. Even considering this conservative lower bound, the local green multiplier yields a net creation of 2.4-2.5 NT jobs. This is particularly important given the harshness of the 2007-2010 recession and the short length of this period compared to the 10-year window that is usually used to estimate local multipliers. A final element of concern in our estimates is that multipliers are generally higher during and just after a deep recession (Auerbach and Gorodnichenko, 2012). While further research is required to assess the green job multiplier in normal times, and more time is needed to assess the potential bottlenecks that will hamper the transition toward a greener economy, our results indicate that green productions have the potential to be a source of employment growth.

6 Conclusions

This paper has focused on one of the most sensitive issues of the lively debate on the challenges and opportunities of embracing environmental sustainability, namely, the labor market effects associated with the transition towards a greener economy. In particular, it has addressed four questions: What is green employment? How has it evolved over time and across geographical space? What are the key drivers? And, finally, what is the impact of a new green job on the local labor market?

Regarding the first issue, we depart from existing approaches that measure green employment as the total workforce dedicated to either the production of ‘green goods and services’ or to the adoption of particular ‘green production processes’. It has been argued that this rationale is ill-suited because it merely infers the green nature of work activities without delving into the type of occupation and the work skills it entails. Rather, we construct an alternative measure of the degree of occupational greenness grounded in the idea that jobs are best defined by their task content and by the set of capabilities that are needed to accomplish those tasks.

We then explored descriptive characteristics of green jobs in a panel of metropolitan and nonmetropolitan areas in the US between 2006 and 2014.

These reveal, first, that the share of total workforce employed in green occupations is between 2 and 3 percent. Second, green jobs pay a positive wage premium of approximately 4 percent relative to comparable occupations. Third, green jobs are more spatially concentrated relative to comparable jobs, although their concentration declines over time due to the catching-up of geographical areas with initially low levels of green employment. Looking at the time trend, all these figures exhibit a contraction during the great recession followed by a more (for green employment) or less (for spatial concentration and the green wage premium) swift recovery in the last four years. Finally, a group of emergent leading areas is characterized by a strong presence of high-tech activities and a bias towards specialization in green technologies.

Because the outbreak of the crisis coincided with the implementation of regulation that revised emission standards, we leverage this exogenous shock to analyze the impact of environmental regulation on the greening of the workforce. Our findings illustrate that changes in environmental regulation are a secondary driver of green employment growth compared to: local endowment of green knowledge, the presence of a federally funded R&D lab and resilience to the great recession. This finding is partially ascribed to the short timespan available to evaluate the effect of the change in ozone standards, which proved to have the strongest impact on green employment. Overall, our results question the effectiveness of command and control regulations for the goal of supporting the establishment of green activities in local economies. At the same time, our findings lend support to the widely accepted idea that the transition towards a green growth path requires an appropriate mix of policies that properly includes policies to sustain innovation.

In the last part of the paper, we take an initial step towards assessing whether becoming greener has positive effects on local labor markets, and we find that one additional green job yields the creation of 4.2 new jobs in non-tradable activities. Remarkably, the magnitude of this effect is closer to that of the high-tech manufacturing multiplier, which is the highest, than to that of an activity concerned with natural resources, such as mining. Not only is the green local multiplier large during the expansionary phase, which is to be expected, but it also remains positive, large and significant at the peak of the recession. In partial contrast to literature that hints at a trade-off between environmental and socio-economic goals, our findings reveal a win-win scenario whereby greening of the workforce has positive spillovers on local employment growth. Clearly, this preliminary interpretation will require more rigorous testing in a fully-fledged cost-benefit analysis. For instance, whether a win-win strategy would have been possible in the absence of the massive investments of the Job Recovery Act remains an open question. Likewise, the question of whether areas with faster growth of green employment are also more successful in reducing emissions remains to be addressed. These and other questions are left for future research.

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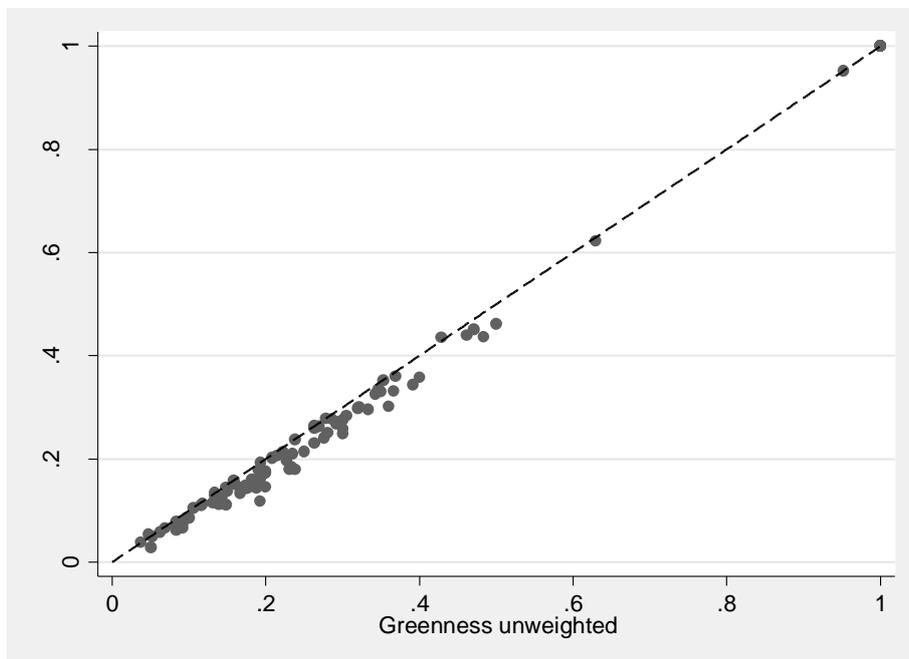
Tables and figures

Table 1: Occupations (8-digit SOC) by macro-occupational group

SOC2	Occupational title	Tot	Green	Green core
11	Management Occupations	59	16	9
13	Business and Financial Operations Occupations	51	12	9
15	Computer and Mathematical Occupations	33	2	0
17	Architecture and Engineering Occupations	71	41	25
19	Life, Physical, and Social Science Occupations	60	16	11
21	Community and Social Services Occupations	14	0	0
23	Legal Occupations	8	1	0
25	Education, Training, and Library Occupations	61	0	0
27	Arts, Design, Entertainment, Sports, and Media Occupations	43	2	2
29	Healthcare Practitioners and Technical Occupations	86	1	1
31	Healthcare Support Occupations	18	0	0
33	Protective Service Occupations	29	0	0
35	Food Preparation and Serving Related Occupations	17	0	0
37	Building and Grounds Cleaning and Maintenance Occupations	8	0	0
39	Personal Care and Service Occupations	32	0	0
41	Sales and Related Occupations	24	3	2
43	Office and Administrative Support Occupations	63	2	1
45	Farming, Fishing, and Forestry Occupations	17	0	0
47	Construction and Extraction Occupations	61	12	8
49	Installation, Maintenance, and Repair Occupations	54	6	4
51	Production Occupations	112	11	8
53	Transportation and Material Moving Occupations	53	3	2
Total		974	128	82

Source: O*NET, release 18.0, July 2012. A green job is defined as a job with greenness greater than one.

Figure 1: Weighted vs unweighted greenness (8-digit SOC occupations)



Source: O*NET, release 18.0, July 2012. Greenness weighted is defined as in equation (1), while Greenness unweighted is defined as the ratio between the raw count of green specific tasks and the raw total count of specific tasks for each 8-digit SOC occupation.

Table 2: Green occupations (8-digit SOC) sorted by greenness

SOC Code	Occupational title	Greenness	Greenness core
11-9041.01	Biofuels/Biodiesel Technology and Product Development Managers	1	1
11-9121.02	Water Resource Specialists	1	1
11-9199.09	Wind Energy Operations Managers	1	1
11-9199.10	Wind Energy Project Managers	1	1
11-9199.11	Brownfield Redevelopment Specialists and Site Managers	1	1
13-1199.01	Energy Auditors	1	1
13-1199.05	Sustainability Specialists	1	1
17-2081.00	Environmental Engineers	1	1
17-2081.01	Water/Wastewater Engineers	1	1
17-2141.01	Fuel Cell Engineers	1	1
17-2199.10	Wind Energy Engineers	1	1
17-2199.11	Solar Energy Systems Engineers	1	1
17-3025.00	Environmental Engineering Technicians	1	1
17-3029.10	Fuel Cell Technicians	1	1
19-1031.01	Soil and Water Conservationists	1	1
19-2041.01	Climate Change Analysts	1	1
19-2041.02	Environmental Restoration Planners	1	1
19-2041.03	Industrial Ecologists	1	1
19-4091.00	Environmental Science and Protection Technicians, Including Health	1	1
41-3099.01	Energy Brokers	1	1
47-2231.00	Solar Photovoltaic Installers	1	1
47-4041.00	Hazardous Materials Removal Workers	1	1
47-4099.02	Solar Thermal Installers and Technicians	1	1
47-4099.03	Weatherization Installers and Technicians	1	1
49-9081.00	Wind Turbine Service Technicians	1	1
49-9099.01	Geothermal Technicians	1	1
51-8099.01	Biofuels Processing Technicians	1	1
51-8099.02	Methane/Landfill Gas Generation System Technicians	1	1
51-8099.03	Biomass Plant Technicians	1	1
51-8099.04	Hydroelectric Plant Technicians	1	1
51-9199.01	Recycling and Reclamation Workers	1	1
53-7081.00	Refuse and Recyclable Material Collectors	1	1
17-2199.03	Energy Engineers	0.9526	0.9487
19-1013.00	Soil and Plant Scientists	0.6218	0.6398
19-2021.00	Atmospheric and Space Scientists	0.4624	0.4365
17-2011.00	Aerospace Engineers	0.4607	0.4039
17-2051.00	Civil Engineers	0.4516	0.3395
49-3023.02	Automotive Specialty Technicians	0.4401	0.1266
19-2042.00	Geoscientists, Except Hydrologists and Geographers	0.4360	0.1650
53-6051.07	Transportation Vehicle, Equipment and Systems Inspectors, Except Aviation	0.4355	0
19-3051.00	Urban and Regional Planners	0.3604	0.3757
17-3029.02	Electrical Engineering Technologists	0.3574	0
17-3029.11	Nanotechnology Engineering Technologists	0.3529	0.3529
47-2152.02	Plumbers	0.3445	0.0614
29-9012.00	Occupational Health and Safety Technicians	0.3340	0.2275
13-1081.01	Logistics Engineers	0.3310	0.1965
17-2161.00	Nuclear Engineers	0.3308	0.1292
17-2199.01	Biochemical Engineers	0.3255	0.2485
17-2199.09	Nanosystems Engineers	0.3014	0.1902
47-2181.00	Roofers	0.3009	0.1734
17-2141.02	Automotive Engineers	0.2979	0.2496
13-2051.00	Financial Analysts	0.2961	0
19-4099.02	Precision Agriculture Technicians	0.2838	0.1582
17-3027.01	Automotive Engineering Technicians	0.2778	0.2778
17-2141.00	Mechanical Engineers	0.2774	0.0671
51-8011.00	Nuclear Power Reactor Operators	0.2752	0.0839
11-3071.03	Logistics Managers	0.2748	0.2026
17-3029.03	Electromechanical Engineering Technologists	0.2718	0
17-1011.00	Architects, Except Landscape and Naval	0.2683	0.2683
47-4011.00	Construction and Building Inspectors	0.2642	0.2535
49-9021.01	Heating and Air Conditioning Mechanics and Installers	0.2631	0.2423
17-1012.00	Landscape Architects	0.2601	0.2601
11-9199.04	Supply Chain Managers	0.2577	0.0537
11-9021.00	Construction Managers	0.2510	0.1731
13-1022.00	Wholesale and Retail Buyers, Except Farm Products	0.2485	0.1053
17-3029.06	Manufacturing Engineering Technologists	0.2405	0.0492
13-2099.01	Financial Quantitative Analysts	0.2381	0.2381
15-1199.05	Geographic Information Systems Technicians	0.2301	0
47-2211.00	Sheet Metal Workers	0.2141	0.0716
27-3031.00	Public Relations Specialists	0.2130	0.1963
17-3026.00	Industrial Engineering Technicians	0.2105	0
11-3071.01	Transportation Managers	0.2060	0.1263
51-8013.00	Power Plant Operators	0.2029	0
17-3023.03	Electrical Engineering Technicians	0.2005	0
17-2072.00	Electronics Engineers, Except Computer	0.1967	0.0767
17-2199.06	Microsystems Engineers	0.1935	0.1935
11-3071.02	Storage and Distribution Managers	0.1849	0
19-4041.01	Geophysical Data Technicians	0.1797	0
17-2051.01	Transportation Engineers	0.1794	0.0541
11-9041.00	Architectural and Engineering Managers	0.1780	0
17-3029.09	Manufacturing Production Technicians	0.1760	0.0990
11-9199.02	Compliance Managers	0.1741	0
11-2021.00	Marketing Managers	0.1720	0
43-5011.01	Freight Forwarders	0.1686	0.0452
13-1081.02	Logistics Analysts	0.1627	0.0545
17-2071.00	Electrical Engineers	0.1607	0
47-2061.00	Construction Laborers	0.1585	0
17-3029.12	Nanotechnology Engineering Technicians	0.1579	0.1579
49-3031.00	Bus and Truck Mechanics and Diesel Engine Specialists	0.1508	0
17-3029.05	Industrial Engineering Technologists	0.1487	0
17-3029.08	Photonics Technicians	0.1457	0

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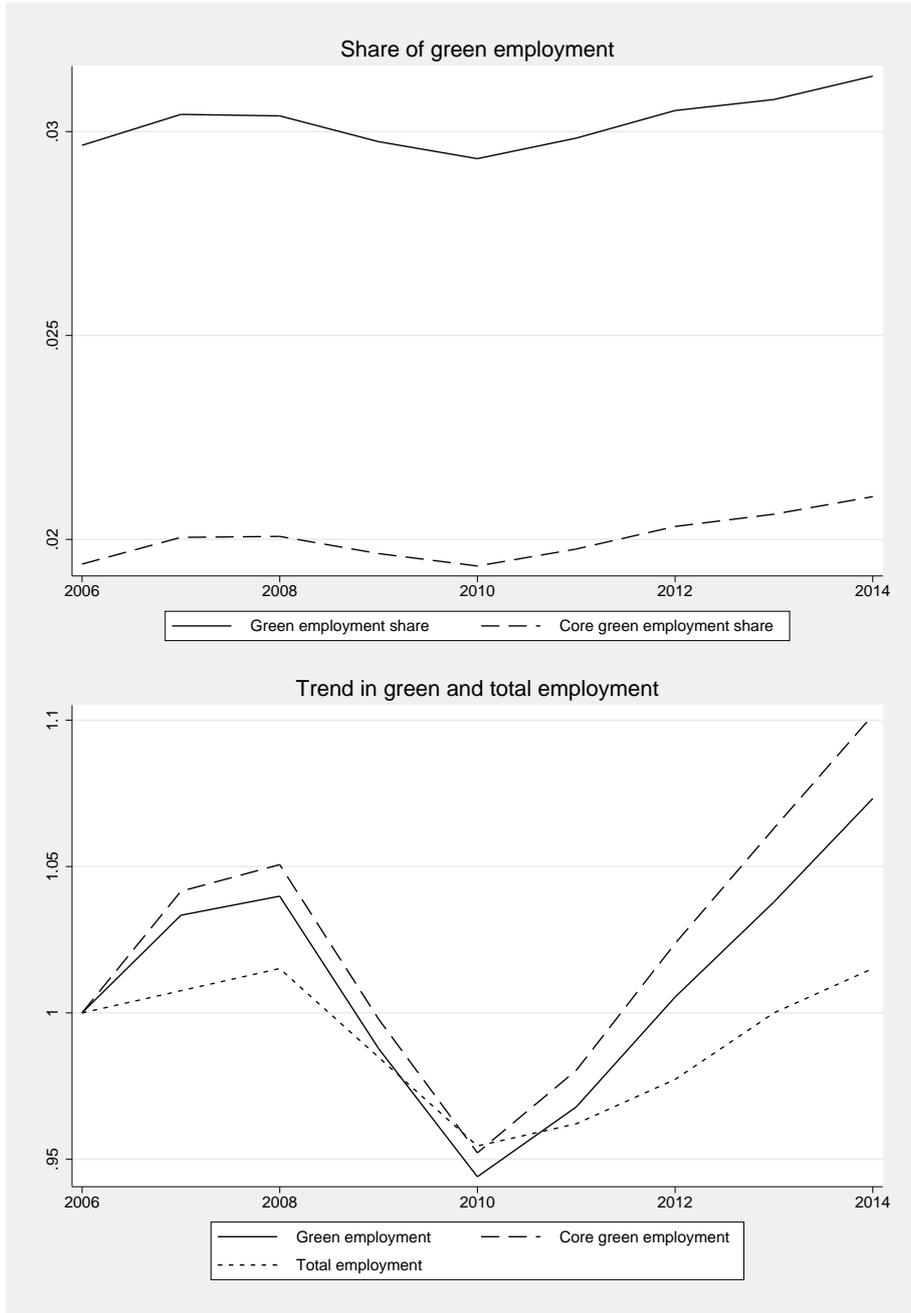
47-5041.00	Continuous Mining Machine Operators	0.1447	0
11-9013.02	Farm and Ranch Managers	0.1444	0
13-1041.07	Regulatory Affairs Specialists	0.1438	0
19-4041.02	Geological Sample Test Technicians	0.1437	0
17-3029.04	Electronics Engineering Technologists	0.1424	0
17-2199.04	Manufacturing Engineers	0.1416	0
47-2152.01	Pipe Fitters and Steamfitters	0.1380	0
49-9071.00	Maintenance and Repair Workers, General	0.1348	0
13-2099.02	Risk Management Specialists	0.1339	0
51-2011.00	Aircraft Structure, Surfaces, Rigging, and Systems Assemblers	0.1295	0
19-3099.01	Transportation Planners	0.1259	0.1001
17-3029.07	Mechanical Engineering Technologists	0.1249	0
17-2199.07	Photonics Engineers	0.1174	0
13-2052.00	Personal Financial Advisors	0.1168	0.0630
19-4099.03	Remote Sensing Technicians	0.1156	0
17-2199.05	Mechatronics Engineers	0.1149	0
11-1021.00	General and Operations Managers	0.1134	0
41-4011.00	Sales Representatives, Wholesale and Manufacturing, Technical and Scientific Products	0.1125	0.0403
11-9199.01	Regulatory Affairs Managers	0.1114	0
19-4011.01	Agricultural Technicians	0.1101	0
13-2099.03	Investment Underwriters	0.1053	0.1053
13-1151.00	Training and Development Specialists	0.0862	0.0597
53-3032.00	Heavy and Tractor-Trailer Truck Drivers	0.0856	0.0414
17-3024.00	Electro-Mechanical Technicians	0.0786	0
17-2199.02	Validation Engineers	0.0769	0
43-5071.00	Shipping, Receiving, and Traffic Clerks	0.0734	0
19-2099.01	Remote Sensing Scientists and Technologists	0.0716	0
15-1199.04	Geospatial Information Scientists and Technologists	0.0694	0
17-3024.01	Robotics Technicians	0.0687	0
51-4041.00	Machinists	0.0658	0.0874
41-3031.03	Securities and Commodities Traders	0.0658	0
17-2199.08	Robotics Engineers	0.0615	0
51-9061.00	Inspectors, Testers, Sorters, Samplers, and Weighers	0.0584	0
51-9012.00	Separating, Filtering, Clarifying, Precipitating, and Still Machine Setters, Operators, and Tenders	0.0540	0.0769
47-5013.00	Service Unit Operators, Oil, Gas, and Mining	0.0501	0
27-3022.00	Reporters and Correspondents	0.0386	0.0423
23-1022.00	Arbitrators, Mediators, and Conciliators	0.0281	0

Table 3: Green Jobs by macro-occupational group

Occupational group	Green employment share, GE (2006)	Growth green employment share, GE (2006-2014)	Average years of education of Green Occ.	Average years of education of non-Green Occ.
11 Management	0.0899	0.1538	15.50	15.32
13 Business and Financial Operations	0.0805	0.0295	14.95	15.28
15 Computer and Mathematical	0.0002	6.3806	15.57	15.38
17 Architecture and Engineering	0.2035	0.0783	15.94	15.43
19 Life, Physical, and Social Science	0.1465	0.1081	16.25	16.87
21 Community and Social Services	-	-	-	16.08
23 Legal	0.0002	0.0232	16.48	17.51
25 Education, Training, and Library	-	-	-	15.87
27 Arts, Design, Entertainment, Sports, and Media	0.0275	-0.0122	15.66	14.54
29 Healthcare Practitioners and Technical	0.0004	0.3669	14.83	15.62
31 Healthcare Support	-	-	-	12.69
33 Protective Service	-	-	-	12.32
35 Food Preparation and Serving Related	-	-	-	10.95
37 Building and Grounds Cleaning and Maintenance	-	-	-	11.45
39 Personal Care and Service	-	-	-	12.57
41 Sales and Related	0.0392	0.5460	13.99	12.38
43 Office and Administrative Support	0.0027	-0.1283	11.96	12.97
45 Farming, Fishing, and Forestry	-	-	-	11.06
47 Construction and Extraction	0.0699	-0.1653	12.13	11.95
49 Installation, Maintenance, and Repair	0.0986	0.0073	12.74	12.72
51 Production	0.0366	-0.2123	12.81	11.87
53 Transportation and Material Moving	0.0281	-0.0348	11.54	11.72

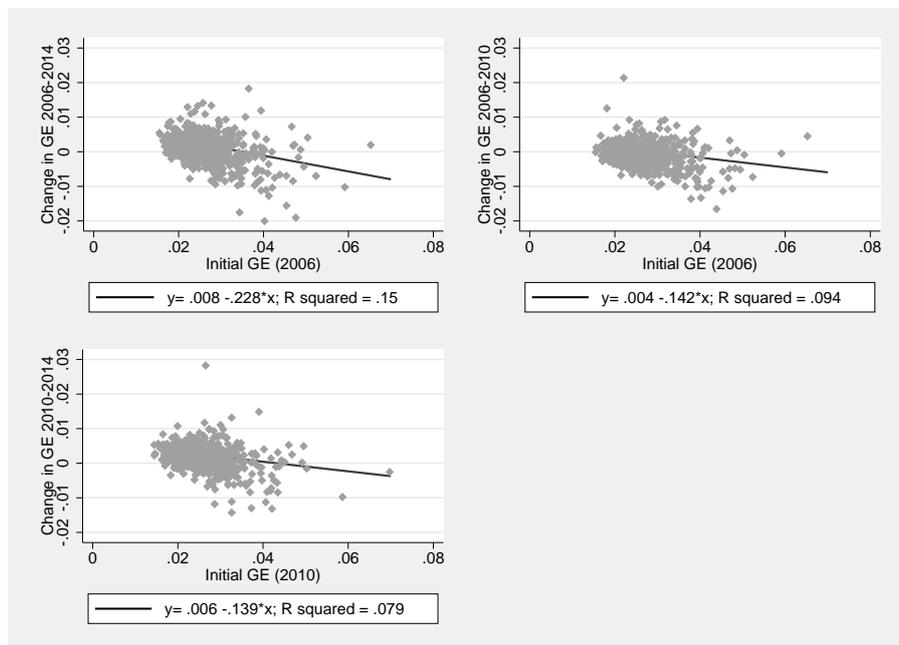
Own elaboration on O*NET, release 18.0, July 2012, and BLS-OES estimates of employment by metropolitan and nonmetropolitan areas. All variables are weighted averages for the 2-digit SOC occupation using total employment at the 6-digit SOC in 2006 as weights. Average years of education is the average years of schooling needed by workers in an occupation.

Figure 2: Trends in green employment



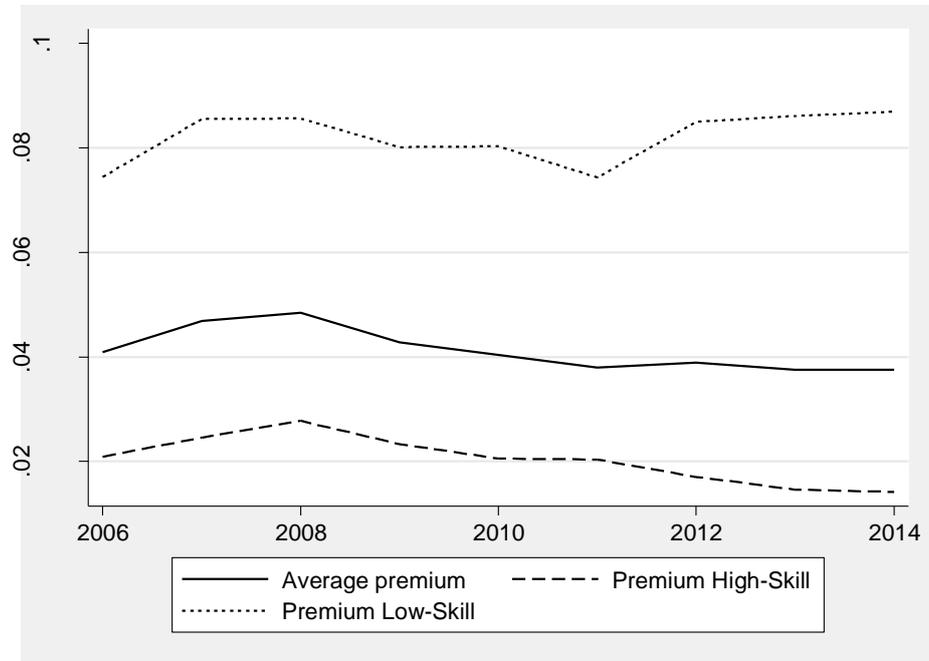
Source: own elaboration on O*NET, release 18.0, July 2012, and BLS-OES estimates of employment by metropolitan and nonmetropolitan areas. US averages are weighted by area's total employment.

Figure 3: Catching-up in green employment share, GE



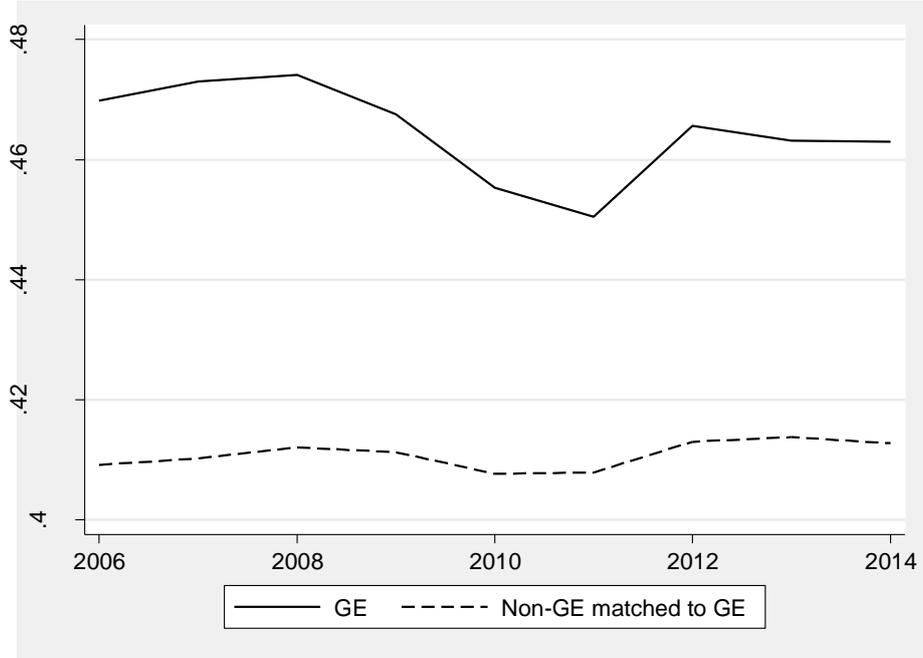
Own elaboration on O*NET, release 18.0, July 2012, and BLS-OES estimates of employment by metropolitan and nonmetropolitan areas. Beta convergence estimated with a cross-sectional regression of the growth in GE on the initial GE, weighted by initial employment by area (N=537).

Figure 4: Wage premium (log difference) for green occupations with respect to non-green occupations within the same 3-digit SOC



Own elaboration on O*NET, release 18.0, July 2012, and BLS-OES estimates of employment by metropolitan and nonmetropolitan areas. The wage premium is computed as the difference in log hourly wages between green and non-green occupations within the same 3-digit SOC group. Premiums at the 3-digit are then averaged using total employment at the 3-digit SOC level as weights. Hourly wage for green occupations within the 3-digit SOC group is computed as the average of hourly wage of green occupations using as weights the product between occupational employment and the greenness. Hourly wage for non-green occupation within the 3-digit SOC group is computed as the average hourly wage of occupations (green and non-green) using as weights the product between occupational employment and (1-greenness). High skill occupations are the ones belonging to the 2-digit SOC codes: 11, 13, 15, 17, 19, 23, 27, 29, 41. Low skill occupations are the ones belonging to the 2-digit SOC codes: 43, 47, 49, 51, 53.

Figure 5: Concentration index for green occupations (*GE*) and for non-green occupations within the same 3-digit SOC (*Non-GE matched to GE*)



Own elaboration on O*NET, release 18.0, July 2012, and BLS-OES estimates of employment by metropolitan and nonmetropolitan areas. The concentration index for green employment is computed as the average concentration index of green occupation weighted by the product between the greenness and occupational employment. The concentration index for non-green 'matched' occupations is computed as the average concentration index for all occupations in 3-digit SOC codes with at least one green occupations weighted by the product between (1-greenness) and occupational employment.

Table 4: Profiling of areas by quintile of initial green employment share (2006)

Quintile of GE (2006)	1 (low GE)	2	3	4	5 (high GE)	Total
GE (2006)	0.0216	0.0260	0.0294	0.0329	0.0395	0.0298
Growth in GE (2006-2014)	0.1181	0.1056	0.0776	0.0127	-0.0075	0.0617
Number of areas	218	105	81	61	72	537
Total empl growth 2006-2014	0.0022	0.0151	0.0286	0.0384	0.0239	0.0220
Unemployment rate	0.0712	0.0692	0.0666	0.0714	0.0677	0.0693
Pop density (2006)	208.4	1143.8	489.9	1024.9	689.8	718.7
Exposure to crisis	-0.0490	-0.0450	-0.0484	-0.0491	-0.0489	-0.0481
Import penetration (2006)	0.0677	0.0646	0.0623	0.0630	0.0631	0.0641
Empl share in manufacturing (2006)	0.1329	0.1058	0.1029	0.1010	0.0996	0.1084
Empl share in utilities (2006)	0.0047	0.0046	0.0037	0.0045	0.0035	0.0042
Empl share in construction (2006)	0.0508	0.0501	0.0563	0.0573	0.0597	0.0548
Empl share in mining (2006)	0.0065	0.0028	0.0017	0.0058	0.0017	0.0038
Empl share high-tech manuf (2006)	0.0333	0.0319	0.0321	0.0335	0.0391	0.0339
Empl share KIBS, NAICS 54 (2006)	0.0288	0.0549	0.0553	0.0624	0.0839	0.0566
Number of areas with R&D labs	4	2	3	4	11	24
Green patent stock per capita	0.0233	0.0449	0.0329	0.0363	0.0510	0.0374
Total patent stock per capita	0.2307	0.6257	0.4244	0.4714	0.7292	0.4909

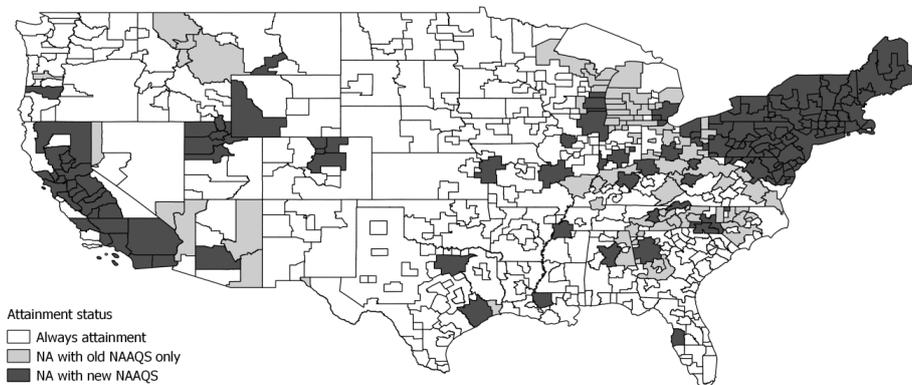
Quintiles of the distribution of green employment share (GE) in 2006 weighted by areas employment in 2006. We computed weighted averages for the variables of interest using employment in 2006 as weights, with the exception of 'Number of areas' and 'Number of areas with R&D labs'.

Table 5: Top 20 areas in 2006 and 2014 by green employment share, GE

2006					
Area name	Green employment share (2006)	R&D lab	Green pat stock per capita (2006)	Empl share in KIBS (2006)	Empl share in high-tech manuf (2006)
Los Alamos County, New Mexico NMA	0.0820	1	0.3616	0.4865	0.0000
Holland-Grand Haven, MI	0.0773	0	0.0118	0.0271	0.1233
St. Mary's County, Maryland NMA	0.0652	0	0.0273	0.1942	0.0004
Kennewick-Pasco-Richland, WA	0.0591	1	0.0373	0.0972	0.0142
San Jose-Sunnyvale-Santa Clara, CA	0.0524	1	0.0606	0.1172	0.1376
Portsmouth, NH-ME	0.0504	0	0.0747	0.0532	0.0477
Fairbanks, AK	0.0495	0	0.0000	0.0313	0.0005
Huntsville, AL	0.0487	0	0.0121	0.1464	0.0868
Other Nevada NMA	0.0482	0	0.0000	0.0471	0.0034
Blacksburg-Christiansburg-Radford, VA	0.0476	0	0.0206	0.0323	0.1212
Bremerton-Silverdale, WA	0.0473	0	0.0009	0.0473	0.0314
Warner Robins, GA	0.0470	0	0.0000	0.0701	0.0027
Palm Bay-Melbourne-Titusville, FL	0.0469	0	0.0035	0.0569	0.0769
Cleveland, TN	0.0466	0	0.0129	0.0219	0.0735
Pocatello, ID	0.0454	0	0.0160	0.0341	0.0290
Crestview-Fort Walton Beach-Destin, FL	0.0454	0	0.0000	0.0751	0.0434
Kankakee-Bradley, IL	0.0439	0	0.0080	0.0000	0.0547
Corvallis, OR	0.0426	0	0.0302	0.0503	0.0510
Jackson, MI	0.0421	0	0.0187	0.0254	0.0728
Detroit-Warren-Livonia, MI	0.0420	0	0.0937	0.0835	0.0824
National average	0.0298		0.0373	0.0538	0.0368
2014					
Area name	Green employment share (2014)	R&D lab	Green pat stock per capita (2006)	Empl share in KIBS (2014)	Empl share in high-tech manuf (2014)
Los Alamos County, New Mexico NMA	0.1266	1	0.3616	0.6458	0.0000
St. Mary's County, Maryland NMA	0.0672	0	0.0273	0.2133	0.0017
Columbus, IN	0.0548	0	0.2616	0.0332	0.2342
Portsmouth, NH-ME	0.0545	0	0.0747	0.0555	0.0436
Cleveland, TN	0.0539	0	0.0129	0.0184	0.0918
Boulder, CO	0.0513	1	0.0724	0.1515	0.0550
Huntsville, AL	0.0494	0	0.0121	0.1542	0.0675
Bremerton-Silverdale, WA	0.0493	0	0.0009	0.0518	0.0629
Kennewick-Pasco-Richland, WA	0.0489	1	0.0373	0.0889	0.0147
Warner Robins, GA	0.0487	0	0.0000	0.0547	0.0035
Other Nevada NMA	0.0466	0	0.0000	0.0309	0.0016
Midland, TX	0.0458	0	0.0000	0.0512	0.0228
San Jose-Sunnyvale-Santa Clara, CA	0.0454	1	0.0606	0.1328	0.1105
Fairbanks, AK	0.0452	0	0.0000	0.0382	0.0008
Denver-Aurora-Broomfield, CO	0.0442	1	0.0207	0.0902	0.0131
Washington-Arlington-Alexandria, DC-VA-MD-WV	0.0433	1	0.0218	0.1549	0.0069
Trenton-Ewing, NJ	0.0429	1	0.1198	0.0950	0.0203
Detroit-Warren-Livonia, MI	0.0420	0	0.0937	0.0963	0.0787
Chattanooga, TN-GA	0.0411	0	0.0158	0.0360	0.0480
San Francisco-Oakland-Fremont, CA	0.0410	1	0.0413	0.1176	0.0218
National average	0.0313		0.0375	0.0586	0.0329

BOLD AREAS TO BE DONE YET... Top areas were selected based on the share of green employment . Areas in bold were in the top 20 both in 2006 and 2014. KIBS includes NAICS codes 54. High-tech manufacturing includes NAICS codes 325, 333, 334, 335, 336.

Figure 6: Attainment status by metropolitan and nonmetropolitan area



Own elaboration based on information from the 'Green Book Nonattainment Areas' available at <https://www3.epa.gov/airquality/greenbook/>. N=537 metropolitan and nonmetropolitan areas. Metropolitan and nonmetropolitan areas are designated as nonattainment if the counties within the area that are nonattainment contribute to at least one third of the total population in the area. Areas in white were designed attainment for all pre-2006 and post-2006 National Ambient Air Quality Standards (NAAQS). Areas in light grey were designed nonattainment for at least one of the pre-2006 NAAQSs (Nitrogen Dioxide 1971, Carbon Monoxide 1971, Sulfur Dioxide 1971, Lead 1978, 1-Hour Ozone 1979, PM-10 1987, PM-2.5 1997, 8-Hour Ozone 1997) and were designed attainment with all post-2006 NAAQSs (PM-2.5 2006, 8-Hour Ozone 2008, Lead 2008, Sulfur Dioxide 2010, PM-2.5 2012). Areas in dark grey were designed nonattainment for any of the post-2006 NAAQSs.

Table 6: Descriptive statistics of regression variables

Variable	Mean	SD	Min	Q1	Median	Q3	Max
Green Employment share, GE	0.0302	0.0063	0.0121	0.0260	0.0300	0.0340	0.1366
Core Green Employment share, CGE	0.0200	0.0055	0.0058	0.0163	0.0195	0.0236	0.1102
Green Empl share predicted by ind structure, GIE	0.0300	0.0038	0.0158	0.0275	0.0302	0.0322	0.0518
NMA dummy	0.1355	0.3423	0.0000	0.0000	0.0000	0.0000	1.0000
Resilience crisis	-0.3458	0.1962	-1.6436	-0.4877	-0.3328	-0.1804	-0.0077
R&D lab	0.2562	0.4366	0.0000	0.0000	0.0000	1.0000	1.0000
Green patent stock per capita (2006)	0.0374	0.0371	0.0000	0.0109	0.0295	0.0511	0.6761
Total patent stock per capita (2006)	0.4909	0.5117	0.0000	0.1235	0.3464	0.7458	4.6684
Trade exposure (2006)	0.0625	0.0141	0.0279	0.0541	0.0605	0.0665	0.1677
Initially NA	0.7298	0.4441	0.0000	0.0000	1.0000	1.0000	1.0000

N=537; T=9 (2006-2014). Statistics weighted by area-by-year total employment.

Table 7: Drivers of green employment share

	GE	CGE	GIE	log(total employment)
Resilience crisis x trend	0.00793 (0.00283)*** [0.00257]***	0.00729 (0.00295)** [0.00259]***	0.00152 (0.00101) [0.000945]	0.100 (0.0302)*** [0.0259]***
R&D lab x trend	0.0000930 (0.0000589) [0.0000567]	0.0000584 (0.0000560) [0.0000507]	-0.0000192 (0.0000579) [0.0000418]	0.00216 (0.00112)* [0.000904]**
Green patent stock per capita (2006) x trend	0.00265 (0.00104)** [0.00115]**	0.00196 (0.000826)** [0.000941]**	0.000959 (0.000540)* [0.000429]**	-0.00611 (0.0128) [0.0146]
Total patent stock per capita (2006) x trend	-0.000140 (0.0000993) [0.000121]	-0.0000990 (0.0000860) [0.000105]	-0.0000728 (0.0000382)* [0.0000440]**	0.00258 (0.00111)*** [0.000965]***
Trade exposure (2006) x trend	-0.00113 (0.00121) [0.00127]	-0.000580 (0.00112) [0.00122]	-0.00131 (0.000867) [0.000698]**	-0.0544 (0.0222)** [0.0220]**
Initially NA x trend	0.000103 (0.0000688) [0.0000574]*	0.0000977 (0.0000742) [0.0000545]*	-0.0000112 (0.0000250) [0.0000310]	0.000453 (0.00110) [0.00110]
Switch to NA	0.000521 (0.000301)* [0.000245]**	0.000457 (0.000291) [0.000232]**	0.0000224 (0.000105) [0.0000994]	-0.00251 (0.00477) [0.00371]
N	4833	4833	4296	4833

Fixed effect model weighted by total employment in 2006. Standard errors clustered by state in parenthesis and by area in brackets. * p<0.1, ** p<0.05, *** p<0.01. Other control variables: year-by-state dummies, year-by-nonmetropolitan Area status dummies.

Table 8: Effects of drivers in the crisis and post-crisis periods

	GE 2006-2010	GE 2010-2014
Resilience crisis	0.0305 (0.0166)* [0.0160]*	0.0159 (0.0109) [0.00966]
R&D lab	0.00155 (0.000494)*** [0.000429]***	-0.000224 (0.000545) [0.000354]
Green patent stock per capita (2006)	-0.000130 (0.00910) [0.00823]	0.0252 (0.0124)** [0.0122]**
Total patent stock per capita (2006)	-0.000282 (0.000805) [0.000787]	-0.00107 (0.000536)* [0.000593]*
Trade exposure (2006)	0.00742 (0.0126) [0.00961]	-0.0109 (0.00849) [0.00838]
Initially NA	0.000588 (0.000450) [0.000389]	0.000509 (0.000447) [0.000426]
Switch to NA	-0.000286 (0.000757) [0.000561]	0.000553 (0.000655) [0.000448]
N	537	537

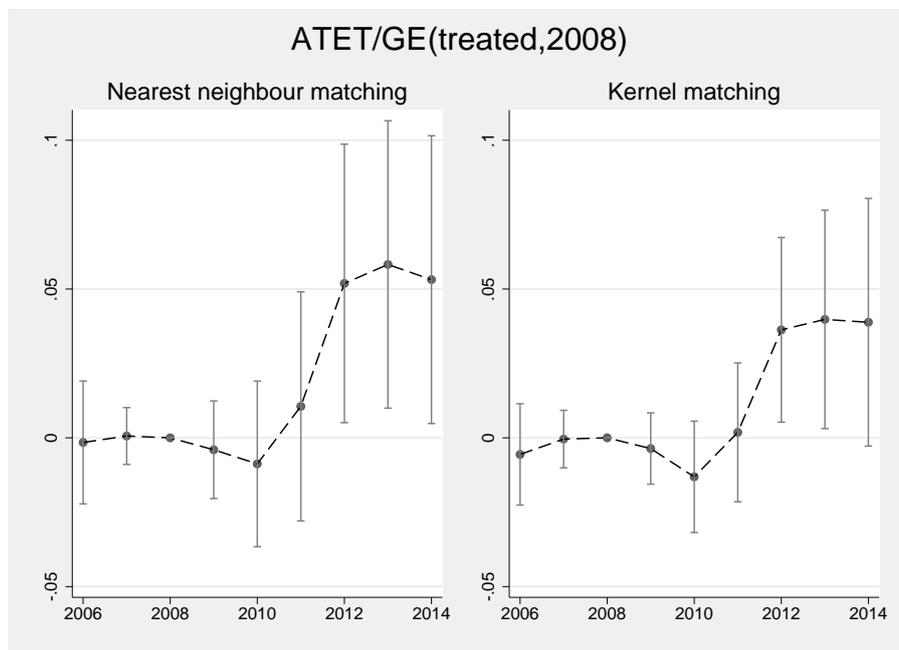
OLS model weighted by total employment in 2006. Standard errors clustered by state in parenthesis and by area in brackets. * p<0.1, ** p<0.05, *** p<0.01. Other control variables: state dummies, year-nonmetropolitan Area status dummy.

Table 9: Drivers of high-skill and low-skill GE and CGE

	GE-HS	GE-LS	CGE-HS	CGE-LS
Resilience crisis x trend	0.00247 (0.00131)* [0.00121]**	0.00546 (0.00263)** [0.00234]**	0.00216 (0.00123)* [0.00108]**	0.00513 (0.00270)* [0.00236]**
R&D lab x trend	0.0000975 (0.0000691) [0.0000567]*	-0.0000445 (0.0000328) [0.0000414]	0.0000688 (0.0000590) [0.0000498]	-0.0000104 (0.0000286) [0.0000354]
Green patent stock per capita (2006) x trend	0.00257 (0.00149)* [0.00146]*	0.0000809 (0.000938) [0.000903]	0.00195 (0.00127) [0.00122]	0.0000120 (0.000893) [0.000881]
Total patent stock per capita (2006) x trend	-0.000106 (0.0000783) [0.0000947]	-0.0000339 (0.0000685) [0.0000665]	-0.0000738 (0.0000693) [0.0000793]	-0.0000252 (0.0000654) [0.0000637]
Trade exposure (2006) x trend	-0.000438 (0.000878) [0.000851]	-0.000690 (0.00128) [0.00102]	-0.000352 (0.000825) [0.000781]	-0.000229 (0.00109) [0.000958]
Initially NA x trend	0.0000325 (0.0000432) [0.0000436]	0.0000703 (0.0000510) [0.0000458]	0.0000221 (0.0000439) [0.0000393]	0.0000755 (0.0000562) [0.0000440]*
Switch to NA	0.000299 (0.000267) [0.000185]	0.000222 (0.000187) [0.000187]	0.000266 (0.000243) [0.000167]	0.000191 (0.000189) [0.000185]
N	4833	4833	4833	4833

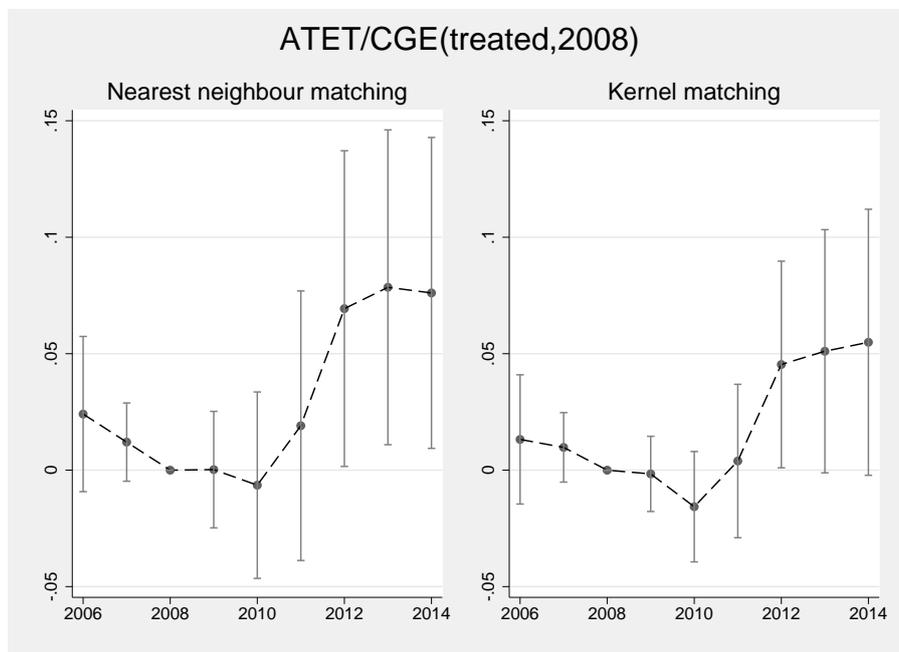
Fixed effect model weighted by total employment in 2006. Standard errors clustered by state in parenthesis and by area in brackets. * p<0.1, ** p<0.05, *** p<0.01. Other control variables: year-by-state dummies, year-by-nonmetropolitan Area status dummies.

Figure 7: Average treatment effect of NA switch based on propensity score for GE



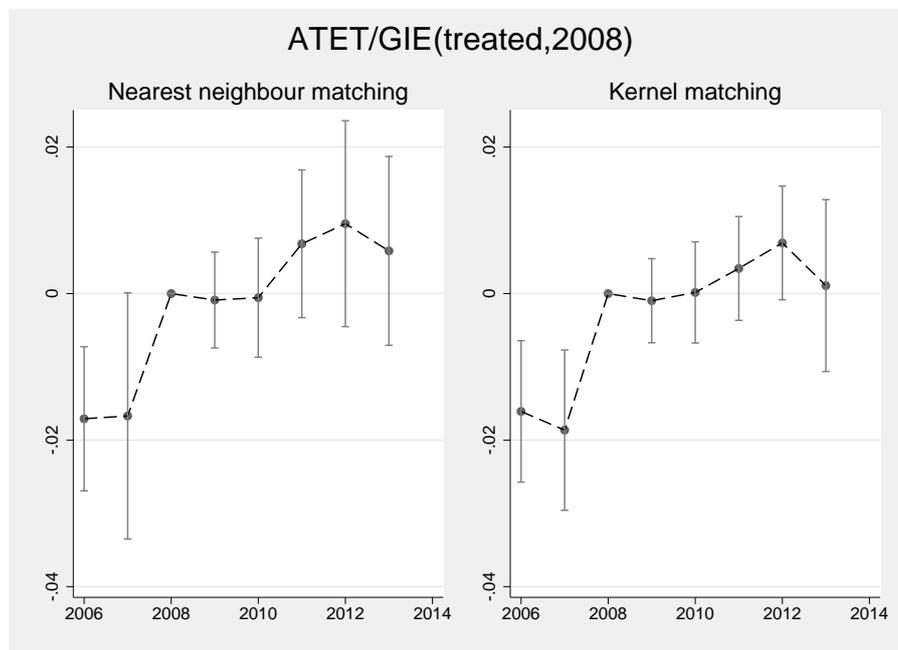
Plots show the estimated average treatment effect on the treated of NA switch on the share of green employment divided by the average GE of treated areas in 2008. NA switching areas are 156. The treatment effect is weighted by the total employment of the treated areas. Bands represent 5% confidence intervals estimated using bootstrap re-sampling (500 repetitions). The average treatment effect on the treated is estimated by means of the difference-in-difference semi-parametric matching estimator. The left panel is based on nearest neighbour matching. The right panel is based on kernel matching.

Figure 8: Average treatment effect of NA switch based on propensity score for CGE



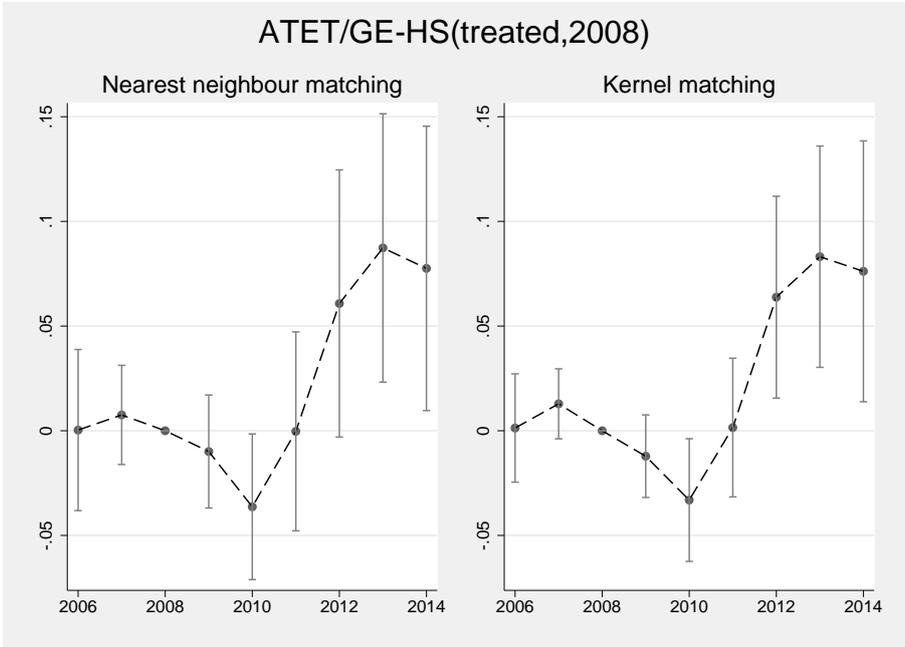
Plots show the estimated average treatment effect on the treated of NA switch on the share of core green employment divided by the average CGE of treated areas in 2008. NA switching areas are 156. The treatment effect is weighted by the total employment of the treated areas. Bands represent 5% confidence intervals estimated using bootstrap re-sampling (500 repetitions). The average treatment effect on the treated is estimated by means of the difference-in-difference semi-parametric matching estimator. The left panel is based on nearest neighbour matching. The right panel is based on kernel matching.

Figure 9: Average treatment effect of NA switch based on propensity score for green employment predicted by the industrial structure, GIE



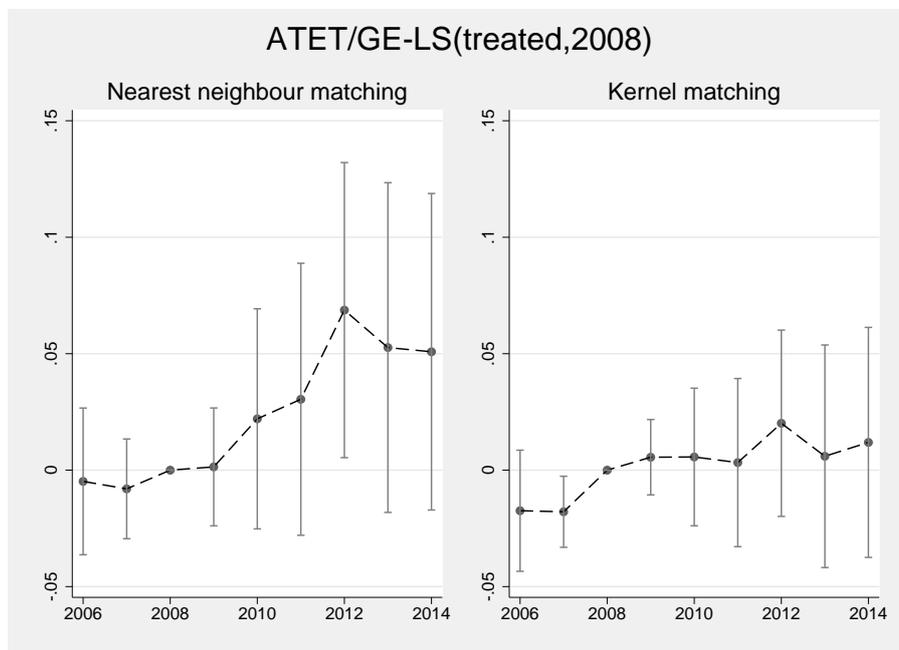
Plots show the estimated average treatment effect on the treated of NA switch on the share of green employment predicted by the industrial structure (GIE) employment divided by the average GIE of treated areas in 2008. NA switching areas are 156. The treatment effect is weighted by the total employment of the treated areas. Bands represent 5% confidence intervals estimated using bootstrap re-sampling (500 repetitions). The average treatment effect on the treated is estimated by means of the difference-in-difference semi-parametric matching estimator. The left panel is based on nearest neighbour matching. The right panel is based on kernel matching.

Figure 10: Average treatment effect of NA switch based on propensity score for high-skill (SOC 11 - SOC 41) green employment



Plots show the estimated average treatment effect on the treated of NA switch on the share of green high-skill (GE-HS) employment divided by the average GE-HS of treated areas in 2008. NA switching areas are 156. The treatment effect is weighted by the total employment of the treated areas. Bands represent 5% confidence intervals estimated using bootstrap re-sampling (500 repetitions). The average treatment effect on the treated is estimated by means of the difference-in-difference semi-parametric matching estimator. The left panel is based on nearest neighbour matching. The right panel is based on kernel matching.

Figure 11: Average treatment effect of NA switch based on propensity score for low-skill (SOC 43 - SOC 53) green employment



Plots show the estimated average treatment effect on the treated of NA switch on the share of green low-skill (GE-LS) employment divided by the average GE-LS of treated areas in 2008. NA switching areas are 156. The treatment effect is weighted by the total employment of the treated areas. Bands represent 5% confidence intervals estimated using bootstrap re-sampling (500 repetitions). The average treatment effect on the treated is estimated by means of the difference-in-difference semi-parametric matching estimator. The left panel is based on nearest neighbour matching. The right panel is based on kernel matching.

Table 10: Local multiplier of green employment on the non-tradable sector

Panel A - All NT (excluding NAICS 54)		
	OLS	IV
Elasticity of growth in empl in NT wrt growth in green employment	0.232*** (0.0400)	0.223** (0.105)
Green employment multiplier	4.324	4.164
Panel B - NT deparated by green employment predicted by the industrial structure in NT		
Elasticity of growth in empl in NT wrt growth in green employment	0.234*** (0.0427)	0.308*** (0.0679)
Green employment multiplier	3.918	5.154

N=537. Robust standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Estimates of the elasticity between green employment logarithmic growth rate (2006-2014) and the logarithmic growth rate of employment in the non-tradable sector are based on cross-sectional regressions that include state dummies and a nonmetropolitan area dummy as control. Regressions are weighted by initial (2006) employment. Green employment growth is instrumented with the growth 2006-2014 in green employment that is predicted given the macro-level growth in green employment (excluding the area) by occupation weighted by the initial (2006) composition of the local labour force by occupation. The green employment multiplier is calculated as the product of the estimated elasticity and the median of the ratio between NT employment (2014) and green employment share (2014). F test on excluded IV in first stage: 81.916.

Table 11: Local multiplier of green employment on the manufacturing sector

	All manufacturing (excluding green employment predicted by the industrial structure in manufact)		Manufact high-tech (excluding green employment predicted by the industrial structure in HT manufact)		Manufact low-tech (excluding green employment predicted by the industrial structure in LT manufact)	
	OLS	IV	OLS	IV	OLS	IV
Elasticity of growth in empl in NT wrt growth in green employment	0.254*** (0.0582)	0.0643 (0.135)	0.353*** (0.0923)	0.262 (0.208)	0.223*** (0.0616)	-0.00344 (0.142)
Green employment multiplier	0.640	0.162	0.338	0.250	0.355	-0.00548

N=537. Robust standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Estimates of the elasticity between green employment logarithmic growth rate (2006-2014) and the logarithmic growth rate of employment in the non-tradable sector are based on cross-sectional regressions that include state dummies and nonmetropolitan area dummy as control. Regressions are weighted by initial (2006) employment. Green employment growth is instrumented with the growth 2006-2014 in green employment that is predicted given the macro-level growth in green employment (excluding the area) by occupation weighted by the initial (2006) composition of the local labour force by occupation. The green employment multiplier is calculated as the product of the estimated elasticity and the median of the ratio between manufacturing (total, HT or LT) employment (2014) and green employment share (2014). F test on excluded IV in first stage: 80.916.

Table 12: Local multiplier of green employment on the non-tradable sector - Crisis and post-crisis

Panel A - All NT (excluding NAICS 54)				
	Crisis		Post-crisis	
	OLS	IV	OLS	IV
Elasticity of growth in empl in NT wrt growth in green employment	0.114*** (0.0291)	0.118 (0.0881)	0.229*** (0.0445)	0.510*** (0.117)
Green employment multiplier	2.132	2.196	4.276	9.531

Panel B - NT deputed by green employment predicted by the industrial structure in NT				
	Crisis		Post-crisis	
	OLS	IV	OLS	IV
Elasticity of growth in empl in NT wrt growth in green employment	0.0939*** (0.0231)	0.142*** (0.0517)	0.226*** (0.0488)	0.632*** (0.113)
Green employment multiplier	1.571	2.377	3.778	10.57

N=537. Robust standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Estimates of the elasticity between green employment logarithmic growth rate (2006-2010 and 2010-2014) and the logarithmic growth rate of employment in the non-tradable sector are based on cross-sectional regressions that include state dummies and nonmetropolitan area dummy as control. Regressions are weighted by initial (2006 for pre-crisis, 2010 for post-crisis) employment. Green employment growth is instrumented with the growth (2006-2010 for pre-crisis, 2010-2014 for post-crisis) in green employment that is predicted given the macro-level growth in green employment (excluding the area) by occupation weighted by the initial (2006) composition of the local labour force by occupation. The green employment multiplier is calculated as the product of the estimated elasticity and the median of the ratio between NT employment (2014) and green employment share (2014). F test on excluded IV in first stage: 54.118 for 'Crisis' and 25.527 for 'Post-crisis'.

A Additional information on O*NET data

Data on the task content of occupations are drawn from the Occupational Information Network (O*NET), a survey created and maintained by the U.S. Department of Labor. O*NET information is organized in six major domains: worker characteristics, worker requirements, experience requirements, occupational requirements, labor market characteristics, and occupation-specific information. Each of these are further separated in specific categories and detailed hierarchies of descriptors. Trained evaluators assign quantitative ratings to each individual descriptor on the basis of both informed assessments and questionnaire data. These scores are based on three dimensions: importance, level, and frequency along a standardized scale. O*NET content is revised and expanded periodically.

The detailed analysis of green employment of this paper relies on two specific sources within O*NET. First, we use the ‘Green Economy’ program to retrieve detailed information on 128 green jobs. Based on the fieldwork analysis of Dierdorff et al (2009), three categories of green occupations have been identified and integrated in the O*NET-SOC system. The first includes “green demand jobs”, that is, existing occupations which will experience a mechanical increase in demand due to the greening of the economy. Examples of these include Construction carpenters, Electronic Engineering Technicians or Refrigeration Mechanics and Installers. The increase in demand does not entail significant changes in either work tasks or worker requirements. Also the second group, “green enhanced skills”, includes existing occupations but these are expected to undergo significant changes in terms of job content which may or may not result in an increase in labour demand. Therein, jobs like Automotive Specialty Technicians, Environmental Engineers or Power Plant Operators will likely take on new work tasks, will acquire new skills and will need to possess new work credentials. Lastly, the greening of the economy will ensue specific activities and technologies which demand unique “green new and emerging occupations” such as, for example, Chief Sustainability Officers or Fuel Cell Technicians. No doubt, the most significant transformations in the skill base of the workforce in the green economy will occur via the latter two categories of occupations, and for the purposes of the present paper we restrain to these. Second, we extract information from the ‘Green Task Development Project’, a catalogue of 1369 green tasks developed specifically for two of the three occupational categories above green enhanced skills and green new and emerging occupations. Accordingly, all green occupations have an initial list of green task statements in the O*NET 18.0 database release (July 2012).

Matching O*NET data on green occupations and green tasks and BLS occupational employment data is challenging because the former are available at 8-digit SOC level while the latter is at 6-digit SOC level. For 715 out of 822 occupations the greenness is immediately defined because the 8-digit and 6-digit data coincide but for 107 occupations the attribution was not straightforward. In particular, some green occupations clearly account for small shares of employment within the relevant 6-digit group and adopting uniform weights for green and non-green jobs would likely lead to over-estimation of the 6-digit greenness. In these problematic cases, we generally take the greenness of the most general occupation to avoid over-estimation of green employment. Examples of problematic cases are “Sales Representatives of Technical and Scientific Products”

(SOC 41-4011), containing “Solar Sales Representatives” (SOC 41-4011.07), or “Chief Executives” (SOC 11-1011.00), containing “Chief Sustainability Officers” (SOC 11-1011.03). Accordingly, we devised a procedure to address each of the following circumstances:

1. When the 6-digit occupational group (i.e. the 8-digit SOC occupation that ends with “.00”) has zero or few (much less than other 8-digit occupations) green tasks, we attribute zero greenness to all the 8-digit occupations within that group to avoid over-estimation of the greenness;
2. When the number of green tasks of 6-digit occupations is greater than zero and not substantially smaller than the one for other 8-digit occupations, we attribute to each 8-digit occupation the average greenness of all the occupations within their 6-digit group.

Table A1 provides details of these problematic occupations, and of the greenness that was attributed following the criterion laid out above.

[Table A1 about here]

B Data sources and variable construction

This appendix describes the details of data sources and variable construction.

B.1 Occupational Employment Statistics (BLS)

Information about the composition of the labour force for the US is obtained from the Occupational Employment Statistics of the Bureau of Labor Statistics. These include estimates on the number of employees and wage distribution with different breakdowns: occupation / industry, occupation / state, occupation / metropolitan-nonmetropolitan area, occupation / state / industry. Information is reported at various level of occupational detail, from 2-digit SOC to 6-digit SOC.

To obtain a balanced panel of information on number of employees and wages by 6-digit SOC occupation and metropolitan/nonmetropolitan area we had to make a number of adjustments. First, there has been a change in the classification of occupations from SOC2006/2009 to SOC2010 for each there is no 1:1 crosswalk. Data from 2006 to 2009 are classified according to the SOC2006/2009 classification, data for 2010-2011 are classified according to a hybrid classification that is in between SOC2006/2009 and SOC2010, while data from 2012 to 2014 are classified according to the SOC2010 classification. We harmonize our data to fit the SOC2010 classification that is generally more detailed for what concerns green occupations than the SOC2006/2009 classification. An example is occupation 47-2231 (Solar Photovoltaic Installers) in SOC2010 that was part of the more general occupation 47-4099 (Construction and Related Workers, All Other) in SOC2006/2009. All cases for which there was no one-to-one or many-to-one match between SOC2006/2009 and SOC2010 classification are reported in Table B1. To account for possible different trends between occupations that were ‘aggregated’ in SOC2006/2009 we extrapolated backward the share of detailed occupations for years 2010-2014 up to 2006. This procedure was done separately for each metropolitan and nonmetropolitan area.

Another adjustment consisted in accounting for censoring of cells with less than 30 employees. This problem is particularly severe in very small metropolitan and nonmetropolitan areas, for which detailed information was available only for a reduced number of 6-digit occupations. In these cases, in a first step we interpolated/extrapolated information at 6-digit level available in only few years for a metropolitan or nonmetropolitan area to other years. In doing so we also considered the fact that extrapolated data should be in accordance with subtotals of employment at the 2-digit SOC level within the area. Finally, for those areas for which this procedure was not allocating all workers to 6-digit SOC occupations, we used information on 2-digit SOC employment at the area level and split the residual unallocated total at the 2-digit SOC into the 6-digit SOC occupations that were not reported by BLS (or interpolated) using national year-specific shares of 6-digit SOC within the 2-digit SOC. As the issue of censoring is relevant for small occupations in small areas, the share of total employment that is allocated through interpolation/extrapolation and by means of national-level information was 5.87 percent.

To compute the GIE measure, we use occupational employment statistics at the national level with a breakdown by occupation (6-digit SOC) and industry (4-digit NAICS).

[Table B1 about here]

B.2 County Business Patterns

The County Business Patterns database contains information on employment and establishment counts by industry, size class and county for the US. As data are censored for small cells to avoid the disclosure of individual information but the number of plants by industry, county and size class is always available, we attribute to all plants within a censored cell the average number of employees in the same size class. We employ data for the period 2006-2013.

B.3 Patent data

We retrieve information triadic patent applications (USPTO, JPTO and EPO) assigned to the county of the inventor (and consequently to metropolitan and nonmetropolitan areas) from the microdata of the OECD-REGPAT database. Green patents have been identified according to the IPC and CPC classes identified as ‘environment-related’ technologies either by the OECD-EnvTech indicator²⁶ or by the Green Inventory selection of IPC classes of the WIPO.²⁷ Patents for the period 1978-2006 were sorted according to their earliest priority year. The stock is built using the perpetual inventory method with a depreciation of 20 percent.

B.4 Federal R&D Laboratories

We retrieved information on the location of national and federal R&D laboratories from the website of the Department of Homeland Security.²⁸ The list of labs is reported in Table B2 while the list of metropolitan and nonmetropolitan areas that host at least one lab is reported in Table B3.

[Tables B2 and B3 about here]

B.5 Import penetration

Import penetration is measured as the ratio between import and ‘domestic consumption’ (defined as import + domestic production - export) at the 4-digit NAICS level for year 2006. Data on total import and export for the US come from Schott (2008) and are available at the following link:

<http://faculty.som.yale.edu/peterschott/sub.international.htm>.

Data on total production at the federal level by 4-digit NAICS manufacturing industries were retrieved from the NBER-CES database. We compute import penetration at the federal level and attribute it to metropolitan and nonmetropolitan areas by multiplying industry-level import penetration by area-level employment share by 4-digit NAICS industry. This latter information, for year 2006, comes from the County Business Patterns database.

²⁶ Available at <http://www.oecd.org/env/indicators-modelling-outlooks/green-patents.htm> (accessed: 29 October 2015).

²⁷ Available at <http://www.wipo.int/classifications/ipc/en/est/> (accessed: 29 October 2015). We excluded the following categories: Bio-fuels, Agriculture/Forestry, Administrative, Regulatory or Design Aspects, Nuclear Power Generation.

²⁸ Available at <https://www.dhs.gov/science-and-technology/national-federal-laboratories-research-centers> (accessed: 29 October 2015).

B.6 Other data on employment from BLS

Information on the distribution of employment by aggregate industry (2-digit NAICS) of metropolitan and nonmetropolitan areas comes from the BLS Quarterly Census of Employment and Wages (CEW). Also information on average establishment size (average employees per establishment) is retrieved from the BLS-CEW.

Data on unemployment at the county level is obtained from the Local Area Unemployment Statistics of the Bureau of Labor Statistics. Unemployment is then aggregated at the metropolitan and nonmetropolitan area level as the weighted average of county-level unemployment.

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

C Additional results for ‘Facts on green employment’

[Figures C1, C2 and C3 about here]

D Robustness checks for drivers of green employment

[Tables D1 and D2 about here]

E Propensity score matching

We estimate two different specifications of propensity score (Table E1). The choice of the covariates to be included in the estimation of the propensity score should consider those variables that influence both the likelihood of being treated and the outcome variable (Smith and Todd, 2005). In a first parsimonious specification we estimate the probability of being treated as a function of average establishment size (in log, year 2008), a dummy for nonmetropolitan areas, population density (logarithm of population per square mile, year 2008), share of employment in the utility sector (NAICS 21, year 2008) and the share of population that resides in counties (within the metro and non-metro area) that were nonattainment for at least one of the ‘old’ standards. As expected, nonattainment status for old NAAQS is a strong predictor of nonattainment designation due to the persistence of the causes of pollution. The probability of being designed as nonattainment is, as expected, positively correlated with population density and on the share of employees in the utilities sector (which includes power generation, among the main responsible for pollution). Conditional on these features, nonattainment designation switch (i.e. the treatment) is negatively correlated to establishment size and positively correlated to the ‘non-metropolitan’ status. In a second richer specification of the propensity score we also condition on the share of employment in the manufacturing (NAICS 31-33, year 2008) and mining (NAICS 21, year 2008), which are also among the main responsible for local pollution, the initial share of green employment (year 2008), to control for systematic differences in pre-treatment green employment level, and our measure of resilience to the crisis. None of these additional covariates, however, is significantly correlated with nonattainment switch.

As the treatment group (156 areas) represents a large share our sample of 537 metropolitan and nonmetropolitan areas (29 percent) we face with a rather small pool of potential control units to be selected as good counterfactual. This may result in a bad matching for some of the treated units as the number of potential matches is small and the selected un-treated unit with the closest estimated propensity score may have a rather different propensity score.

For what concerns the choice of the matching algorithm, nearest neighbour matching is the one that, in theory, should guarantee the best balancing of matching variables as only the best matches are retained (small bias) at the cost of higher variance as only little information is retained. Tables E2 and E3 report the means comparison between treated, potential controls and matched controls for our set of matching variables for both specification of the propensity score (parsimonious and extend) and both choices of matching algorithm (nearest neighbour and kernel). The share of population in counties within the area that were nonattainment for old NAAQS was very unbalanced before the matching and well balanced after the matching. Past nonattainment is a strong predictor of nonattainment according to the new standard. Employment share in utilities and average establishment size were already balanced before the matching and remain balanced. Treated areas are on average more densely populated than untreated areas. The matching reduces the magnitude of the difference in population density between treated and controls even though the difference, reversed in sign, remains significant at the 5 percent level for the nearest neighbour matching based on the parsimonious specification. The balancing of the nonmetropolitan status worsens with the matching. While, overall, non-

metropolitan areas were overrepresented in non-switching areas, once we match treated and control units nonmetropolitan areas only represent a very small share of areas in the control group. This means that only few non-switching nonmetropolitan areas represent a good counterfactual for switching metropolitan areas, that are often matched with metropolitan areas. In the extended specification of the propensity score, the matching improves the balancing for the share of mining and extraction workers. Finally, for what concerns the share of manufacturing workers and the resilience to the crisis, while the nearest neighbour matching does not allow to attain the balancing, kernel-based matching results in no significant difference in these variables between treated and matched control. All in all, the matching reduces differences in pre-treatment stringency in regulation, but it is less successful in balancing other covariates. The small potential pool of control areas and the peculiarities of some of the treated areas (e.g. most of the largest treated areas, such as Los Angeles CA or New York NY, cannot be easily matched with other non-treated areas) are the main reasons for this unsatisfactory result. As already discussed in the text, this may induce a bias in the estimate of the average treatment effect on the treated.

The balancing is generally satisfied for most variables. The only notable exception is the NMA dummy: the share of nonmetropolitan areas in the treatment group is always significantly greater than the share of nonmetropolitan areas in the matched controls.

We report here the tables that corresponds to the results reported in figures in the main text (Tables E4, E5, E6, E7 and E8 for, respectively, Figures 7, 8, 9, 10 and 11) as well as additional results based on the ‘extended’ specification of the propensity score (columns 3 and 4). While the statistical significance of the estimated effects for GE and CGE in the ‘extended’ specification is slightly lower than the one found with the ‘parsimonious’ specification, the magnitude of the effects remains almost unchanged in all cases.

[Tables E1, E2, E3, E4, E5, E6, E7 and E8 about here]

F Propensity score for ozone switch

As highlighted by Curtis (2015), the change of the Ozone standard in 1997 (nonattainment designation occurred in 2004) has been a very large shock for businesses compared to other changes in NAAQS. For this reason, we provide evidence about the impact exerted by the Ozone 2008 shock alone (nonattainment designation occurred in 2012). A first signal of the potentially larger relevance of this shock with respect to other shocks is that, when pooling together all the nonattainment switches, we only found a significant impact from 2012 onwards. For this reason, we repeat our analysis based on the difference-in-differences semi-parametric matching estimator only for those areas (87) that were designed nonattainment for Ozone in 2012 according to the Ozone 2008 NAAQS. We repeat the matching (Table F1), the test on balancing (Tables F2 and F3) and the estimate of the ATET for GE (Tables F4). We exclude from the potential group of controls those areas that were designed nonattainment for other standards and were instead designed as attainment for the Ozone 2008 standard. Also in this case the strongest predictor for nonattainment designation for the Ozone 2008 standard is the nonattainment status for old NAAQS. The balancing of covariates given by the matching is in this case even less satisfactory than in the case in which all nonattainment switch were evaluated together (see Appendix F). While nonattainment status for old NAAQS is balanced by the matching, all variables except the employment share in the utility industry, in the mining and extraction industry and the resilience to the crisis remain unbalanced after the matching. Also in this case the unsatisfactory balancing may bias the estimate of the average treatment effect on the treated.

The ATET of the switch to nonattainment of the Ozone standard is always positive and significant in terms of GE share. Moreover, the impact is larger in magnitude (but not statistically different) for the one estimated for all nonattainment switches together.

[Tables F1, F2, F3 and F4 about here]

G Additional results for job multipliers

[Table G1 about here]

Table A1: Problematic occupations

8-Digit SOC	Occupational title	Total Tasks	Green Tasks	Greenness
11-1011.00	Chief Executives	32	0	zero
11-1011.03	Chief Sustainability Officers	18	18	
11-2011.00	Advertising and Promotions Managers	25	0	zero
11-2011.01	Green Marketers	16	16	
11-3051.00	Industrial Production Managers	14	0	zero
11-3051.01	Quality Control Systems Managers	27	0	
11-3051.02	Geothermal Production Managers	17	17	
11-3051.03	Biofuels Production Managers	14	14	
11-3051.04	Biomass Power Plant Managers	18	18	
11-3051.05	Methane/Landfill Gas Collection System Operators	21	21	
11-3051.06	Hydroelectric Production Managers	19	19	
11-3071.01	Transportation Managers	28	5	average
11-3071.02	Storage and Distribution Managers	30	7	
11-3071.03	Logistics Managers	30	9	
11-9013.01	Nursery and Greenhouse Managers	20	0	average
11-9013.02	Farm and Ranch Managers	28	4	
11-9013.03	Aquacultural Managers	19	0	
11-9041.01	Biofuels/Biodiesel Technology and Product Development Managers	19	19	
11-9121.00	Natural Sciences Managers	16	0	average
11-9121.01	Clinical Research Coordinators	33	0	
11-9121.02	Water Resource Specialists	21	21	
11-9199.01	Regulatory Affairs Managers	27	4	average
11-9199.02	Compliance Managers	30	6	
11-9199.03	Investment Fund Managers	20	0	
11-9199.04	Supply Chain Managers	30	9	
11-9199.07	Security Managers	30	0	
11-9199.08	Loss Prevention Managers	27	0	
11-9199.09	Wind Energy Operations Managers	16	16	
11-9199.10	Wind Energy Project Managers	15	15	
11-9199.11	Brownfield Redevelopment Specialists and Site Managers	22	22	
13-1041.01	Environmental Compliance Inspectors	25	0	average
13-1041.02	Licensing Examiners and Inspectors	11	0	
13-1041.03	Equal Opportunity Representatives and Officers	16	0	
13-1041.04	Government Property Inspectors and Investigators	12	0	
13-1041.06	Coroners	20	0	
13-1041.07	Regulatory Affairs Specialists	32	6	
13-1081.00	Logisticians	21	0	average
13-1081.01	Logistics Engineers	30	11	
13-1081.02	Logistics Analysts	31	6	
13-1199.01	Energy Auditors	21	21	average
13-1199.02	Security Management Specialists	24	0	
13-1199.03	Customs Brokers	23	0	
13-1199.04	Business Continuity Planners	21	0	
13-1199.05	Sustainability Specialists	14	14	
13-1199.06	Online Merchants	34	0	
13-2099.01	Financial Quantitative Analysts	21	5	average
13-2099.02	Risk Management Specialists	24	4	
13-2099.03	Investment Underwriters	19	2	
13-2099.04	Fraud Examiners, Investigators and Analysts	23	0	
15-1199.01	Software Quality Assurance Engineers and Testers	28	0	average
15-1199.02	Computer Systems Engineers/Architects	28	0	
15-1199.03	Web Administrators	35	0	
15-1199.04	Geospatial Information Scientists and Technologists	24	2	
15-1199.05	Geographic Information Systems Technicians	19	5	
15-1199.06	Database Architects	18	0	
15-1199.07	Data Warehousing Specialists	18	0	
15-1199.08	Business Intelligence Analysts	17	0	
15-1199.09	Information Technology Project Managers	21	0	
15-1199.10	Search Marketing Strategists	36	0	
15-1199.11	Video Game Designers	24	0	
15-1199.12	Document Management Specialists	23	0	
17-2051.00	Civil Engineers	17	8	average
17-2051.01	Transportation Engineers	26	6	
17-2072.00	Electronics Engineers, Except Computer	23	5	Value of 17-2072.00
17-2072.01	Radio Frequency Identification Device Specialists	21	0	
17-2081.00	Environmental Engineers	28	28	average
17-2081.01	Water/Wastewater Engineers	27	27	
17-2141.00	Mechanical Engineers	27	7	average
17-2141.01	Fuel Cell Engineers	26	26	
17-2141.02	Automotive Engineers	25	8	

(continue)

(continue)				
17-2199.01	Biochemical Engineers	35	12	average
17-2199.02	Validation Engineers	22	2	
17-2199.03	Energy Engineers	21	20	
17-2199.04	Manufacturing Engineers	24	4	
17-2199.05	Mechatronics Engineers	23	3	
17-2199.06	Microsystems Engineers	31	6	
17-2199.07	Photonics Engineers	26	5	
17-2199.08	Robotics Engineers	24	2	
17-2199.09	Nanosystems Engineers	25	9	
17-2199.10	Wind Energy Engineers	16	16	
17-2199.11	Solar Energy Systems Engineers	13	13	
17-3023.01	Electronics Engineering Technicians	19	0	average
17-3023.03	Electrical Engineering Technicians	24	5	
17-3024.01	Robotics Technicians	23	2	
17-3027.00	Mechanical Engineering Technicians	18	0	average
17-3027.01	Automotive Engineering Technicians	18	5	
17-3029.01	Non-Destructive Testing Specialists	16	0	average
17-3029.02	Electrical Engineering Technologists	20	8	
17-3029.03	Electromechanical Engineering Technologists	17	5	
17-3029.04	Electronics Engineering Technologists	23	4	
17-3029.05	Industrial Engineering Technologists	23	4	
17-3029.06	Manufacturing Engineering Technologists	29	8	
17-3029.07	Mechanical Engineering Technologists	21	3	
17-3029.08	Photonics Technicians	30	6	
17-3029.09	Manufacturing Production Technicians	30	6	
17-3029.10	Fuel Cell Technicians	16	16	
17-3029.11	Nanotechnology Engineering Technologists	17	6	
17-3029.12	Nanotechnology Engineering Technicians	19	3	
19-1031.01	Soil and Water Conservationists	33	33	average
19-1031.02	Range Managers	16	0	
19-1031.03	Park Naturalists	16	0	
19-2041.00	Environmental Scientists and Specialists, Including Health	22	0	average
19-2041.01	Climate Change Analysts	14	14	
19-2041.02	Environmental Restoration Planners	22	22	
19-2041.03	Industrial Ecologists	38	38	
19-3011.00	Economists	12	0	zero
19-3011.01	Environmental Economists	19	19	
19-4011.01	Agricultural Technicians	25	3	average
19-4011.02	Food Science Technicians	15	0	
19-4041.01	Geophysical Data Technicians	21	5	average
19-4041.02	Geological Sample Test Technicians	16	3	
19-4051.01	Nuclear Equipment Operation Technicians	17	7	zero
19-4051.02	Nuclear Monitoring Technicians	18	0	
19-4099.01	Quality Control Analysts	26	0	average
19-4099.02	Precision Agriculture Technicians	23	7	
19-4099.03	Remote Sensing Technicians	22	3	
41-3031.01	Sales Agents, Securities and Commodities	18	0	average
41-3031.02	Sales Agents, Financial Services	8	0	
41-3031.03	Securities and Commodities Traders	22	2	
41-4011.00	Sales Representatives, Wholesale and Manufacturing, Technical and Scientific Products	38	4	Value of 41-4011.00
41-4011.07	Solar Sales Representatives and Assessors	13	13	
43-5011.00	Cargo and Freight Agents	24	0	average
43-5011.01	Freight Forwarders	31	6	
47-1011.00	First-Line Supervisors of Construction Trades and Extraction Workers	15	0	zero
47-1011.03	Solar Energy Installation Managers	15	15	
47-2152.01	Pipe Fitters and Steamfitters	20	3	average
47-2152.02	Plumbers	23	9	
47-4099.02	Solar Thermal Installers and Technicians	21	21	average
47-4099.03	Weatherization Installers and Technicians	18	18	
49-3023.01	Automotive Master Mechanics	24	0	average
49-3023.02	Automotive Specialty Technicians	25	10	
49-9021.01	Heating and Air Conditioning Mechanics and Installers	30	7	average
49-9021.02	Refrigeration Mechanics and Installers	21	0	
51-8099.01	Biofuels Processing Technicians	19	19	average
51-8099.02	Methane/Landfill Gas Generation System Technicians	17	17	
51-8099.03	Biomass Plant Technicians	16	16	
51-8099.04	Hydroelectric Plant Technicians	21	21	
53-1021.00	First-Line Supervisors of Helpers, Laborers, and Material Movers, Hand	23	0	zero
53-1021.01	Recycling Coordinators	23	23	
53-6051.01	Aviation Inspectors	15	0	average
53-6051.07	Transportation Vehicle, Equipment and Systems Inspectors, Except Aviation	22	9	
53-6051.08	Freight and Cargo Inspectors	20	0	

Table B1: Crosswalk between SOC2006/2009 and SOC2010 for which extrapolation of shares was needed

SOC2006/2009	SOC2010
11-9199	11-3071
11-9199	11-9199
13-1079	13-1071
13-1079	13-1075
11-9199	13-1199
15-1071	15-1122
15-1099	15-1134
15-1071	15-1142
15-1081	15-1143
15-1099	15-1143
15-1081	15-1152
15-1099	15-1199
17-2051	17-2051
17-2051	17-2081
23-2092	23-1012
23-2092	23-2011
25-2041	25-2051
25-2041	25-2052
25-3099	25-2059
25-3099	25-3099
11-9111	29-1141
29-1199	29-1151
29-2099	29-1161
29-1199	29-1171
29-1199	29-1199
29-2034	29-2034
29-2099	29-2057
29-2099	29-2092
29-2034	29-2099
29-2099	29-2099
29-9099	29-9092
29-9099	29-9099
31-1012	31-1014
31-1012	31-1015
31-9093	31-9099
33-9099	33-9093
33-9099	33-9099
47-4099	47-2231
47-4099	47-4099
49-9099	49-9081
49-9099	49-9099
51-5021	51-5112
51-5021	51-5113

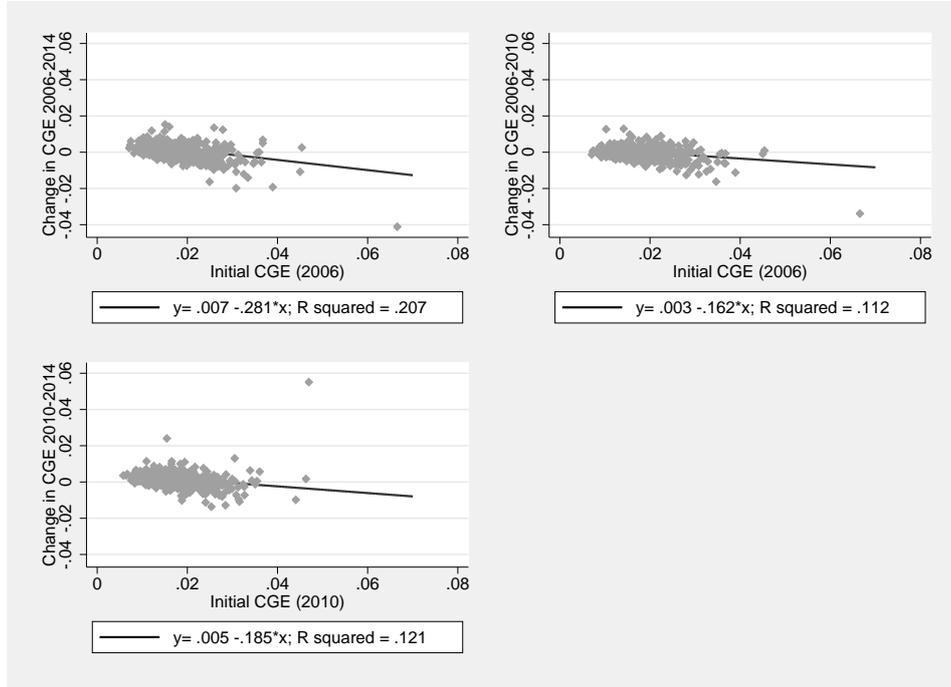
Table B2: List of national and federal R&D labs

Lab name	City	State
AUI National Radio Astronomy Observatory	Green Bank	WV
AUI-Natl Radio Astronomy Obs	Green Bank	WV
Aerospace Corporation	Los Angeles	CA
Aerospace FFRDC	Los Angeles	CA
Ames Laboratory	Ames	IA
Argonne National Laboratory	Argonne	IL
Argonne Natl Laboratory	Argonne	IL
Arroyo Center	Santa Monica	CA
Brookhaven National Laboratory	Upton	NY
C3I Federally Funded Research & Development Center	McLean	VA
C3I Federally Funded Research and Development Center	McLean	VA
Center for Advanced Aviation System Development	McLean	VA
Center for Communications and Computing	Alexandria	VA
Center for Enterprise Modernization	McLean	VA
Center for Naval Analyses	Alexandria	VA
Center for Nuclear Regulatory Analyses	San Antonio	TX
Center for Nuclear Waste Regulatory Analyses	San Antonio	TX
Centers for Communication and Computing	Alexandria	VA
Centers for Medicare and Medicaid Services FFRDC	Baltimore	MD
Fermi National Accelerator Laboratory	Batavia	IL
Fermi Natl Accel Lab	Batavia	IL
Frederick National Laboratory for Cancer Research	Frederick	MD
Homeland Security Institute	Arlington	VA
Homeland Security Studies & Analysis Institute	Arlington	VA
Homeland Security Studies and Analysis Institute	Arlington	VA
Homeland Security Systems Engineering and Development Institute	McLean	VA
IRS FFRDC	McLean	VA
Idaho National Laboratory	Idaho Falls	ID
Institute for Defense Analyses Comm & Computing	Alexandria	VA
Institute for Defense Analyses Communication & Computing	Alexandria	VA
Institute for Defense Analyses Studies & Analyses	Alexandria	VA
Internal Revenue Service FFRDC	McLean	VA
Internal Revenue Service and Department of Veterans Affairs FFRDC	McLean	VA
Jet Propulsion Laboratory	Pasadena	CA
Judiciary Engineering and Modernization Center	McLean	VA
Lawrence Berkeley Lab	Berkeley	CA
Lawrence Berkeley National Laboratory	Berkeley	CA
Lawrence Livermore Lab	Livermore	CA
Lawrence Livermore National Laboratory	Livermore	CA
Lincoln Laboratory	Lexington	MA
Los Alamos National Lab	Los Alamos	NM
Los Alamos National Laboratory	Los Alamos	NM
MIT Lincoln Laboratory	Lexington	MA
Massachusetts Institute of Technology Lincoln Laboratory	Lexington	MA
NCI Frederick Cancer Research & Development Center	Frederick	MD
National Astronomy and Ionosphere Center	Ithaca	NY
National Biodefense Analysis and Countermeasures Center	Frederick	MD
National Cancer Institute at Frederick	Frederick	MD
National Center for Atmospheric Research	Boulder	CO
National Defense Research Institute	Santa Monica	CA
National Optical Astronomy Observatories	Tucson	AZ
National Optical Astronomy Observatory	Tucson	AZ
National Radio Astronomy Observatory	Green Bank	WV
National Renewable Energy Laboratory	Golden	CO
National Renewable Energy Research Laboratory	Golden	CO
National Security Engineering Center	McLean	VA
Natl Ctr Atmospheric Res	Boulder	CO
Natl Optical Astro Obs	Tucson	AZ
Oak Ridge National Laboratory	Oak Ridge	TN
Pacific Northwest National Laboratories	Richland	WA
Pacific Northwest National Laboratory	Richland	WA
Plasma Physics Lab	Princeton	NJ
Plasma Physics Laboratory	Princeton	NJ
Princeton Plasma Physics Laboratory	Princeton	NJ
Project Air Force	Santa Monica	CA
SLAC National Accelerator Laboratory	Stanford	CA
Sandia National Laboratories	Albuquerque	NM
Sandia National Laboratory	Albuquerque	NM
Savannah River National Laboratory	Aiken	SC
Savannah River Technology Center	Aiken	SC
Science and Technology Policy Institute	Arlington	VA
Science and Technology Policy Institute, The	Arlington	VA
Software Engineering Inst	Pittsburgh	PA
Software Engineering Institute	Pittsburgh	PA
Stanford Linear Accel Ctr	Stanford	CA
Stanford Linear Accelerator Center	Stanford	CA
Studies and Analyses Center	Alexandria	VA
Systems and Analyses Center	Alexandria	VA
T J Natl Accel Facility	Newport News	VA
The Science and Technology Policy Institute	Arlington	VA
Thomas Jefferson National Accelerator Facility	Newport News	VA

Table B3: Metropolitan and nonmetropolitan areas hosting R&D labs

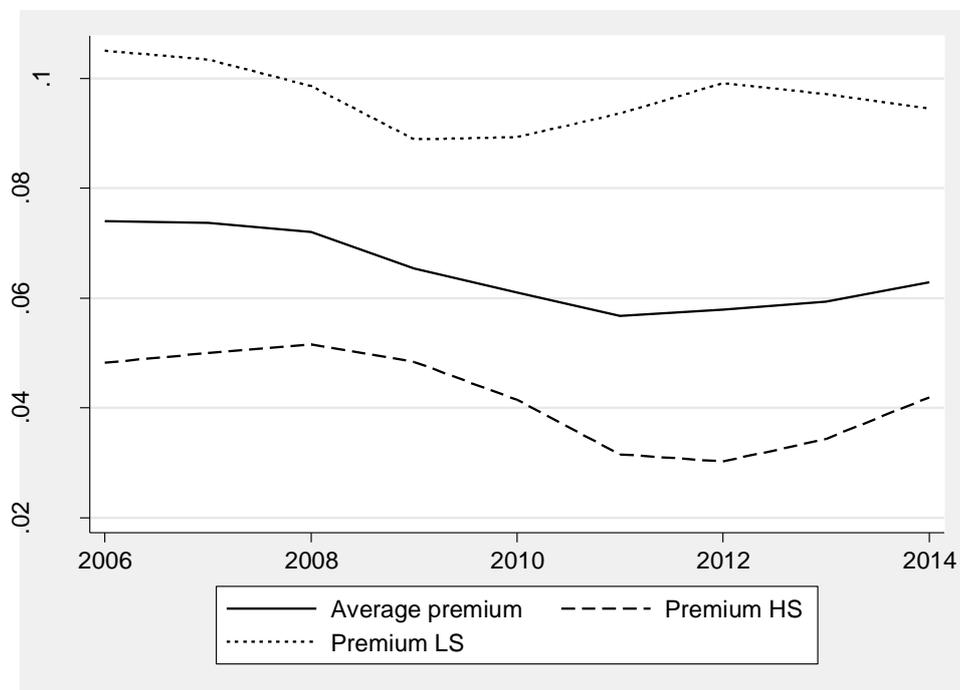
Tucson, AZ
Los Angeles-Long Beach-Santa Ana, CA
San Francisco-Oakland-Fremont, CA
San Jose-Sunnyvale-Santa Clara, CA
Boulder, CO
Denver-Aurora-Broomfield, CO
Washington-Arlington-Alexandria, DC-VA-MD-WV
Augusta-Richmond County, GA-SC
Ames, IA
Idaho Falls, ID
Chicago-Joliet-Naperville, IL-IN-WI
Boston-Cambridge-Quincy, MA-NH
Baltimore-Towson, MD
Trenton-Ewing, NJ
Albuquerque, NM
Los Alamos County, New Mexico nonmetropolitan area
Ithaca, NY
New York-Northern New Jersey-Long Island, NY-NJ-PA
Pittsburgh, PA
Knoxville, TN
San Antonio-New Braunfels, TX
Virginia Beach-Norfolk-Newport News, VA-NC
Kennewick-Pasco-Richland, WA
Southeastern Wyoming nonmetropolitan area

Figure C1: Catching-up in Core Green Employment share, CGE



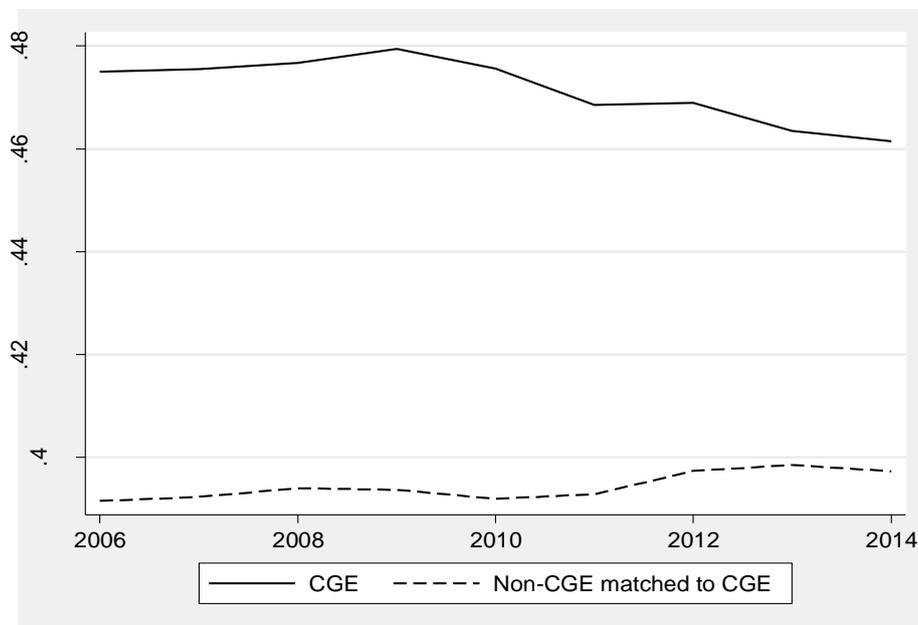
Own elaboration on O*NET, release 18.0, July 2012, and BLS-OES estimates of employment by metropolitan and nonmetropolitan areas. Beta convergence estimated with a cross-sectional regression of the growth in CGE on the initial CGE, weighted by initial employment by area (N=537).

Figure C2: Wage premium (log difference) for CGE employment with respect to employees in non-CGE employment within the same 3-digit SOC



Own elaboration on O*NET, release 18.0, July 2012, and BLS-OES estimates of employment by metropolitan and nonmetropolitan areas. The wage premium is computed as the difference in log hourly wages between core green and non-core green occupations within the same 3-digit SOC group. Premiums at the 3-digit are then averaged using total employment at the 3-digit SOC level as weights. Hourly wage for core green occupations within the 3-digit SOC group is computed as the average of hourly wage of core green occupations using as weights the product between occupational employment and the core greenness. Hourly wage for non-core green occupation within the 3-digit SOC group is computed as the average hourly wage of occupations (core green and non-core green) using as weights the product between occupational employment and 1 minus the core greenness. High skill occupations are the ones belonging to the 2-digit SOC codes: 11, 13, 15, 17, 19, 23, 27, 29, 41. Low skill occupations are the ones belonging to the 2-digit SOC codes: 43, 47, 49, 51, 53.

Figure C3: Concentration index for core green employment (*CGE*) and for non-core green employment within the same 3-digit SOC (*Non-CGE matched to CGE*)



Own elaboration on O*NET, release 18.0, July 2012, and BLS-OES estimates of employment by metropolitan and nonmetropolitan areas. The concentration index for CGE employment is computed as the average concentration index of core green occupation weighted by the product between the core greenness and occupational employment. The concentration index for non-CGE 'matched' occupations is computed as the average concentration index for all occupations in 3-digit SOC codes with at least one core green occupations weighted by the product between (1-core greenness) and occupational employment.

Table D1: Impact of regulation using share of population in NA counties

	GE	CGE	GIE	log(total employment)
Resilience crisis x trend	0.00799 (0.00286)***	0.00734 (0.00298)**	0.00151 (0.00101)	0.1000 (0.0305)***
R&D lab x trend	[0.00259]*** 0.0000913 (0.0000583)	[0.00261]*** 0.0000570 (0.0000555)	[0.000939] -0.0000183 (0.0000579)	[0.0260]*** 0.00216 (0.00113)*
Green patent stock per capita (2006) x trend	[0.0000567] 0.00263 (0.00105)**	[0.0000508] 0.00194 (0.000839)**	[0.0000420] 0.000971 (0.000530)*	[0.000905]** -0.00607 (0.0128)
Total patent stock per capita (2006) x trend	[0.00115]** -0.000139 (0.0000997)	[0.000940]** -0.0000982 (0.0000865)	[0.000427]** -0.0000730 (0.0000381)*	[0.0146] 0.00258 (0.00111)**
Trade exposure (2006) x trend	[0.000121] -0.00117 (0.00121)	[0.000105] -0.000620 (0.00111)	[0.0000440]* -0.00132 (0.000861)	[0.000963]** -0.0542 (0.0223)**
Initially NA x trend	[0.00127] 0.000102 (0.0000679)	[0.00121] 0.0000979 (0.0000735)	[0.000698]* -0.00000819 (0.0000257)	[0.0220]** 0.000432 (0.00116)
Share of population in NA switching counties	[0.0000578]* 0.000562 (0.000355)	[0.0000549]* 0.000484 (0.000350)	[0.0000311] -0.0000166 (0.000113)	[0.00115] -0.00239 (0.00551)
	[0.000283]**	[0.000268]*	[0.000114]	[0.00438]
N	4833	4833	4296	4833

Fixed effect model weighted by total employment in 2006. Standard errors clustered by state in parenthesis and by area in brackets. * p<0.1, ** p<0.05, *** p<0.01. Other control variables: year-by-state dummies, year-by-NMA status dummies.

Table D2: Impact of regulation using differential impact for multiple switches

	GE	CGE	GIE	log(total employment)
Resilience crisis x trend	0.00797 (0.00285)***	0.00729 (0.00296)**	0.00145 (0.000983)	0.0983 (0.0303)***
R&D lab x trend	[0.00259]*** 0.0000845 (0.0000601)	[0.00261]*** 0.0000586 (0.0000560)	[0.000943] -0.00000239 (0.0000614)	[0.0260]*** 0.00261 (0.00119)**
Green patent stock per capita (2006) x trend	[0.0000601] 0.00263 (0.00107)**	[0.0000550] 0.00196 (0.000832)**	[0.0000441] 0.00102 (0.000539)*	[0.000960]** -0.00487 (0.0130)
Total patent stock per capita (2006) x trend	[0.00114]** -0.000139 (0.0000998)	[0.000934]** -0.0000990 (0.0000863)	[0.000435]** -0.0000766 (0.0000394)*	[0.0144] 0.00252 (0.00108)**
Trade exposure (2006) x trend	[0.000121] -0.00111 (0.00122)	[0.000105] -0.000581 (0.00112)	[0.0000438]* -0.00133 (0.000861)	[0.000959]** -0.0556 (0.0221)**
Initially NA x trend	[0.00128] 0.000101 (0.0000699)	[0.00122] 0.0000977 (0.0000746)	[0.000692]* -0.00000812 (0.0000250)	[0.0218]** 0.000541 (0.00110)
First switch to NA	[0.0000580]* 0.000522 (0.000299)*	[0.0000554]* 0.000457 (0.000291)	[0.0000314] 0.0000247 (0.000110)	[0.00110] -0.00255 (0.00481)
Second switch to NA	[0.000244]** 0.000651 (0.000387)*	[0.000233]* 0.000454 (0.000334)	[0.000102] -0.000209 (0.000252)	[0.00366] -0.00940 (0.00641)
	[0.000411]	[0.000381]	[0.000201]	[0.00610]
N	4833	4833	4296	4833

Fixed effect model weighted by total employment in 2006. Standard errors clustered by state in parenthesis and by area in brackets. * p<0.1, ** p<0.05, *** p<0.01. Other control variables: year-by-state dummies, year-by-NMA status dummies.

Table E1: Estimate of the propensity score

Dep var: Pr(Treat=1)	Parsimonious	Extended
log(estab size, 2008)	-1.477*** (0.426)	-1.780*** (0.504)
NMA dummy	0.568** (0.259)	0.466* (0.277)
log(density, 2008)	0.350*** (0.0901)	0.363*** (0.0938)
Empl share utilities (2008)	53.39** (21.77)	51.86** (22.29)
Share of pop in counties NA with old standards	2.602*** (0.230)	2.643*** (0.238)
GE (2008)		-3.351 (11.80)
Empl share in manufacturing (2008)		2.033 (1.649)
Empl share in mining and extraction (2008)		5.955 (4.918)
Resilience crisis		9.761 (7.423)
Pseudo R2	0.513	0.519
N	537	537

Probit model. Dependent variable: switch to NA=1. Standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01.

Table E2: Balancing for the parsimonious specification

	Treated	Unmatched Control	t-test	Nearest neighbour Control	t-test	Kernel Control	t-test
log(estab size, 2008)	2.7159	2.7317	-0.73	2.7076	0.35	2.6971	0.78
NMA dummy	0.21154	0.35958	-3.38***	0.01923	5.56***	0.05552	4.15***
log(density, 2008)	5.3892	4.3244	8.95***	5.6181	-1.97**	5.5241	-1.08
Empl share utilities (2008)	0.00457	0.00405	1.50	0.00399	1.43	0.00423	0.78
Share of pop in counties NA with old standards	0.93101	0.20932	22.86***	0.94309	-0.52	0.93566	-0.19

Average values for matching variables. 156 treated areas. Average for matched control areas are weighted by matching weights. t-test compares averages for treated areas and averages for non-treated areas. * p<0.1, ** p<0.05, *** p<0.01.

Table E3: Balancing for the extended specification

	Treated	Unmatched Control	t-test	Nearest neighbour Control	t-test	Kernel Control	t-test
GE (2008)	0.02767	0.02732	0.52	0.02997	-2.87***	0.02982	-2.70***
log(estab size, 2008)	2.7159	2.7317	-0.73	2.7217	-0.26	2.7127	0.13
Empl share in manufacturing (2008)	0.11927	0.13054	-1.59	0.10502	2.23**	0.11202	1.05
Empl share in mining and extraction (2008)	0.00317	0.00801	-2.75***	0.00298	0.17	0.00257	0.55
NMA dummy	0.21154	0.35958	-3.38***	0.03205	5.02***	0.05245	4.26***
log(density, 2008)	5.3892	4.3244	8.95***	5.5658	-1.45	5.5301	-1.15
Empl share utilities (2008)	0.00457	0.00405	1.50	0.00439	0.43	0.00448	0.20
Resilience crisis	-0.04787	-0.05037	1.80*	-0.04521	-2.21**	-0.04672	-0.93
Share of pop in counties NA with old standards	0.93101	0.20932	22.86***	0.94091	-0.42	0.93253	-0.06

Average values for matching variables. 156 treated areas. Average for matched control areas are weighted by matching weights. t-test compares averages for treated areas and averages for non-treated areas. * p<0.1, ** p<0.05, *** p<0.01.

Table E4: Average treatment effect of NA switch based on propensity score for green employment share, GE

	(1)	(2)	(3)	(4)
Change 2006-2008	0.0000489 (0.000331)	0.000175 (0.000273)	0.000464 (0.000453)	0.000483 (0.000323)
Change 2007-2008	-0.0000192 (0.000153)	0.0000132 (0.000155)	0.000294 (0.000344)	0.0000552 (0.000155)
Change 2008-2009	-0.000126 (0.000263)	-0.000113 (0.000192)	-0.000177 (0.000374)	0.0000578 (0.000188)
Change 2008-2010	-0.000275 (0.000446)	-0.000412 (0.000300)	-0.000188 (0.000511)	-0.000143 (0.000277)
Change 2008-2011	0.000332 (0.000617)	0.0000577 (0.000374)	-0.0000162 (0.000731)	0.000216 (0.000321)
Change 2008-2012	0.00163** (0.000750)	0.00114** (0.000497)	0.00127 (0.000874)	0.00117** (0.000489)
Change 2008-2013	0.00183** (0.000774)	0.00125** (0.000588)	0.00130 (0.000932)	0.00133** (0.000547)
Change 2008-2014	0.00167** (0.000775)	0.00122* (0.000667)	0.00167* (0.000915)	0.00162** (0.000567)
Specification of the PS Matching algorithm	Parsimon NN	Parsimon Kernel	Extended NN	Extended Kernel

N=156. Bootstrap standard errors (500 repetitions) in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. The Parsimonious specification of the propensity score includes the logarithm of average establishment size, the NMA dummy, the employment share in the utilities sector, the share of population in counties that were NA according to old standards. The Extended specification of the propensity score also includes the share of green employment, the share of employment in the manufacturing sector, the share of employment in the mining and extraction sector and the resilience to the crisis.

Table E5: Average treatment effect of NA switch based on propensity score for core green employment share, CGE share

	(1)	(2)	(3)	(4)
Change 2006-2008	-0.000500 (0.000353)	-0.000274 (0.000294)	-0.000304 (0.000507)	0.000168 (0.000274)
Change 2007-2008	-0.000250 (0.000178)	-0.000203 (0.000158)	-0.0000178 (0.000280)	-0.0000339 (0.000130)
Change 2008-2009	0.00000454 (0.000265)	-0.0000334 (0.000171)	0.000370 (0.000327)	0.00000654 (0.000140)
Change 2008-2010	-0.000134 (0.000424)	-0.000326 (0.000251)	0.000430 (0.000475)	-0.000198 (0.000210)
Change 2008-2011	0.000396 (0.000613)	0.0000814 (0.000349)	0.000981* (0.000570)	-0.0000573 (0.000296)
Change 2008-2012	0.00144** (0.000718)	0.000942** (0.000470)	0.00138* (0.000735)	0.000545 (0.000471)
Change 2008-2013	0.00163** (0.000716)	0.00106* (0.000553)	0.00113 (0.000790)	0.000663 (0.000549)
Change 2008-2014	0.00158** (0.000707)	0.00114* (0.000605)	0.00160** (0.000745)	0.00109** (0.000531)
Specification of the PS Matching algorithm	Parsimon NN	Parsimon Kernel	Extended NN	Extended Kernel

N=156. Bootstrap standard errors (500 repetitions) in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. The Parsimonious specification of the propensity score includes the logarithm of average establishment size, the NMA dummy, the employment share in the utilities sector, the share of population in counties that were NA according to old standards. The Extended specification of the propensity score also includes the share of green employment, the share of employment in the manufacturing sector, the share of employment in the mining and extraction sector and the resilience to the crisis.

Table E6: Average treatment effect of NA switch based on propensity score for green employment share predicted by the industrial structure, GIE

	(1)	(2)	(3)	(4)
Change 2006-2008	0.000548*** (0.000161)	0.000516*** (0.000158)	0.000287 (0.000194)	0.000339** (0.000168)
Change 2007-2008	0.000536* (0.000275)	0.000598*** (0.000179)	0.000126 (0.000123)	0.000673** (0.000272)
Change 2008-2009	-0.0000283 (0.000107)	-0.0000312 (0.0000939)	0.0000565 (0.000110)	-0.0000668 (0.0000807)
Change 2008-2010	-0.0000181 (0.000133)	0.00000513 (0.000113)	-0.0000208 (0.000150)	-0.0000741 (0.000105)
Change 2008-2011	0.000218 (0.000165)	0.000110 (0.000116)	-0.0000330 (0.000186)	-0.000110 (0.000128)
Change 2008-2012	0.000306 (0.000230)	0.000222* (0.000127)	0.000219 (0.000181)	-0.0000703 (0.000126)
Change 2008-2013	0.000187 (0.000211)	0.0000350 (0.000192)	-0.0000593 (0.000198)	-0.000106 (0.000183)
Specification of the PS	Parsimon	Parsimon	Extended	Extended
Matching algorithm	NN	Kernel	NN	Kernel

N=156. Bootstrap standard errors (500 repetitions) in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. The Parsimonious specification of the propensity score includes the logarithm of average establishment size, the NMA dummy, the employment share in the utilities sector, the share of population in counties that were NA according to old standards. The Extended specification of the propensity score also includes the share of green employment, the share of employment in the manufacturing sector, the share of employment in the mining and extraction sector and the resilience to the crisis.

Table E7: Average treatment effect of NA switch based on propensity score for high-skill green employment

	(1)	(2)	(3)	(4)
Change 2006-2008	-0.00000465 (0.000281)	-0.0000187 (0.000189)	0.000283 (0.000282)	0.000202 (0.000234)
Change 2007-2008	-0.000108 (0.000173)	-0.000184 (0.000122)	0.0000879 (0.000195)	-0.0000467 (0.000144)
Change 2008-2009	-0.000142 (0.000197)	-0.000174 (0.000144)	0.000232* (0.000140)	-0.000152 (0.000153)
Change 2008-2010	-0.000520** (0.000254)	-0.000474** (0.000214)	0.00000587 (0.000287)	-0.000271 (0.000244)
Change 2008-2011	-0.00000420 (0.000347)	0.0000217 (0.000242)	0.000332 (0.000342)	0.000209 (0.000238)
Change 2008-2012	0.000870* (0.000466)	0.000913*** (0.000352)	0.000706 (0.000440)	0.00102*** (0.000365)
Change 2008-2013	0.00125*** (0.000468)	0.00119*** (0.000386)	0.000819* (0.000454)	0.00119*** (0.000374)
Change 2008-2014	0.00111** (0.000496)	0.00109** (0.000455)	0.00106** (0.000479)	0.00126*** (0.000350)
Specification of the PS	Parsimon	Parsimon	Extended	Extended
Matching algorithm	NN	Kernel	NN	Kernel

N=156. Bootstrap standard errors (500 repetitions) in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. The Parsimonious specification of the propensity score includes the logarithm of average establishment size, the NMA dummy, the employment share in the utilities sector, the share of population in counties that were NA according to old standards. The Extended specification of the propensity score also includes the share of green employment, the share of employment in the manufacturing sector, the share of employment in the mining and extraction sector and the resilience to the crisis. High-skill GE belong to SOC 2-digit codes: 11, 13, 15, 17, 19, 23, 27, 29, 41.

Table E8: Average treatment effect of NA switch based on propensity score for low-skill green employment

	(1)	(2)	(3)	(4)
Change 2006-2008	0.000535 (0.000178)	0.000193 (0.000147)	0.000281 (0.000199)	0.000307** (0.000152)
Change 2007-2008	0.000890 (0.000121)	0.000198** (0.0000862)	0.000315*** (0.000115)	0.000216** (0.000100)
Change 2008-2009	0.000155 (0.000143)	0.0000615 (0.0000914)	0.0000377 (0.000123)	-0.000101 (0.0000931)
Change 2008-2010	0.000244 (0.000267)	0.0000626 (0.000167)	-0.00000679 (0.000226)	-0.000285 (0.000180)
Change 2008-2011	0.000337 (0.000330)	0.0000360 (0.000204)	-0.0000133 (0.000325)	-0.000447* (0.000250)
Change 2008-2012	0.000761** (0.000358)	0.000223 (0.000226)	0.0000334 (0.000389)	-0.000426 (0.000309)
Change 2008-2013	0.000583 (0.000400)	0.0000660 (0.000270)	-0.0000722 (0.000422)	-0.000499 (0.000357)
Change 2008-2014	0.000563 (0.000384)	0.000132 (0.000279)	-0.000139 (0.000390)	-0.000410 (0.000370)
Specification of the PS Matching algorithm	Parsimon NN	Parsimon Kernel	Extended NN	Extended Kernel

N=156. Bootstrap standard errors (500 repetitions) in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. The Parsimonious specification of the propensity score includes the logarithm of average establishment size, the NMA dummy, the employment share in the utilities sector, the share of population in counties that were NA according to old standards. The Extended specification of the propensity score also includes the share of green employment, the share of employment in the manufacturing sector, the share of employment in the mining and extraction sector and the resilience to the crisis. High-skill GE belong to SOC 2-digit codes: 43, 47, 49, 51, 53.

Table F1: Estimate of the propensity score

Dep var: Pr(Treat=1)	Parsimonious	Extended
log(estab size, 2008)	-1.278** (0.514)	-16.10 (16.33)
NMA dummy	1.329*** (0.346)	-1.173** (0.592)
log(density, 2008)	0.394*** (0.118)	-1.346 (2.106)
Empl share utilities (2008)	45.89 (28.37)	9.784* (5.415)
Share of pop in counties NA with old standards	3.131*** (0.380)	1.466*** (0.371)
GE (2008)		0.491*** (0.127)
Empl share in manufacturing (2008)		39.90 (29.14)
Empl share in mining and extraction (2008)		10.69 (9.960)
Resilience crisis		3.163*** (0.399)
Pseudo R2	0.530	0.549
N	468	468

Probit model. Dependent variable: switch to NA for Ozone = 1. Standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01.

Table F2: Balancing for the parsimonious specification

	Treated	Unmatched Control	t-test	Nearest neighbour Control	t-test	Kernel Control	t-test
log(estab size, 2008)	2.656	2.6893	-1.18	2.581	2.04**	2.6025	2.21**
NMA dummy	0.3448	0.3596	-0.26	0.0805	4.48***	0.0955	3.02***
log(density, 2008)	5.1887	4.3244	5.80***	5.6365	-2.63***	5.533	-1.78*
Empl share utilities (2008)	0.00375	0.00405	-0.72	0.00445	-1.45	0.00402	-0.46
Share of pop in counties NA with old standards	0.94454	0.20932	248.9***	0.9354	0.31	0.9241	0.44***

Average values for matching variables. 87 treated areas. Average for matched control areas are weighted by matching weights. t-test compares averages for treated areas and averages for non-treated areas. * p<0.1, ** p<0.05, *** p<0.01.

Table F3: Balancing for the extended specification

	Treated	Unmatched Control	t-test	Nearest neighbour Control	t-test	Kernel Control	t-test
GE (2008)	0.0265	0.0267	-0.25	0.0288	-2.19**	0.0289	-1.90*
log(estab size, 2008)	2.656	2.6893	-1.18	2.5593	2.70***	2.5941	2.32**
Empl share in manufacturing (2008)	0.1156	0.1305	-1.65*	0.0959	2.33**	0.0950	2.30**
Empl share in mining and extraction (2008)	0.00385	0.00801	-1.78*	0.00485	-0.36	0.00431	-0.12
NMA dummy	0.3448	0.3596	-0.26	0.1379	3.27***	0.0878	3.62***
log(density, 2008)	5.1887	4.3244	5.80***	5.6389	-2.36**	5.6299	-2.41**
Empl share utilities (2008)	0.00375	0.00405	-0.72	0.00330	1.11	0.00374	0.09
Resilience crisis	-0.0461	-0.0504	2.40**	-0.0469	0.51	-0.0462	0.08
Share of pop in counties NA with old standards	0.94454	0.20932	248.9***	0.9189	0.79	0.9250	0.49

Average values for matching variables. 87 treated areas. Average for matched control areas are weighted by matching weights. t-test compares averages for treated areas and averages for non-treated areas. * p<0.1, ** p<0.05, *** p<0.01.

Table F4: Average treatment effect of NA switch based on propensity score for green employment share, GE

	(1)	(2)	(3)	(4)
Change 2006-2008	-0.000213 (0.000555)	0.000783 (0.000481)	0.000910 (0.000641)	0.000773 (0.000504)
Change 2007-2008	0.000471 (0.00103)	0.000573 (0.000439)	0.000522 (0.000718)	0.000478 (0.000478)
Change 2008-2009	0.000865 (0.000947)	0.000488 (0.000370)	0.000191 (0.000516)	0.0000708 (0.000435)
Change 2008-2010	0.000850 (0.000767)	0.000290 (0.000225)	-0.000456 (0.000344)	-0.000236 (0.000266)
Change 2008-2011	0.000104 (0.000539)	0.000331** (0.000151)	-0.0000785 (0.000267)	0.0000352 (0.000158)
Change 2008-2012	0.00216*** (0.000573)	0.00137*** (0.000322)	0.00138*** (0.000397)	0.00110*** (0.000314)
Change 2008-2013	0.00234*** (0.000545)	0.00162*** (0.000407)	0.00177*** (0.000451)	0.00153*** (0.000415)
Change 2008-2014	0.00253*** (0.000821)	0.00144*** (0.000424)	0.00214*** (0.000494)	0.00178*** (0.000519)
Specification of the PS Matching algorithm	Parsimon NN	Parsimon Kernel	Extended NN	Extended Kernel
N	87	79	87	82

Bootstrap standard errors (500 repetitions) in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. The Parsimonious specification of the propensity score includes the logarithm of average establishment size, the NMA dummy, the employment share in the utilities sector, the share of population in counties that were NA according to old standards. The Extended specification of the propensity score also includes the share of green employment, the share of employment in the manufacturing sector, the share of employment in the mining and extraction sector and the resilience to the crisis.

Table G1: Local multiplier of green employment on the non-tradable sector - metropolitan areas only

Panel A - All NT (excluding NAICS 54)		
	OLS	IV
Elasticity of growth in empl in NT wrt growth in green employment	0.220*** (0.0433)	0.235* (0.131)
Green employment multiplier	3.672	3.910
Panel B - NT deparated by green employment predicted by the industrial structure in NT		
	OLS	IV
Elasticity of growth in empl in NT wrt growth in green employment	0.184*** (0.0354)	0.334*** (0.0787)
Green employment multiplier	3.066	5.562

N=367 metropolitan areas. Robust standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Estimates of the elasticity between green employment logarithmic growth rate (2006-2014) and the logarithmic growth rate of employment in the non-tradable sector are based on cross-sectional regressions that include state dummies as controls. Regressions are weighted by initial (2006) employment. green employment growth is instrumented with the growth 2006-2014 in green employment that is predicted given the macro-level growth in green employment (excluding the area) by occupation weighted by the initial (2006) composition of the local labour force by occupation. The green employment multiplier is calculated as the product of the estimated elasticity and the median of the ratio between NT employment (2014) and green employment share(2014).

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