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

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US

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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. The main methodological novelty consists of a new measure of green employment based on the task content of occupations. Descriptive analysis reveals that: 1. the share of green employment is between 2 and 3 percent, with a strongly pro-cyclical trend; 2. the green wage premium is 4 percent; 3. green jobs are more geographically concentrated than similar non-green jobs; and 4. the top green areas are mostly high-tech. As regards to the drivers, direct changes in environmental regulation are a secondary force in explaining the 8-years growth of green jobs compared to the local amount of green subsidies within the American Recovery and Reinvestment Act (ARRA), the endowment of green knowledge and the resilience to the great recession. Assessing the impact of moving to greener activities, we find that one additional green job is associated with 4.2 (2.2 in the crisis period) new local jobs in non-tradable activities, and that this effect can be mostly ascribed to the green ARRA package.

**Keywords:** green employment, local labor markets, task-based approach, local multipliers, green American Recovery and Reinvestment Act, environmental policies.

**JEL:** J23, O33, Q52, R23

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# 1 Introduction

This paper provides a comprehensive overview of the magnitude, the drivers and the effect of green employment in the local labor markets of the United States (US) over the period 2006-2014. The current debate on the extent and the timing of environmental challenges calls for systematic analysis of, among other things, structural changes in the labor market associated with the transition towards a more sustainable economy. Recent interventions both in the form of environmental regulation or of subsidies - as in the American Recovery and Reinvestment Act of 2009 - revive the attention to policy sensitive issues of the role of environmental policies in creating and destroying jobs. Empirical evidence to inform such a debate is however is still scant, and we propose to fill this gap by analyzing the scale of green employment in the US, its correlation with structural features of metropolitan and non-metropolitan areas as well as the effects in terms of job creation in the local labor markets.

An essential prerequisite for such an endeavor is the availability of a reliable measure of green employment that varies both over time and across geographical areas. In Section 2 we argue that research on these themes has lagged behind because green employment escapes easy measurement. Accordingly, we propose a novel approach based on empirical studies 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 occupations (6 digit of the Standard Occupational Classification, SOC) across 537 metropolitan and non-metropolitan areas over the period 2006-2014. The value added of this method is that the 'greenness' of an occupation - or engagement with environmental work tasks - is based on job-specific characteristics rather than being inferred from employment statistics of green goods or services activities. Our task-based measure adds to prior studies because it captures both the within-sector component of green employment as well as green job creation in industries that are not directly affected by regulation such as engineering services, consulting and machinery production. In doing so, we offer empirical support to the claim that green growth is a widespread phenomenon that extends beyond flagship sectors like renewable energy and electric vehicle production.

Section 3 outlines key stylized facts. First, although we use a novel measure, our aggregate figure of green employment resonates with previous cross-sectional estimates that situate the US green workforce in the region of 2-3 percent employment share (e.g. Deschenes, 2013). We also observe that, after a contraction in coincidence with the great recession, green employment has grown relatively fast. Second, compared to similar occupations green jobs pay on average a 4 percent wage premium that increases to almost 8 percent among low-skilled manual workers. Third, 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. Lastly, leading green employment areas exhibit a strong presence of high-tech activities, as signified by a rate of green patents of resident inventors that is three times higher than the national average.

Section 4 is devoted to the analysis of the drivers of green employment. Important to this goal is the coincidence between the onset of crisis, on the one hand, and the adoption of policies to promote the green economy, on the other. Over the timespan under analysis, two environmental policies have been implemented: i) direct regulation to modify emission standards for four criteria pollutants (PM2.5, Lead, SO2 and Ozone);[1] and ii) subsidies to green production and technology within the American Recovery and Reinvestment Act (ARRA henceforth) which account for 13% of the generous stimulus package approved in 2009 by the US congress.[2] Ours is the first paper to measure directly the amount of ARRA green subisidies to the local economy using public available data of the Department of Energy and the Environmental Protection Agency. To compare the influence of new environmental policies with structural forces such as resilience to the financial crisis and local exposure to trade and technol-

[1]The literature on the labor market outcomes of these environmental regulations 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 Cole 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), industry relocation (Kahn and Mansur, 2013) and earnings loss due to job-to-job transitions (Walker, 2013).

[2]Two papers directly evaluate the ARRA exploiting exogenous variations in the amount of the stimulus at the state level (Feyrer and Sacerdote, 2011; Wilson, 2012). Both papers find an modest-to-large effect that is in line with the ex-ante predictions of the US administration. In particular, a new job costed to the tax payer between 125,000 and 260,000 US dollars.

ogy, we regress the 8-years change of green employment share over initial levels of these drivers, environmental policies and a host of auxiliary controls. Our empirical analysis draws on recent research on the local labor market response to changes in trade, technology and to the crisis. 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. (2013) find that regions with higher exposure to China's trade competition experienced a threefold decline in manufacturing employment during the 2000s. 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. These forces are likely to be also important for the green economy. Openness to trade can affect the local composition of manufacturing productions, including the offshoring of polluting segments of the value chain (Cherniwchan, 2017) and the production of green equipment such as wind turbines or solar photovoltaic cells (Sawhney and Kahn, 2012). In turn, 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. This leads us to expect that the local endowment of green knowledge is likely a key discriminant for the attractiveness of a specific location and thus for green employment growth. We contribute to this literature by investigating the relation of these structural factors with the creation of new jobs in emerging green activities.

Our estimation results corroborate the stylized facts highlighted so far. Indeed, changes in emission standards are a secondary force in explaining the growth of green jobs compared to the local amount of green grants within the ARRA package, the endowment of green knowledge and the resilience in the face of the great recession. Green jobs appear also significantly less affected by international competition than non-green jobs. Although we remain cautious in inferring causality (e.g., the local green ARRA subsidies are significantly higher in initially greener areas), we believe that our results represent a first important step towards bringing environmental sustainability into the above literature on structural changes in the labor market. With this caveat in mind, we add to the literature on the labor market impact of environmental policies (Greenstone, 2002; Walker, 2011; Kahn and Mansur, 2013) by highlighting the constructive side of these policies in contrast to the traditional emphasis on negative effects in terms of job destruction in polluting industries.

Section 5 provides an assessment of the use of green investments as an industrial policy. If the expansion of new activities were capable of generating positive employment effects in the local economy, well-designed green policies could act as effective place-based policies beyond the remit of environmental sustainability. This intuition is compounded by the finding that the green ARRA stimulus is the only driver to be positively correlated with both green and non-green employment creation. We explore more rigorously this association by analyzing the job multiplier effect of green employment on local labor markets. In particular, we use the reduced-form empirical strategy proposed by Moretti (2010) based on a standard shift-share instrument to account for endogeneity in green employment creation.

The main finding is that one additional green job generates 4.2 new jobs in the non-tradable sector. This result is very robust to various definitions of non tradable goods. Also, as expected, the effect is much lower than that implied in our analysis of the drivers of green employment since the shift-share IV strategy is designed to depurate the green local multiplier from idiosyncratic shocks in the local labor market. Still, the green multiplier is large compared to what previous studies find (e.g. Moretti, 2010; Marchand, 2012). To illustrate, our result is close to that observed in high-tech manufacturing jobs (upper bound) and well above that found in mining jobs. Moreover, the green multiplier hangs on around a remarkable 2.2 during the recessionary phase, 2006-2010. Because local green ARRA subsidies are strongly correlated with both green and total job creation, this result lends support to arguments in favor of using green subsidies as place-based policy. At the same time, while the green multiplier is larger than the multiplier of a generic subsidy within the ARRA stimulus package (Feyrer and Sacerdote, 2011; Wilson, 2012), our reduced-form specification cannot isolate the multiplier effect associated with ARRA from that of other drivers. A better grasp of the differential impact of the green economy on growth and of the green stimulus package calls for further analysis at different levels of geographical aggregation based on data on green productions and exports. Given the exploratory nature of this paper, this and other promising avenues are left for future research. Section 6 concludes and summarizes our main findings.

# 2 Measuring green employment

Section 2.1 discusses the existing approaches to measuring green employment. Section 2.2 presents the data sources 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 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.

A survey of existing methods for quantifying employment associated with environmental sustainability reveals important limitations. First, green jobs are inferred only indirectly from industry or product characteristics, and this prevents an exact quantification of the time spent by workers in performing green activities. Our proposed measure uses occupational tasks as main unit of analysis to capture directly the environmental activities that are actually carried out in the workplace, and to what extent. Second, environmental issues are pervasive in several industries, and this leads to expect that much of the variation in the share of green employment is observed within rather than between industries. Environmental issues affect industries that are directly responsible for environmental degradation (e.g., electricity power plants) but also industries that supply polluting industries with equipment (e.g., wind turbines) and consulting activities (e.g., architectural services).[3] We propose that the occupation-based approach outlined below 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. Lastly, data on green employment are usually collected by means of surveys that are not repeated over time, and this limits the possibility of capturing the dynamics of green employment.[4]

## 2.2 Measuring green employment with O*NET

The main data source is the Green Economy program of O*NET.[5] Our proposed measure of green employment exploits the distinction between green tasks and non-green tasks in O*NET to quantify the portion of work time that each occupation dedicates to green activities.

Following the methodology laid out in Vona et al. (2015), for each occupation $i$, our measure is the weighted average of the green-specific and non-green tasks:

$$Greenness_i = \sum_{j=1}^{n} w_{ij} \times 1_{\{j \in green\}}, \tag{1}$$

where $1_{\{j \in green\}}$ is an indicator dummy for 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.[6]

[3] Antoni et al. (2015) identify the establishments active in the renewable energy sector using membership to the Renewable Energy Federation in Germany, a country leader in renewable energy innovations. Interestingly, besides in power generation and transmission, these establishments are mostly concentrated in manufacturing of electronic components, including general purpose and electric machines, construction activities related to installation and architectural and engineering activities. This reflects the fact that the renewable energy value chain covers a broad range of activities.

[4] Becker and Shadbegian (2009) examine the relationship between green productions and workforce skills at the plant level and show that for a given level of output and factor usage, plants producing green goods and services employ a lower share of production workers. Similar evidence is also presented at the industry level in the recent paper of Elliott and Lindley (2017).

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

[6] Weighting tasks by their importance is crucial to estimate the time that an occupation devotes to green activities. While occupations with no green tasks (845 out of 974) have greenness equal to zero, those with some green tasks (129 out of 974) exhibit substantial heterogeneity in their importance. In particular, green tasks are 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 $w_{ij}$ with $1/n$ in (1)) greenness for the 8-digit green occupations. Figure A1 illustrates that the unweighted greenness systematically over-estimates the greenness of an occupation compared to the weighted greenness.

Weighting tasks by their importance allows us to interpret the greenness indicator as a proxy of the time that each occupation is expected to devote to environmental activities. Table A3 shows the occupational ranking by greenness. Therein, jobs that carry an unquestionably green character (e.g., Environmental Engineers, Solar Photovoltaic Installers or Biomass Plant Technicians) have greenness equal to 1, while other occupations have a mixed profile, meaning that environmental work tasks are embedded within a broader spectrum of other activities (e.g., Electrical Engineers, Metal Sheet Workers or Roofers). Importantly, the greenness index allows the identification of 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.

In general, green tasks are relatively more concentrated among relatively less important activities, which is to be expected considering the novel nature of green employment (Lin, 2011).[7] To control for any possible bias due to this, we exploit the distinction that is made in O*NET between an occupation's 'core' tasks (i.e. critical to the occupation) and 'supplemental' (i.e. secondary) tasks and compute a lower-bound measure of "core greenness" based only on core tasks:

$$Core\ Greenness_i = \sum_{j=1}^{n} \tilde{w}_{ij} \times 1_{\{j \in core\}} \times 1_{\{j \in green\}}, \tag{2}$$

where $1_{\{j \in core\}}$ 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 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 537 metropoli-

[7] For example, "Electrical Engineering Technologists" includes 20 specific tasks, 7 of which are green but not all are core, so the estimated greenness (i.e. 0.14) is an upper bound. Two 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 missing values with the minimum importance score attributed to all other tasks.

tan and non-metropolitan 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 occupation (6-digit SOC) across various dimensions: by state, by metropolitan and non-metropolitan areas, and by industry (4-digit NAICS).[8]

Our benchmark measure of green employment share is:

$$GE_{jt} = \sum_{i=1}^{I} Greenness_i \times \frac{L_{ijt}}{L_{jt}}, \tag{3}$$

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

$$CGE_{jt} = \sum_{i=1}^{I} Core\ Greenness_i \times \frac{L_{ijt}}{L_{jt}}. \tag{4}$$

Comparing task-based and industry-based measures of green employment is important to gauge how much this is a within-industry phenomenon rather than being due to compositional changes in the industry structure. Since data limitations do not allow building a measure of green employment that varies across regions, occupations and industries (see the Appendix B for a discussion), we construct a counter-factual industry-based measure following the assumption 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:

$$GIE_{jt} = \sum_{k=1}^{K} Greenness_{kt} \times \frac{L_{kjt}}{L_{jt}}, \tag{5}$$

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 $t$.[9] We use the County Business Patterns Database, available for the years 2006-2013, to obtain detailed data on the employment

[8] 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. The Appendix A provides detailed information on the procedure used to match O*NET and BLS in this paper.

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

shares of industry $k$ at the county level and subsequently aggregate it at the metropolitan and non-metropolitan area level. Next section presents new facts on the evolution and geographical distribution of green employment in the US.

## 3 Facts about green employment

**Size and aggregate dynamics**

Figure 1 illustrates the evolution of our two main measures of green employment in the US between 2006 and 2014. 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 share of CGE is around 2 percent, thus consistent with the stricter criteria used to built this measure. Reassuringly, both CGE and GE employment shares are not dissimilar from estimates of the size of the 'green' economy elaborated by previous literature using different data sources. In particular, 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 indicate that the share of green jobs was between 2.4 percent in 2010 (Deschenes, 2013) and 2.6 percent in 2011 (Elliott and Lindley (2017)).

[Figure 1 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 1 which plots 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 1 about here]

In Table 1, 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 SOC occupational 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 employed in sectors that experienced jobless recovery after the recession (Jaimovich and Siu, 2012). Among other fast-growing occupations are 'sales green jobs', a sub-group of highly educated sales occupations involved in selling technical products and in commodity trading.[10] Indeed, comparing columns (4) and (5) of Table 1, sales occupations are the only ones that exhibit a large educational gap between green and non-green jobs. For this reason, sales green jobs are classified as high-skilled.

**Green wage premium**

Because green activities receive various forms of public support, like subsidies and tax credits, it is important to assess whether these provide diffused benefits. To explore this issue, we estimate the green wage premium both in aggregate and split between skilled and unskilled workers. In particular, we use average hourly wage estimates by occupation (6-digit SOC) and area from the Occupational Employment Statistics of BLS, and tighten the comparison of hourly wages in green and non-green jobs by considering only a sub-sample of 3-digit SOC occupations that contains at least one green job. This allows us to make more precise statements regarding the wage earned in green occupations compared to occupations with similar skill and training requirements. We first compute the unconditional wage premium between green and non-green occupations at the 3-digit SOC level by allocating the wage of an occupation with greenness lower

[10]Sales 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).

than 1 proportionally to its greenness. 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.[11][12]

[Figure 2 about here]

Figure 2 shows that the green wage premium is positive at approximately 0.04 log points and declines slightly after the peak of 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. While the green wage premium for high-skilled jobs steadily declines from 2008 onwards, the premium for low-skilled jobs is stable before 2011 and increases afterwards. It is important to remark that, although comparing green and non-green jobs within 3-digit SOC occupations improves the reliability of our results, the unobservable sorting of heterogeneous workers to jobs prevents a precise estimation of the returns to greenness. Our findings should therefore be taken as merely indicative.

**Spatial dynamics**

The top-left panel of Figure 3 plots the long-term (2006-2014) growth rate in the share of green employment against the initial share of green employment by area and reports the estimated $\beta$-convergence coefficient.

[Figure 3 about here]

From this we conclude that areas with initially lower shares of green jobs did catch up. Splitting the sample between the beginning of the crisis (2006-2010, top-right panel of Figure 3) and the post-crisis period (2010-2014, bottom-left panel of Figure 3) shows that catching-up is uniform across the two periods,

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

[12] Descriptive evidence on educational requirements in Table 1 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.

with no significant differences in the estimated $\beta$-convergence.[13] This pattern can either reflect a true decline in the geographical concentration of green jobs or can hide structural differences in occupational characteristics, notably in terms of intrinsic scope for clustering together green and non-green activities. To further explore this issue, we compare the evolution of geographical concentration, measured using a locational Gini coefficient (Krugman, 1992), for green and matched non-green 3-digit SOC occupations. In so doing we control for occupational similarity and track the genuine differential pattern in the concentration of green jobs. Figure 4 confirms the catching-up as green jobs exhibit a decline in concentration that contrasts with the flat movement of matched non-green jobs. However, in spite of a decrease in concentration, green jobs remain approximately 10 percent more spatially concentrated than comparable non-green jobs. Moreover, the growth of concentration of green employment from 2011 onwards partially offsets the earlier decline in concurrence with the great recession.

[Figure 4 about here]

**Profiling top areas**

Table 2 shows a synthetic profile of geographical areas ranked by quintiles of initial green employment share. Therein the average area in each quintile of the initial distribution of green employment is profiled using various structural characteristics.

[Table 2 about here]

The higher growth of green employment in the bottom two quintiles confirms the catching-up observed 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

[13] We include 2010 as the last year of the crisis, as unemployment keeps increasing until 2010.

other areas in terms of three important drivers that are likely to influence both green and non-green employment dynamics: resilience to the great recession[14], innovativeness[15] and trade exposure.[16]

[Table 3 about here]

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 3 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 throughout 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.[17] Overall, despite the observed catching-up,

[14]The ideal measure of exposure to the great recession is that of Mian and Sufi (2014), but this is not available for non-metropolitan areas. Our measure of resilience to the great financial crisis is the shift-share counterfactual change in local employment given the initial industrial structure of the area:
$Resilience\ crisis_j = \sum_k Growth_k^{07-10} \times Share_{kj}^{2006}$
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 $Share_{kj}^{2006}$ 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.

[15]See Autor et al. (2003), Acemoglu and Autor (2011) and Beaudry et al. (2016). Local innovation capacity is proxied by the stock of triadic total and green patents filled by local inventors per inhabitant and, given the importance of public R&D for energy research, by 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.

[16]See Autor et al. (2013) and Acemoglu et al. (2016). We measure trade exposure using import penetration (import/[import+production-export]) in year 2006 at the macro level for 4-digit NAICS industries and attributed to metropolitan and non-metropolitan areas by means of their initial (2006) industry composition (source: County Business Patterns).

[17]Three areas stand out as highly innovative in green technologies. The Metropolitan Area of Denver (CO), which is home to the largest research facility in Wind Energy Technology (the National Wind Technology Center). Boulder (CO) has a long-standing history of commitment to environmental issues and is the home of an important facility, the US National Center for Atmospheric Research. Lastly, Columbus (IN), which does not host any environmentally specific industrial or research activity but is a consolidated base for equipment manufacturing and specialized workers such as production occupations and mechanical engineers (the highest concentration of any metro area in the US). Other renowned manufacturing hubs like 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 non-metropolitan area with a long-standing tradition in science and technology due to some of the country's largest research facilities specialized in renewable energy and material science, among many other disciplines.

few persistent leading areas emerge with a distinct profile in that they are home to high-tech manufacturing and knowledge-intensive service activities.

# 4 Drivers of green employment

The descriptive evidence presented above indicates that green employment is strongly tied to the innovativeness of the local labor market, and especially to green innovation. The mild catching-up observed in the period under analysis did not affect the consolidation of a group of high-tech green leading areas. A plausible explanation 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. Similarly, the green ARRA package may have favoured areas that have been most affected by the great recession and that possibly were less high-tech and green to start with. This section investigates these issues using econometric techniques.

## 4.1 Estimation issues

We analyze structural drivers of green employment growth in local labor markets using previous literature on trade, technology, the great financial crisis and environmental regulation as a guide. The main issue for such an exercise is the trade-off between identifying a causal effect and assessing the relative importance of different drivers.

On the one hand, to give a causal interpretation to the estimated coefficients, one would need to focus on a single driver such as, for example, environmental regulation (Angrist and Pischke, 2009). The literature on the labor market effect of environmental regulation often uses a quasi-experimental research design that exploits exogenous change in environmental regulation across different jurisdictions that are as similar as possible in all other characteristics, including the structural factors mentioned above (e.g. Greenstone, 2002; Kahn and Mansur, 2013). This implies that, to estimate the causal effect of environmental regulation on green employment, we would have to refrain from assessing the role of other structural drivers or policies, such as the green ARRA package. On the other hand, a multivariate regression framework, jointly considering all drivers, can identify interesting correlations, but not causal effects. Endogeneity concerns can be only mitigated using initial values of the variables of interest, under the assumption that these variables are predetermined. Given the exploratory nature of this paper, we focus on the estimation of correlations between green employment growth and the policy and structural drivers brought to the fore above.[18]

We estimate the following equation for 537 metropolitan and non-metropolitan areas over the periods 2006-2014, 2006-2010 (crisis) and 2010-2014 (post-crisis):

$$\Delta y_j = \mathbf{X}'_{\mathbf{j0}}\boldsymbol{\beta} + \mathbf{P}'_{\mathbf{j}}\boldsymbol{\gamma} + \eta_s + \tau_n + \varepsilon_j, \tag{6}$$

where $\eta_s$ are state fixed effects to capture unobservable state-level policies; $\tau_n$ is a dummy equal to one for non-metropolitan areas; and $\varepsilon_j$ is a standard error term. Our dependent variable $\Delta y_j$ is the long difference of each of the green employment measures defined in Section 2. We take the long-difference to eliminate unobservable fixed characteristics of the local labor market, potentially correlated with both our variables of interest and the level and the growth rate of green employment. The vector of structural drivers $\mathbf{X}_{\mathbf{j0}}$ includes our measure of resilience to the financial crisis (see footnote 14), import penetration (see footnote 16), the green and total stock of triadic patents filled by local inventors per capita (footnote 15) and a dummy equal to 1 for areas that host a federally funded R&D lab. All these variables are set at their values in the initial period (2006). To illustrate, the shift-share variable capturing the exposure to the financial crisis is the product between the 2006 shares of employment of each industry in the local labor market and the national change in employment of that industry during the recession (2007-2009). Table 4 provides descriptive statistics for the green employment drivers.

[Table 4 about here]

[18] In a previous working paper we used the semi-parametric matching estimator proposed by Heckman et al. (1997) and Heckman et al. (1998) to estimate the causal effect of environmental regulation on green employment (Vona et al., 2016). This analysis deserves to be pursued in a separate paper.

The vector of environmental policies $\mathbf{P_j}$ includes emission regulation and the green ARRA package. The former consisted in a change of stringency criteria of National Ambient Air Quality Standards (NAAQS) for four (out of six) criteria pollutants as mandated by the Clean Air Act (CAA). Counties that do not comply with these standards are designed as nonattainment by EPA, which triggers the enforcement of measures to improve air quality on the part of state-level authorities.[19] In the period under analysis, new nonattainment designations for four update NAAQS took place: PM 2.5 (designation in 2009), lead (designation in 2010), SO2 (designation in 2011) and Ozone (designation in 2012). As a consequence of these updates of NAAQS, 156 metropolitan and non-metropolitan areas experienced an increased stringency of environmental regulation switching to a nonattainment designation. As discussed extensively in Appendix B, we classify as nonattainment metropolitan and non-metropolitan areas in which at least 1/3 of the population resides in nonattainment counties. Because the timing of designation differs for each pollutant, the year in which the new nonattainment designation first takes effect varies across regions, depending on the pollutant that is responsible for the switch. Since equation 6 is estimated in long-differences, our measure of regulation counts the number of years of exposure to new nonattainment designations measured in 2014. We also include a dummy variable to identify areas with nonattainment status for at least one of the pre-NAAQS in 2006 and that, in other words, were already exposed to stringent environmental policy. This is relevant to distinguish between the persistent effect of an old nonattainment designation and the effect of the new emission standards.

The second component of the policy vector $\mathbf{P_j}$ is the green ARRA package which amounts to approximately 13% of the overall stimulus (92 US $ billion, or 0.09% of the US GDP). A distinguishing feature sets ARRA apart from previous subsidies to renewable energy and environmentally-related activities: the availability of cash grants through the Treasury, the States, the Department of Energy (DoE) and the Environmental Protection Agency (EPA) (Mundaca and

[19]Nonattainment 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 nonattainment area. See Walker (2011) for further details.

Richter, 2015). The bulk of these grants are allocated to renewable energy and energy efficiency as well as remediation activities and environmental management (see Appendix B7 for further details). Both DoE and EPA post online the data on the grants by recipients, years, amount awarded and, particularly important for the goals of our research, the recipient city. It is worth noting that the sum of the grants awarded by the DoE and the EPA makes up a substantial fraction of the green stimulus package, 40.7 billions of US dollars. The inclusion of state dummies should account for the provisions that cannot be observed directly such as transfer payments or tax credits. Our measure of local green subsidies is the sum of DoE and EPA grants awarded per capita between 2009 and 2012.

Because the award of ARRA grants is likely to suffer from selection bias, the coefficient associated with the ARRA subsidies per capita in equation 6 can be interpreted at best as a correlation. To illustrate, Table 5 shows that, while areas switching to nonattainment are more concentrated in the first quintile of the GE share, ARRA subsidies per capita benefit disproportionately areas that were already greener and, thus, more high-tech.[20] In general, green ARRA subsidies have been highly geographically concentrated: the last two quintiles in terms of ARRA green subsidies account for 88.6% of the total awarded funds. This bias is likely to be amplified if we were able to observe co-funding that played an important role especially for renewable energy technologies (Mundaca and Richter, 2015). To deal with such an uneven geographical distribution of green ARRA grants, we assign each area to a quintile of the weighted distribution of the per capita green funds received over the period under analysis. These quintiles are included as explanatory variables in equation 6.[21]

## 4.2 Estimation results

Table 6 illustrates the main results for our three measures of the share of green employment. The analysis is repeated for the crisis (Panel B) and post-crisis

[20] Interestingly, areas highly affected by the recession do not received more green subsidies than less affected areas (the correlation between subsidies per capita and our indicator of resilience to the recession is actually positive, but small, 0.099, see Table B5).

[21] Results are qualitatively unchanged if we deal with the skewness of the distribution of green ARRA grants using the log of the per capita grants. However, the inclusion of the quintiles highlights the nonlinearity in the relationship between green employment growth and the subsidies.

(Panel C) period to detect structural breaks in the influence of the different drivers.

[Table 6 about here]

Estimates confirm the indications provided by the descriptive evidence. In particular, resilience to the crisis, the presence of public R&D labs and of green inventors are all significantly associated with long-term growth of green employment, while exposure to international trade is not. The estimated correlations are not large but economically meaningful. To illustrate, an increase in resilience equivalent to one inter-quartile range (i.e., 1.6 percent) is associated with a 2 percent growth in the share of green employment and a 2.9 percent growth in the share of core green employment. Not surprisingly, the resilience variable is positively correlated with GE growth at conventional statistical level only in the crisis period (see Panel B and C). The initial advantage in green technologies displays an even larger association with the change in green employment: increasing the green patent stock per capita by one interquartile range corresponds to a 2.8 percent growth in GE (3.3 percent on CGE). The technology input is captured also by the presence of a federally funded R&D lab, which accounts for another 4.6 percent increase in GE (5.6% on CGE) and plays a crucial role especially in the crisis period (Panel B). Finally, all drivers have stronger impacts on task-based measures than on the alternative industry-based measure (column 1-2 versus column 3), suggesting that these drivers are predominantly associated with the within-industry changes in workforce greenness rather than with compositional changes in favor of greener industries.[22]

The second set of results concerns the association between the growth of GE and environmental policies. Bearing in mind the usual caveats about causality, our main finding is that ARRA subsidies are far more effective in stimulating green job creation than direct environmental regulations. The estimated coefficient for new nonattainment designation is positive but not statistically significant at conventional levels, while the areas in two top quintiles of green subsidies experienced a significantly higher long-term growth in the share of

[22]Since our descriptive analysis points to a mild catching in the GE share, Tables C1 and C2 in Appendix C includes a catching-up term, i.e. the initial share of green employment. While this has the expected negative sign, other results are qualitatively unchanged.

GE. In particular, the share of GE increases 4.5% more than the average in areas that are in the top quintile of green ARRA subsidies. Even if ARRA subsidies were granted from 2009, the positive relationship between green ARRA subsidies and GE growth is fully concentrated in the second period where the largest part of the subsidies has been assigned (2010-2014, see Panels B and C). The latter result together with the statistically significant coefficient of ARRA only in the last two quintiles suggest that green subsidies should pass a minimal threshold to be effective. Overall, this is consistent with the commonly shared view that, unlike direct subsidies, regulating emissions cannot be used as a industrial policy to create jobs and spur comparative advantage to green industries. However, this conclusion should be taken with caution because areas designed as nonattainment for old standard experienced a 3.5% faster GE growth than the average area. Further research is certainly required to discern the merits of these two policies in greening the US economy.

[Table 7 about here]

Table 7 presents results for the log of green employment, the log of total employment and for green high- and low-skill employment separately (see footnote 12). The first two columns of the Table illustrate the difference between high- and low-skilled green jobs. Not surprisingly, technology drivers are positively correlated only with the growth in the share of high-skilled green workers, while our proxy for resilience to the crisis has a significantly larger influence on low-skilled green workers. Importantly, ARRA green subsidies increase both the share of high-skilled and low-skilled green employment, reflecting the fact that these subsidies financed not only high-tech projects in renewable technologies but also remediation activities, infrastructures and building retrofitting. It is also worth noting that the coefficient of old nonattainment designation remains statistically significant at conventional levels only for low-skilled green workers. This, together with the substantial wage premium for low-skilled green jobs in comparison to similar jobs, suggests that greening the US economy may provide new opportunities to the workers that bear the bulk of the costs of automation and international competition.

The last two columns of Table 7 contrast the results for, respectively, green and non-green employment. The main finding is that compositional effects on the denominator of our GE share measures do not drive our main results. The coefficient of resilience to the crisis is positive and statistically significant for both total and green employment, but significantly larger for the latter. Also the estimated coefficients associated with green patents, the R&D lab dummy and old NA designation are statistically significant only for green employment. In contrast and consistent with the literature (Acemoglu et al., 2016), higher import penetration has a negative and significant effect on total employment, but not on green employment. This implies that international competition has, at best, a compositional impact on green employment.

Particularly important for the next section is the role played by ARRA subsidies on green and total employment. Observe first that ARRA subsidies are the only driver that has a significant and positive influence on both green and total employment. Using the estimated coefficients, back-to-the-envelope calculations suggests that green ARRA subsidies are responsible for the creation of $61,137$ new green jobs in the fourth quintile and of $63,829$ in the fifth quintile.[23] Similarly, ARRA green subsidies are associated with between 638,474 and 783,979 new non-green jobs in, respectively, the fourth and fifth quintiles. The implied cost of a green job for the US economy is thus in the region of 282,120 dollars, which is slightly higher than the estimated cost of a new job for a generic ARRA subsidy (Feyrer and Sacerdote, 2011; Wilson, 2012). Since each new non-green job created by the green ARRA subsidies costed around 24,785 dollars, the implied green local multiplier of these subsidies would be slightly above 11 if we assumed that all local non-green jobs can be confidently ascribed to green subsidies. Clearly not only this assumption is unrealistic but also such rough estimates of the local green multiplier are heavily affected by endogeneity concerns. Indeed, both green and total job creation are correlated with observable and unobservable regional characteristics and shocks that are not accounted for in these estimates. The next section takes an initial step in providing a more sound estimate of the green job multiplier and of the welfare effects associated with the greening of the US economy.

[23] Predicted changes in green jobs for quintile $q$ are $(e^{\hat{\beta}_q} - 1)Green_{q,0}$, where $Green_{q,0}$ is the average number of green jobs in areas in the $qth$ quintile of ARRA green subsidies.

# 5 Green job local multiplier

In this last section we focus on welfare aspects, in particular the local labor market effects that can be ascribed to exogenous shocks like the implementation of active green policies. Our aim is to explore how industrial policy in the form of green investments correlates with job creation in local labor markets. If the expansion of new activities were capable of generating positive employment outcomes in the local economy, well-designed green policies could act as effective place-based policies beyond the remit of environmental sustainability. The American Recovery and Reinvestment Act of 2009 is a good case in point and our analysis is motivated by the fact that, unlike other drivers of green employment, the local green ARRA subsidies are positively correlated with both green and non-green job creation. Although this indicates that green subsidies are an effective form of place-based policy, we need a more rigorous identification strategy to corroborate this statement. Following Moretti (2010), we estimate a reduced-form equation where the change in total employment in region $j$ is expressed as a function of the change in green employment, using a shift-share instrument that depurates the change in green employment from the influence of idiosyncratic shocks to the local labor market.

Theoretically, the aggregate employment effect of a new green job is a combination of two forces. 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 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 studies show that the magnitude 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). Thus, high-tech manufacturing generates larger multipliers than oil and mining due to stronger agglomeration and pecuniary (via higher wages) externalities. Our goal is to position green activities in this ranking.

To address this issue, we estimate the following reduced-form specification:

$$\Delta ln(L_j^k) = \alpha + \beta \Delta ln(Green_j) + \mu_s + \eta_n + \varepsilon_j, \quad (7)$$

where the long-term change in the log of employment in industry $k$ (non-tradable, NT) is regressed on the long-term change in the log of green employment,[24] a constant, and state $\mu_s$ and nonmetro area $\eta_n$ dummies. These dummies depurate the green local multiplier from, respectively, state-specific and nonmetro 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 sector in terms of green employment.

An important caveat is necessary at this point. The reduced-form specification of 7 does not allow us to estimate the direct job multiplier of green ARRA subsidies and it is not therefore directly comparable with existing estimates of the job multiplier associated with other ARRA subsidies (e.g. Feyrer and Sacerdote, 2011; Wilson, 2012). We can only estimate the multiplier effect of new green jobs regardless of the underlying mechanisms. However, as highlighted in the previous section, green ARRA subsidies are the only driver of both green and non-green job creation in the local labor market, and thus are more likely to trigger positive multiplier effects compared to other drivers.

Two issues should be addressed to correctly estimate the green job multiplier with our data. First, in estimating equation 7, we cannot measure the number of green jobs in the local tradable or non-tradable sector. This is due to a major constraint in our data that 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 $\Delta ln(Green_j)$. Although this correlation should be very small because green jobs represent a rather small fraction of NT jobs and professional service jobs are excluded from the computation of NT employment, we minimize concerns by testing the robustness of our results to a different definition of NT non-green employment. This alternative measure indirectly identifies NT green employment in local labor markets. As for the Green Industry Employment measure (see eq. 5), 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 results.[25]

[24]That is: $Green_{jt} = \sum_{i=1}^{I} Greenness_i \times L_{ijt}$.

[25]These results are also very robust to the use of alternative definitions of NT employment,

The second identification issue regards endogeneity due to the correlation between changes in green employment and unobservable local shocks. To isolate the share of green employment attributed to aggregate shocks - i.e. subsidies to clean energy or the green stimulus package - from 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 8 about here]

Table 8 illustrates the main results divided in two panels, one for each of the different measures of non-tradable employment. Therein we report both the elasticity of NT to green employment and the implied local multiplier, which is the product of this elasticity and of the weighted median number of NT jobs for each green job in 2014. The key finding is a large green job multiplier irrespective of NT employment and to the estimation technique. Our favorite IV estimates reveal that each new green job creates 4.2 new NT jobs in the local economy (Panel 1). This increases up to 5.1 new NT jobs when we depurate 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). In assessing the economic implications of investing in green rather than brown activities, we note that the effect observed here is 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 effects of high-tech activities is not surprising given the high

such as those proposed by Jensen and Kletzer (2005).

average quality of green employment in terms of both educational requirement and average wages. For the reasons discussed above, the longer timespan of our analysis and because we cannot capture nationwide global impacts of green ARRA, it is extremely difficult to compare the green ARRA job multiplier with those estimated in previous studies for any ARRA stimulus. However, it is worth emphasizing that our estimates appear significantly larger than those of other studies (e.g. Feyrer and Sacerdote, 2011; Wilson, 2012).

Next, we further contextualize by assessing separately the extent of structural breaks in the green job multiplier during the crisis (2006-2010) and after (2010-2014). Table 9 illustrates the estimates with instruments that were modified to account for the growth rate in national green employment and initial occupational composition in each sub-period.

[Table 9 about here]

Our estimates provide bounds to the green job multiplier: a lower bound in deep recession and an upper bound during recovery. Remarkably, while as expected 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 2.2 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 concern is that multipliers are generally higher during and just after a deep recession (Auerbach and Gorodnichenko, 2012).

Although further research is required to fully grasp the job creation effect during non recessionary times, and a longer time span is needed to assess the potential bottlenecks that hamper the transition toward a greener economy, our findings lend support to the argument that green productions have the potential to be a source of employment growth. Moreover, given the strong correlation of local green ARRA subsidies with both green and total job creation, we argue that this positive effect should be primarily be attributed to green subsidies that thus appear as a particularly effective type of place-based policy.

# 6 Conclusions

This paper has focused on one of the most sensitive issues of the 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?

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' and, instead, construct a novel measure 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.

Using this measure we then explored descriptive characteristics of green jobs in a panel of metropolitan and non-metropolitan 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 various forms of support to the green economy via new emission standards and the ARRA stimulus package, we compare the influence of these policies and of other structural factors on the greening of the workforce. Our results show that changes in environmental regulation are a secondary driver of green employment growth compared to: local amount of green subsidies within the American Recovery and Reinvestment Act (ARRA), local endowment of green knowledge, the presence of a federally funded R&D lab and resilience to the great recession. Overall, direct subsidies are found to be more effective than command and control regulation for the goal of supporting the growth 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 subsidies to innovation and skill formation.

In the last part of the paper, we provide an assessment of green investments as industrial policy and 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 point to a win-win scenario whereby greening of the workforce has positive spillovers on local employment growth. Interestingly, given the strong correlation of local green subsidies with both green and total job creation, the ARRA stimulus emerges as the main factor behind this large local multiplier. Clearly, this is a preliminary interpretation that requires more rigorous testing in a fully-fledged cost-benefit analysis of the green ARRA package. In particular, whether a win-win strategy would have been possible in the absence of the massive investments of the American Recovery and Reinvestment 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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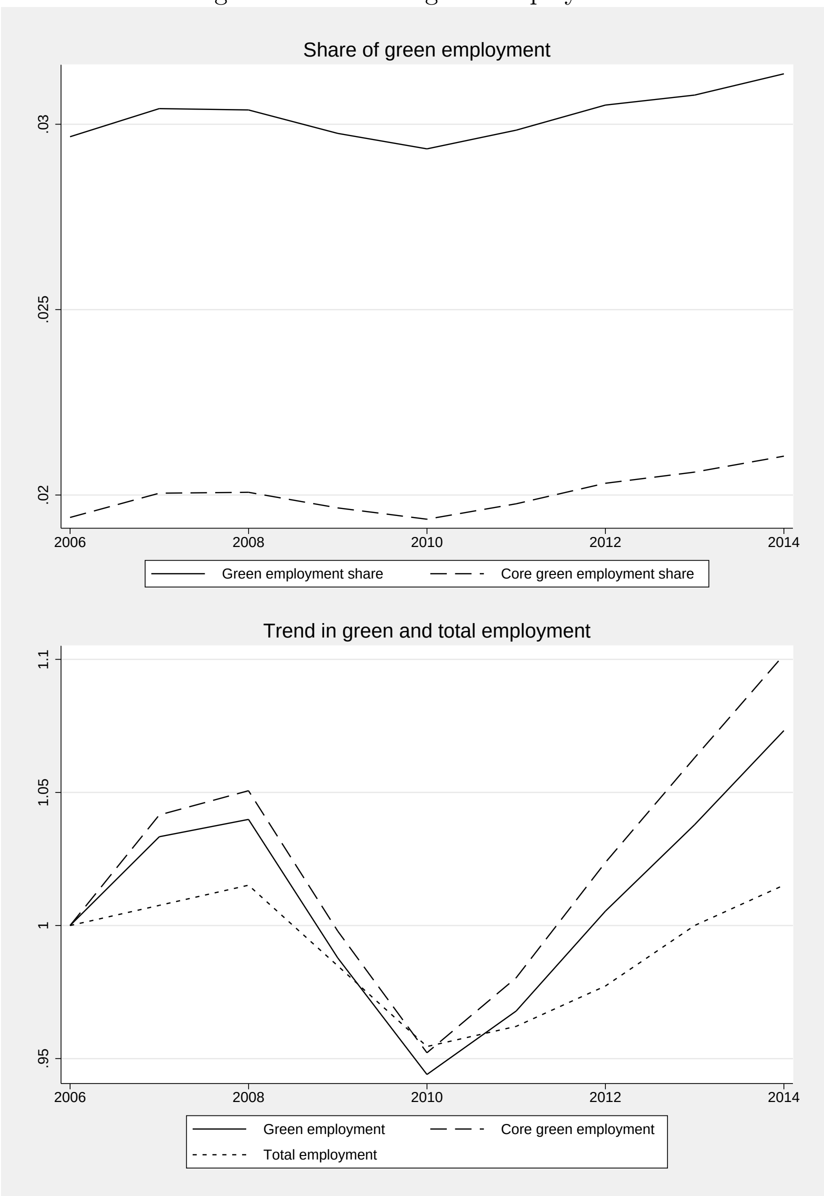
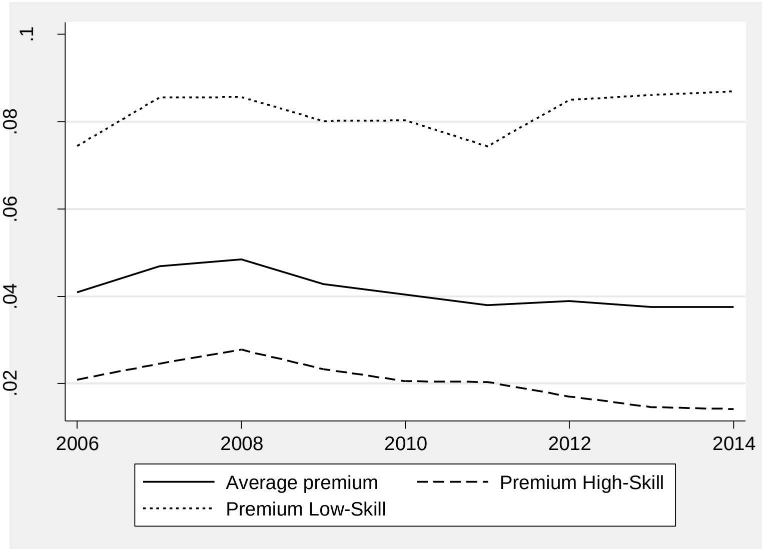
Wilson, D. J. (2012, August). Fiscal Spending Jobs Multipliers: Evidence from the 2009 American Recovery and Reinvestment Act. *American Economic Journal: Economic Policy 4*(3), 251–282.

Figure 1: Trends in green employment



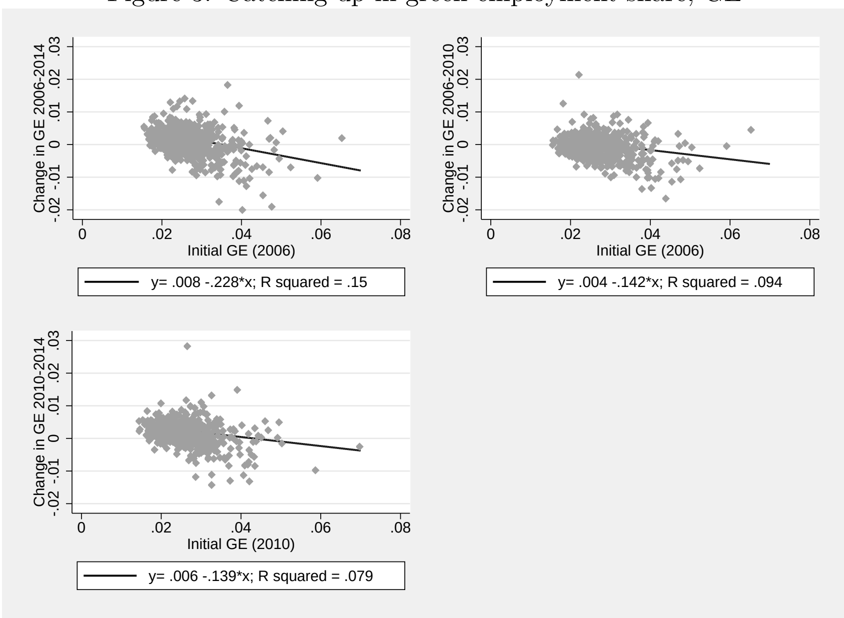

Source: own elaboration on O*NET, release 18.0, July 2012, and BLS-OES estimates of employment by metropolitan and nonmetropolitan areas. US averages are weighted by area's total employment.

Figure 2: Wage premium (log difference) for green occupations with respect to non-green occupations within the same 3-digit SOC



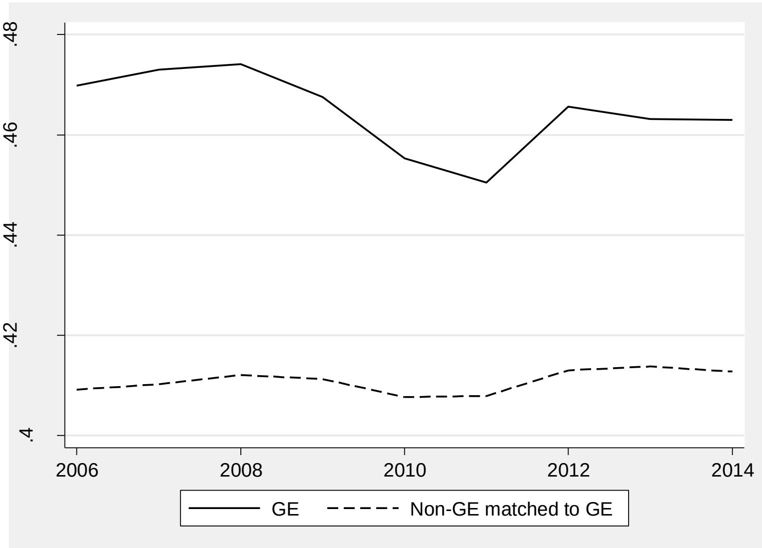

Own elaboration on O*NET, release 18.0, July 2012, and BLS-OES estimates of employment by metropolitan and nonmetropolitan areas. The wage premium is computed as the difference in log hourly wages between green and non-green occupations within the same 3-digit SOC group. Premiums at the 3-digit are then 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 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: 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 1: 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.

Table 2: 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 area's 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 3: 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 |

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.

Table 4: 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 |

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

Table 5: **Policies by quintile of GE**

| Quintile of GE (2006) | 1 (low GE) | 2 | 3 | 4 | 5 (high GE) | Total |
|---|---|---|---|---|---|---|
| Count of initially NA areas | 74 | 46 | 38 | 27 | 23 | |
| Count of switching to NA areas | 51 | 34 | 30 | 21 | 20 | |
| Share of pop in initially NA areas | 0.5099 | 0.6341 | 0.6978 | 0.7009 | 0.5860 | |
| Share of pop in switch NA areas | 0.3423 | 0.5652 | 0.6756 | 0.6313 | 0.5811 | |
| ARRA DoE+EPA per capita (1000$) | 0.0696 | 0.0986 | 0.1288 | 0.1393 | 0.2166 | |

Quintiles of the distribution of green employment share (GE) in 2006 weighted by area's population in 2006.

Table 6: Drivers of green employment share

| Panel A - Growth 2006-2014 | | | |
|---|---|---|---|
| | GE share | CGE share | GIE share |
| Resilience crisis | 0.0363** | 0.0350** | -0.0000289 |
| | (0.0170) | (0.0168) | (0.00797) |
| R&D lab | 0.00139** | 0.00110** | -0.000268 |
| | (0.000548) | (0.000481) | (0.000332) |
| Total patent stock per capita | -0.00142 | -0.00113 | -0.000626* |
| | (0.000945) | (0.000816) | (0.000345) |
| Green patent stock per capita | 0.0304** | 0.0238* | 0.00840* |
| | (0.0144) | (0.0126) | (0.00440) |
| Trade exposure | 0.00235 | 0.00482 | -0.00938 |
| | (0.00989) | (0.00934) | (0.00573) |
| NA with old NAAQS (designation pre-2006) | 0.00105** | 0.00103** | 0.000181 |
| | (0.000462) | (0.000438) | (0.000300) |
| Years of nonattainment with new NAAQS | 0.000115 | 0.0000794 | -0.0000860 |
| | (0.000117) | (0.000115) | (0.0000567) |
| Q2 of DoE and EPA ARRA funds per capita | 0.000317 | 0.000498 | -0.000352 |
| | (0.000474) | (0.000447) | (0.000272) |
| Q3 of DoE and EPA ARRA funds per capita | -0.000110 | -0.000114 | -0.000292 |
| | (0.000659) | (0.000582) | (0.000344) |
| Q4 of DoE and EPA ARRA funds per capita | 0.00138*** | 0.00129*** | -0.000359 |
| | (0.000478) | (0.000436) | (0.000414) |
| Q5 of DoE and EPA ARRA funds per capita | 0.00145*** | 0.00148*** | -0.000191 |
| | (0.000477) | (0.000457) | (0.000271) |
| Panel B - Growth 2006-2010 | | | |
| | GE share | CGE share | GIE share |
| Resilience crisis | 0.0306* | 0.0291* | 0.00975 |
| | (0.0162) | (0.0156) | (0.00608) |
| R&D lab | 0.00135*** | 0.00102*** | 0.000462* |
| | (0.000425) | (0.000389) | (0.000249) |
| Total patent stock per capita | -0.000369 | -0.000287 | -0.0000811 |
| | (0.000769) | (0.000658) | (0.000235) |
| Green patent stock per capita | -0.00104 | -0.00394 | 0.00539 |
| | (0.0131) | (0.0124) | (0.00389) |
| Trade exposure | 0.00976 | 0.0109 | -0.00772* |
| | (0.00975) | (0.00923) | (0.00438) |
| NA with old NAAQS (designation pre-2006) | 0.000333 | 0.000277 | 0.000268* |
| | (0.000421) | (0.000409) | (0.000161) |
| Years of nonattainment with new NAAQS | 0.0000643 | 0.0000553 | -0.0000499 |
| | (0.000115) | (0.000116) | (0.0000475) |
| Q2 of DoE and EPA ARRA funds per capita | 0.000475 | 0.000627 | -0.0000852 |
| | (0.000436) | (0.000419) | (0.000187) |
| Q3 of DoE and EPA ARRA funds per capita | 0.000376 | 0.000345 | -0.000254 |
| | (0.000558) | (0.000528) | (0.000286) |
| Q4 of DoE and EPA ARRA funds per capita | 0.000564 | 0.000581 | 0.0000372 |
| | (0.000470) | (0.000464) | (0.000236) |
| Q5 of DoE and EPA ARRA funds per capita | 0.000335 | 0.000441 | 0.0000880 |
| | (0.000435) | (0.000421) | (0.000179) |
| Panel C - Growth 2010-2014 | | | |
| | GE share | CGE share | GIE share |
| | GE share | CGE share | GIE share |
| Resilience crisis | 0.00724 | 0.00707 | -0.00931 |
| | (0.00934) | (0.00843) | (0.00580) |
| R&D lab | 0.0000249 | 0.0000621 | -0.000740*** |
| | (0.000429) | (0.000406) | (0.000215) |
| Total patent stock per capita | -0.00108** | -0.000871** | -0.000554*** |
| | (0.000420) | (0.000377) | (0.000206) |
| Green patent stock per capita | 0.0335** | 0.0295** | 0.00300 |
| | (0.0142) | (0.0117) | (0.00267) |
| Trade exposure | -0.00725 | -0.00587 | -0.00197 |
| | (0.00841) | (0.00765) | (0.00440) |
| NA with old NAAQS (designation pre-2006) | 0.000750** | 0.000786** | -0.0000687 |
| | (0.000366) | (0.000345) | (0.000239) |
| Years of nonattainment with new NAAQS | 0.0000454 | 0.0000205 | -0.0000357 |
| | (0.0000915) | (0.0000819) | (0.0000406) |
| Q2 of DoE and EPA ARRA funds per capita | -0.000213 | -0.000173 | -0.000272 |
| | (0.000367) | (0.000343) | (0.000207) |
| Q3 of DoE and EPA ARRA funds per capita | -0.000484 | -0.000455 | -0.0000308 |
| | (0.000467) | (0.000414) | (0.000211) |
| Q4 of DoE and EPA ARRA funds per capita | 0.000763* | 0.000666* | -0.000361 |
| | (0.000431) | (0.000395) | (0.000317) |
| Q5 of DoE and EPA ARRA funds per capita | 0.00107*** | 0.000991*** | -0.000277 |
| | (0.000381) | (0.000367) | (0.000209) |

N=537. OLS estimates weighted by initial level of total employment. Robust standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. State dummies and a dummy for non-metro areas included in all regressions.

Table 7: Drivers of green and total employment - alternative measures

| | GE share HS | GE share LS | log(GE) | log(non-GE emp) |
|---|---|---|---|---|
| **Panel A - Growth 2006-2014** | | | | |
| Resilience crisis | 0.0170* | 0.0194 | 1.330*** | 0.345 |
| | (0.00933) | (0.0143) | (0.477) | (0.227) |
| R&D lab | 0.00123*** | 0.000161 | 0.0661*** | 0.0180** |
| | (0.000460) | (0.000331) | (0.0198) | (0.00762) |
| Total patent stock per capita | -0.00127* | -0.000155 | -0.0105 | 0.0227*** |
| | (0.000703) | (0.000473) | (0.0211) | (0.00740) |
| Green patent stock per capita | 0.0347* | -0.00430 | 0.359 | -0.291** |
| | (0.0180) | (0.0127) | (0.359) | (0.145) |
| Trade exposure | 0.00280 | -0.000452 | -0.230 | -0.446** |
| | (0.00706) | (0.00703) | (0.354) | (0.179) |
| NA with old NAAQS (designation pre-2006) | 0.000420 | 0.000635* | 0.0341** | 0.00446 |
| | (0.000334) | (0.000352) | (0.0161) | (0.00889) |
| Years of nonattainment with new NAAQS | 0.000123 | -0.00000793 | 0.00103 | -0.00141 |
| | (0.000103) | (0.000100) | (0.00375) | (0.00184) |
| Q2 of DoE and EPA ARRA funds per capita | 0.000681** | -0.000364 | 0.0129 | -0.00163 |
| | (0.000313) | (0.000352) | (0.0165) | (0.00967) |
| Q3 of DoE and EPA ARRA funds per capita | -0.000324 | 0.000214 | 0.0115 | 0.0119 |
| | (0.000588) | (0.000414) | (0.0233) | (0.0102) |
| Q4 of DoE and EPA ARRA funds per capita | 0.000781* | 0.000601* | 0.0725*** | 0.0253** |
| | (0.000433) | (0.000340) | (0.0181) | (0.00997) |
| Q5 of DoE and EPA ARRA funds per capita | 0.000773** | 0.000680* | 0.0753*** | 0.0313*** |
| | (0.000359) | (0.000347) | (0.0163) | (0.00855) |
| **Panel B - Growth 2006-2010** | GE share HS | GE share LS | log(GE) | log(non-GE emp) |
| Resilience crisis | 0.0101 | 0.0204 | 2.012*** | 1.135*** |
| | (0.00729) | (0.0132) | (0.497) | (0.148) |
| R&D lab | 0.000960*** | 0.000395 | 0.0583*** | 0.00851* |
| | (0.000327) | (0.000279) | (0.0155) | (0.00472) |
| Total patent stock per capita | -0.000619 | 0.000250 | 0.00663 | 0.00479 |
| | (0.000524) | (0.000365) | (0.0180) | (0.00448) |
| Green patent stock per capita | 0.000381 | -0.00142 | -0.215 | -0.0949 |
| | (0.00817) | (0.00917) | (0.312) | (0.0973) |
| Trade exposure | 0.0110* | -0.00123 | 0.180 | -0.205* |
| | (0.00597) | (0.00644) | (0.340) | (0.108) |
| NA with old NAAQS (designation pre-2006) | 0.0000847 | 0.000248 | 0.00353 | -0.00474 |
| | (0.000273) | (0.000299) | (0.0152) | (0.00448) |
| Years of nonattainment with new NAAQS | 0.0000783 | -0.0000140 | -0.00175 | -0.00231* |
| | (0.0000680) | (0.0000906) | (0.00372) | (0.00121) |
| Q2 of DoE and EPA ARRA funds per capita | 0.000841*** | -0.000366 | 0.0220 | 0.000242 |
| | (0.000257) | (0.000324) | (0.0153) | (0.00456) |
| Q3 of DoE and EPA ARRA funds per capita | 0.000119 | 0.000257 | 0.0186 | -0.00108 |
| | (0.000427) | (0.000376) | (0.0201) | (0.00624) |
| Q4 of DoE and EPA ARRA funds per capita | 0.000472 | 0.0000926 | 0.0366** | 0.00916 |
| | (0.000301) | (0.000304) | (0.0167) | (0.00672) |
| Q5 of DoE and EPA ARRA funds per capita | 0.000322 | 0.0000130 | 0.0291* | 0.0154*** |
| | (0.000322) | (0.000305) | (0.0155) | (0.00444) |
| **Panel C - Growth 2010-2014** | GE share HS | GE share LS | log(GE) | log(non-GE emp) |
| Resilience crisis | 0.00817 | -0.000924 | -0.614 | -0.780*** |
| | (0.00787) | (0.00655) | (0.397) | (0.161) |
| R&D lab | 0.000265 | -0.000240 | 0.00729 | 0.00928* |
| | (0.000374) | (0.000206) | (0.0152) | (0.00539) |
| Total patent stock per capita | -0.000702 | -0.000379* | -0.0167 | 0.0182*** |
| | (0.000449) | (0.000217) | (0.0116) | (0.00457) |
| Green patent stock per capita | 0.0377** | -0.00417 | 0.573* | -0.210** |
| | (0.0183) | (0.00659) | (0.334) | (0.102) |
| Trade exposure | -0.00854 | 0.00129 | -0.404 | -0.243* |
| | (0.00638) | (0.00557) | (0.308) | (0.130) |
| NA with old NAAQS (designation pre-2006) | 0.000337 | 0.000414 | 0.0312** | 0.00920 |
| | (0.000270) | (0.000271) | (0.0137) | (0.00741) |
| Years of nonattainment with new NAAQS | 0.0000394 | 0.00000597 | 0.00266 | 0.000948 |
| | (0.0000792) | (0.0000573) | (0.00312) | (0.00132) |
| Q2 of DoE and EPA ARRA funds per capita | -0.000196 | -0.0000168 | -0.0111 | -0.00196 |
| | (0.000264) | (0.000261) | (0.0150) | (0.00807) |
| Q3 of DoE and EPA ARRA funds per capita | -0.000443 | -0.0000409 | -0.00668 | 0.0133* |
| | (0.000378) | (0.000282) | (0.0169) | (0.00762) |
| Q4 of DoE and EPA ARRA funds per capita | 0.000252 | 0.000511* | 0.0345** | 0.0161** |
| | (0.000393) | (0.000273) | (0.0168) | (0.00640) |
| Q5 of DoE and EPA ARRA funds per capita | 0.000419 | 0.000646** | 0.0447*** | 0.0160** |
| | (0.000297) | (0.000297) | (0.0142) | (0.00679) |

N=537. OLS estimates weighted by initial level of total employment. Robust standard errors in parenthesis.
* p<0.1, ** p<0.05, *** p<0.01. State dummies and a dummy for non-metro areas included in all regressions.

Table 8: 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*** | 0.223** |
| | (0.0400) | (0.105) |
| Green employment multiplier | 4.324 | 4.164 |
| **Panel B - NT depurated by green employment predicted by the industrial structure in NT** | | |
| Elasticity of growth in empl in NT wrt growth in green employment | 0.234*** | 0.308*** |
| | (0.0427) | (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 9: 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*** | 0.118 | 0.229*** | 0.510*** |
| | (0.0291) | (0.0881) | (0.0445) | (0.117) |
| Green employment multiplier | 2.132 | 2.196 | 4.276 | 9.531 |
| **Panel B - NT depurated 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*** | 0.142*** | 0.226*** | 0.632*** |
| | (0.0231) | (0.0517) | (0.0488) | (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'.

## APPENDIX: Not for publication

# 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 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 an 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]

It is informative to look at the structure of the O*NET data on green jobs. Table A2 shows the distribution of 128 8-digit SOC green jobs across the traditional 2-digit macro-categories ('major groups') 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 & 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).

[Table A2 about here]

To conclude our technical discussion about our measure of green employment, we report in Figure A1 the relationship between weighted and un-weighted greenness as discussed in section 2.2.

[Figure A1 about here]

# B Data sources and variables

This appendix describes the details of data sources and of the definition of variables.

## 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 indicator[26] 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 Description of the policy change

The Clean Air Act (CAA) sets federal air concentration 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 nonattainment 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 nonattainment 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 nonattainment (NA) counties experience a more stringent environmental policy.[29] Areas characterized by nonattainment designation according to the updated NAAQS (156 areas) represent a large share of the 537 metropolitan and non-metropolitan areas (156/537=29 percent) and an even larger share of the total US population (56 percent). Figure B1 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.[30] 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 B1 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

[29] Nonattainment 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 nonattainment area. See Walker (2011) for further details.

[30] Due 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 nonattainment for the Ozone 8h NAAQS. See Sheriff et al. (2015) for further details.

nonmetro areas. While our data are aggregated at the level of metropolitan and non-metropolitan areas as defined by the U.S. Census Bureau, attainment status is defined by county. 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 that includes the county that is designed as nonattainment even if other counties within the area are designed as attainment (see Sheriff et al., 2015). Second, the share of population that resides in counties that are affected by the new nonattainment designation in metro and nonmetro areas is highly skewed towards 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 nonmetro 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 nonattainment designation.

## B.7 Description of the Green Part of the ARRA

The green component of ARRA is articulated by means of the following programs: (1) Basic research programs through institutions such as the National Science Foundation and the Department of Energys Office of Science to create expertise and accelerate advanced research into a clean energy economy; (2) Extension of two types of tax credits for the development of off-the-shelf technologies: (i) Production tax credits consisting in a 3% per kilowatt-hour incentive for the first ten years of operation; and (ii) Investment tax credits (ITC) providing a 30% credit on investments in solar energy, fuel cells and small wind, and a 10% credit for investments in geothermal, micro-turbines, and combined heat and power; (3) Cash grants: payments of up to 30% of the cost for RE properties in lieu of tax credits. This was intended for renewable energy businesses eligible for tax credits that were too small or not profitable enough to fully enjoy the benefits; (4) Tax credit for clean energy manufacturing: a new program that subsidized up to 30% of the cost of energy manufacturing (battery, vehicle, smart grid, and RE); (5) Targeted loan guarantee: an ARRA addition to the existing Department of Energys Loan Guarantee Program targeting renewable energy systems, power transmission systems, and biofuels that commenced construction before September 30, 2011; (6) Training grants: allocated to state agencies and non-profit organizations to support programs that trained workers for jobs in clean energy: the State Energy Section Partnership (SESP), Pathways Out of Poverty (Pathways), and the Energy Training Partnership (ETP).

Recovery Act Recipient Data are drawn from two official sources: the Department of Energy (https://www.energy.gov/downloads/recovery-act-recipient-data) and the Environmental Protection Agency (https://epamap17.epa.gov/arra/).

Table B4 provides a snapshot of the main recipient areas of ARRA funding. As expected there are several overlaps between this list and that of areas hosting R&D labs (Table B3). Here, Los Alamos stands out as having obtained significant funding for a project that aims at deactivating and demolishing the famous Los Alamos National Laboratory (LANL) Tritium Systems Test Assembly structure, which involves removing several hundred feet of process contaminated waste lines and any associated soil contamination.

[Table B4 about here]

Table B5 confirms the strong and positive association between capacity to attract ARRA funding and various dimensions of technological capabilities such as R&D lab and Green patent stock per capita. As a matter of fact, a large part of the funds have been assigned to national research labs, which confirms the selection bias in our results. The majority of these funds are assigned to remediation (demolish, cleaning-up, elimination, restoring, etc) activities even in non-energy related fields such as water, waste management land.

[Table B5 about here]

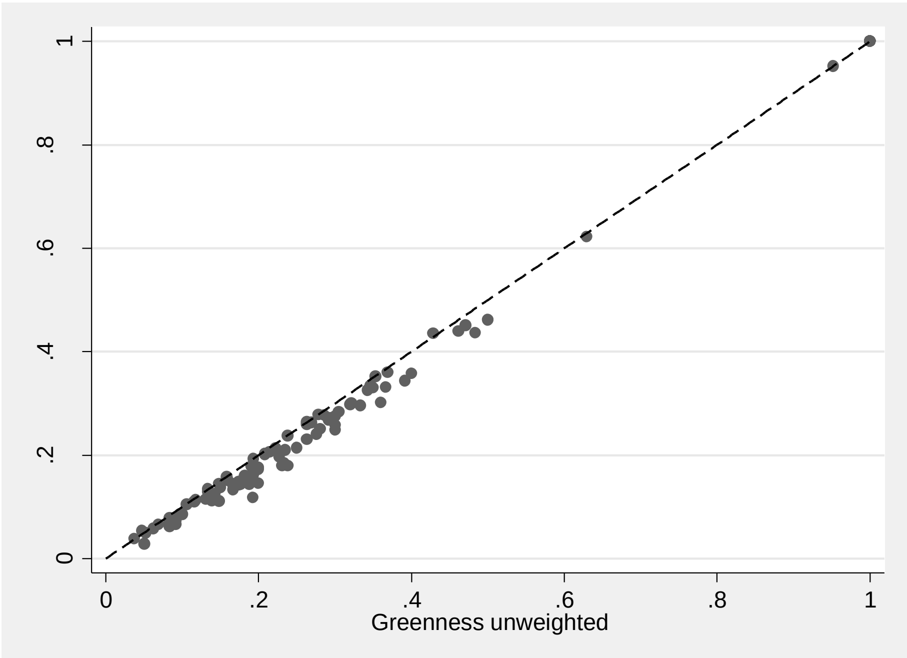
# C Robustness checks for drivers of green employment

[Tables C1 and C2 about here]

# D Additional results for job multipliers

[Table D1 about here]

Figure A1: 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 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 | |

(continue)

(continue)

| | | | | |
|---|---|---|---|---|
| 17-2141.00 | Mechanical Engineers | 27 | 7 | average |
| 17-2141.01 | Fuel Cell Engineers | 26 | 26 | |
| 17-2141.02 | Automotive Engineers | 25 | 8 | |
| 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 | |

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| | | | | |
|---|---|---|---|---|
| 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 A2: 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.

Table A3: 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 |

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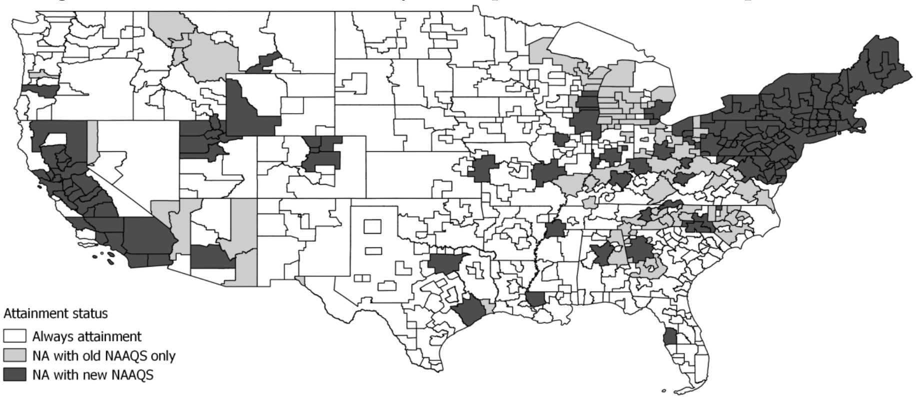
| | | | |
|---|---|---|---|
| 13-1081.02 | Logistics Analysts | 0.1627 | 0.0545 |
| 17-2071.00 | Electrical Engineers | 0.1607 | 0 |
| 47-2061.00 | Construction Laborers | 0.1585 | 0 |
| 17-3029.12 | Nanotechnology Engineering Technicians | 0.1579 | 0.1579 |
| 49-3031.00 | Bus and Truck Mechanics and Diesel Engine Specialists | 0.1508 | 0 |
| 17-3029.05 | Industrial Engineering Technologists | 0.1487 | 0 |
| 17-3029.08 | Photonics Technicians | 0.1457 | 0 |
| 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 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 |

Figure B1: 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 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 |

Table B4: Top recipient areas of ARRA (DOE and EPA) funds per capita

| Area name | ARRA from DOE and EPA (in 1000$ per capita) |
|---|---|
| Los Alamos County, New Mexico NMA | 15.161 |
| Kennewick-Pasco-Richland, WA | 9.205 |
| Idaho Falls, ID | 3.750 |
| Springfield, IL | 3.191 |
| Augusta-Richmond County, GA-SC | 2.927 |
| Carson City, NV | 1.676 |
| Knoxville, TN | 1.656 |
| Tallahassee, FL | 1.623 |
| Odessa, TX | 1.550 |
| Decatur, IL | 1.508 |
| Jefferson City, MO | 1.429 |
| Lansing-East Lansing, MI | 1.390 |
| Albany-Schenectady-Troy, NY | 1.341 |
| Harrisburg-Carlisle, PA | 1.135 |
| West Central Illinois, NMA | 1.101 |
| Durham-Chapel Hill, NC | 1.083 |
| Cheyenne, WY | 1.050 |
| Olympia, WA | 1.032 |
| Northern Wisconsin, NMA | 1.014 |
| Bismarck, ND | 1.013 |

Table B5: Correlation between ARRA (DOE and EPA) per capita and structural drivers of green employment (weighted by employment)

| | Correlation with ARRA (DOE + EPA) per capita |
|---|---|
| Resilience crisis | 0.0993 |
| R&D Lab | 0.0853 |
| Total patent stock per capita | 0.0537 |
| Green patent stock per capita | 0.1181 |
| Trade exposure | -0.0571 |
| NA with old NAAQS (designation pre-2006) | -0.0341 |
| Years of nonattainment with new NAAQS | -0.0295 |

Table C1: Drivers of green employment accounting for the initial share of green employment

| Panel A - Growth 2006-2014 | | | |
|---|---|---|---|
| | GE share | CGE share | GIE share |
| Initial level of dep variable | -0.281*** | -0.382*** | -0.134*** |
| | (0.0777) | (0.0897) | (0.0417) |
| Resilience crisis | 0.0295** | 0.0293** | -0.00614 |
| | (0.0130) | (0.0120) | (0.00724) |
| R&D lab | 0.00188*** | 0.00169*** | -0.0000927 |
| | (0.000609) | (0.000523) | (0.000335) |
| Total patent stock per capita | -0.000386 | -0.000111 | -0.000340 |
| | (0.000745) | (0.000644) | (0.000327) |
| Green patent stock per capita | 0.0315** | 0.0267** | 0.00837** |
| | (0.0142) | (0.0122) | (0.00410) |
| Trade exposure | 0.00300 | 0.00435 | -0.00794 |
| | (0.00932) | (0.00852) | (0.00572) |
| NA with old NAAQS (designation pre-2006) | 0.00125*** | 0.00122*** | 0.000301 |
| | (0.000415) | (0.000371) | (0.000295) |
| Years of nonattainment with new NAAQS | 0.000159 | 0.000125 | -0.0000505 |
| | (0.000118) | (0.000108) | (0.0000540) |
| Q2 of DoE and EPA ARRA funds per capita | 0.000372 | 0.000494 | -0.000283 |
| | (0.000421) | (0.000381) | (0.000272) |
| Q3 of DoE and EPA ARRA funds per capita | 0.000116 | 0.000177 | -0.000242 |
| | (0.000686) | (0.000584) | (0.000327) |
| Q4 of DoE and EPA ARRA funds per capita | 0.00195*** | 0.00185*** | -0.000131 |
| | (0.000522) | (0.000454) | (0.000408) |
| Q5 of DoE and EPA ARRA funds per capita | 0.00212*** | 0.00218*** | 0.0000423 |
| | (0.000487) | (0.000459) | (0.000260) |
| **Panel B - Growth 2006-2010** | | | |
| | GE share | CGE share | GIE share |
| Initial level of dep variable | -0.284*** | -0.379*** | -0.0726* |
| | (0.0709) | (0.0774) | (0.0394) |
| Resilience crisis | 0.0236* | 0.0235** | 0.00646 |
| | (0.0125) | (0.0110) | (0.00606) |
| R&D lab | 0.00185*** | 0.00161*** | 0.000557** |
| | (0.000453) | (0.000426) | (0.000253) |
| Total patent stock per capita | 0.000681 | 0.000729 | 0.0000731 |
| | (0.000547) | (0.000473) | (0.000244) |
| Green patent stock per capita | 0.0000503 | -0.00109 | 0.00537 |
| | (0.0111) | (0.0100) | (0.00370) |
| Trade exposure | 0.0104 | 0.0104 | -0.00694* |
| | (0.00906) | (0.00846) | (0.00420) |
| NA with old NAAQS (designation pre-2006) | 0.000527 | 0.000467 | 0.000333** |
| | (0.000363) | (0.000331) | (0.000169) |
| Years of nonattainment with new NAAQS | 0.000109 | 0.000100 | -0.0000308 |
| | (0.000109) | (0.000101) | (0.0000477) |
| Q2 of DoE and EPA ARRA funds per capita | 0.000530 | 0.000623* | -0.0000478 |
| | (0.000390) | (0.000361) | (0.000190) |
| Q3 of DoE and EPA ARRA funds per capita | 0.000604 | 0.000634 | -0.000227 |
| | (0.000556) | (0.000515) | (0.000278) |
| Q4 of DoE and EPA ARRA funds per capita | 0.00114** | 0.00113** | 0.000160 |
| | (0.000495) | (0.000451) | (0.000255) |
| Q5 of DoE and EPA ARRA funds per capita | 0.00101** | 0.00113*** | 0.000214 |
| | (0.000436) | (0.000405) | (0.000190) |
| **Panel C - Growth 2010-2014** | | | |
| | GE share | CGE share | GIE share |
| Initial level of dep variable | -0.141*** | -0.193*** | -0.0772** |
| | (0.0383) | (0.0468) | (0.0335) |
| Resilience crisis | 0.00776 | 0.00949 | -0.0122** |
| | (0.00902) | (0.00820) | (0.00557) |
| R&D lab | 0.000465 | 0.000567 | -0.000603** |
| | (0.000468) | (0.000420) | (0.000236) |
| Total patent stock per capita | -0.000613 | -0.000411 | -0.000397* |
| | (0.000460) | (0.000417) | (0.000215) |
| Green patent stock per capita | 0.0340** | 0.0303** | 0.00345 |
| | (0.0146) | (0.0122) | (0.00268) |
| Trade exposure | -0.00588 | -0.00435 | -0.00178 |
| | (0.00827) | (0.00735) | (0.00453) |
| NA with old NAAQS (designation pre-2006) | 0.000896** | 0.000936*** | 0.0000234 |
| | (0.000366) | (0.000339) | (0.000236) |
| Years of nonattainment with new NAAQS | 0.0000765 | 0.0000535 | -0.0000191 |
| | (0.0000929) | (0.0000828) | (0.0000382) |
| Q2 of DoE and EPA ARRA funds per capita | -0.000116 | -0.0000501 | -0.000240 |
| | (0.000356) | (0.000328) | (0.000208) |
| Q3 of DoE and EPA ARRA funds per capita | -0.000318 | -0.000242 | -0.0000228 |
| | (0.000499) | (0.000436) | (0.000207) |
| Q4 of DoE and EPA ARRA funds per capita | 0.00113** | 0.00106** | -0.000229 |
| | (0.000457) | (0.000414) | (0.000308) |
| Q5 of DoE and EPA ARRA funds per capita | 0.00145*** | 0.00143*** | -0.000136 |
| | (0.000397) | (0.000384) | (0.000209) |

N=537. OLS estimates weighted by initial level of total employment. Robust standard errors in parenthesis. * $p<0.1$, ** $p<0.05$, *** $p<0.01$. State dummies and a dummy for non-metro areas included in all regressions.

Table C2: Drivers of green and total employment accounting for the initial share of green employment - alternative measures

| | | | | |
|---|---|---|---|---|
| Panel A - Growth 2006-2014 | | | | |
| | GE share HS | GE share LS | log(GE) | log(non-GE emp) |
| Initial level of dep variable | -0.0436 | -0.618*** | 0.0185*** | 0.0110*** |
| | (0.0441) | (0.0707) | (0.00671) | (0.00344) |
| Resilience crisis | 0.0186* | -0.0182** | 1.444*** | 0.405* |
| | (0.00963) | (0.00736) | (0.491) | (0.225) |
| R&D lab | 0.00133*** | -0.000275 | 0.0438* | 0.00525 |
| | (0.000505) | (0.000261) | (0.0229) | (0.00910) |
| Total patent stock per capita | -0.00107 | -0.000672*** | -0.0139 | 0.0218*** |
| | (0.000678) | (0.000218) | (0.0186) | (0.00828) |
| Green patent stock per capita | 0.0345* | 0.00173 | 0.432 | -0.245 |
| | (0.0179) | (0.00536) | (0.339) | (0.157) |
| Trade exposure | 0.00307 | -0.00278 | -0.223 | -0.441** |
| | (0.00703) | (0.00501) | (0.343) | (0.175) |
| NA with old NAAQS (designation pre-2006) | 0.000506 | -0.000164 | 0.0175 | -0.00510 |
| | (0.000348) | (0.000291) | (0.0181) | (0.00960) |
| Years of nonattainment with new NAAQS | 0.000129 | -0.00000183 | -0.00239 | -0.00336* |
| | (0.000104) | (0.0000661) | (0.00361) | (0.00188) |
| Q2 of DoE and EPA ARRA funds per capita | 0.000695** | -0.000439* | -0.00172 | -0.0101 |
| | (0.000311) | (0.000260) | (0.0175) | (0.00944) |
| Q3 of DoE and EPA ARRA funds per capita | -0.000231 | -0.000606* | -0.0223 | -0.00760 |
| | (0.000586) | (0.000319) | (0.0249) | (0.0108) |
| Q4 of DoE and EPA ARRA funds per capita | 0.000914** | -0.0000306 | 0.0461** | 0.0104 |
| | (0.000428) | (0.000267) | (0.0208) | (0.00982) |
| Q5 of DoE and EPA ARRA funds per capita | 0.000946** | -0.000318 | 0.0550*** | 0.0204** |
| | (0.000380) | (0.000324) | (0.0181) | (0.00864) |
| Panel B - Growth 2006-2010 | | | | |
| | GE share HS | GE share LS | log(GE) | log(non-GE emp) |
| Initial level of dep variable | -0.0347 | -0.540*** | 0.0133** | 0.000428 |
| | (0.0385) | (0.0634) | (0.00617) | (0.00206) |
| Resilience crisis | 0.0114 | -0.0124** | 2.094*** | 1.137*** |
| | (0.00736) | (0.00620) | (0.503) | (0.150) |
| R&D lab | 0.00104*** | 0.0000141 | 0.0423** | 0.00801 |
| | (0.000359) | (0.000233) | (0.0186) | (0.00567) |
| Total patent stock per capita | -0.000462 | -0.000201 | 0.00416 | 0.00476 |
| | (0.000517) | (0.000198) | (0.0163) | (0.00449) |
| Green patent stock per capita | 0.000176 | 0.00385 | -0.163 | -0.0931 |
| | (0.00813) | (0.00459) | (0.290) | (0.0981) |
| Trade exposure | 0.0112* | -0.00327 | 0.186 | -0.204* |
| | (0.00597) | (0.00453) | (0.329) | (0.108) |
| NA with old NAAQS (designation pre-2006) | 0.000153 | -0.000450* | -0.00842 | -0.00511 |
| | (0.000289) | (0.000229) | (0.0166) | (0.00505) |
| Years of nonattainment with new NAAQS | 0.0000834 | -0.00000866 | -0.00421 | -0.00239* |
| | (0.0000689) | (0.0000535) | (0.00377) | (0.00129) |
| Q2 of DoE and EPA ARRA funds per capita | 0.000852*** | -0.000432* | 0.0115 | -0.0000862 |
| | (0.000258) | (0.000224) | (0.0160) | (0.00474) |
| Q3 of DoE and EPA ARRA funds per capita | 0.000193 | -0.000459 | -0.00569 | -0.00184 |
| | (0.000444) | (0.000298) | (0.0235) | (0.00691) |
| Q4 of DoE and EPA ARRA funds per capita | 0.000578* | -0.000459* | 0.0176 | 0.00859 |
| | (0.000343) | (0.000275) | (0.0198) | (0.00686) |
| Q5 of DoE and EPA ARRA funds per capita | 0.000460 | -0.000859*** | 0.0145 | 0.0150*** |
| | (0.000358) | (0.000270) | (0.0174) | (0.00499) |
| Panel C - Growth 2010-2014 | | | | |
| | GE share HS | GE share LS | log(GE) | log(non-GE emp) |
| Initial level of dep variable | -0.0714*** | -0.352*** | 0.000975 | 0.0107*** |
| | (0.0267) | (0.0641) | (0.00460) | (0.00222) |
| Resilience crisis | 0.0114 | -0.0155** | -0.61 | -0.730*** |
| | (0.00809) | (0.00659) | (0.398) | (0.161) |
| R&D lab | 0.000509 | -0.000345* | 0.00607 | -0.00316 |
| | (0.000417) | (0.000196) | (0.0169) | (0.00634) |
| Total patent stock per capita | -0.000422 | -0.000597*** | -0.0169 | 0.0172*** |
| | (0.000444) | (0.000165) | (0.0115) | (0.00556) |
| Green patent stock per capita | 0.0372** | -0.000662 | 0.577* | -0.163 |
| | (0.0182) | (0.00439) | (0.333) | (0.109) |
| Trade exposure | -0.00746 | -0.000652 | -0.404 | -0.236* |
| | (0.00628) | (0.00500) | (0.308) | (0.126) |
| NA with old NAAQS (designation pre-2006) | 0.000485* | 0.0000440 | 0.0303** | -0.000128 |
| | (0.000277) | (0.000258) | (0.0142) | (0.00747) |
| Years of nonattainment with new NAAQS | 0.0000555 | 0.00000434 | 0.00248 | -0.000944 |
| | (0.0000797) | (0.0000564) | (0.00319) | (0.00131) |
| Q2 of DoE and EPA ARRA funds per capita | -0.000113 | -0.000186 | -0.0119 | -0.0102 |
| | (0.000264) | (0.000243) | (0.0157) | (0.00790) |
| Q3 of DoE and EPA ARRA funds per capita | -0.000283 | -0.000417 | -0.00849 | -0.00577 |
| | (0.000391) | (0.000265) | (0.0184) | (0.00779) |
| Q4 of DoE and EPA ARRA funds per capita | 0.000503 | 0.000186 | 0.0330* | 0.00165 |
| | (0.000377) | (0.000229) | (0.0175) | (0.00623) |
| Q5 of DoE and EPA ARRA funds per capita | 0.000726** | 0.0000892 | 0.0436*** | 0.00517 |
| | (0.000293) | (0.000278) | (0.0156) | (0.00644) |

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 D1: 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***<br>(0.0433) | 0.235*<br>(0.131) |
| Green employment multiplier | 3.672 | 3.910 |
| **Panel B - NT depurated 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***<br>(0.0354) | 0.334***<br>(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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