DAVID POPP
Syracuse University

GIOVANNI MARIN
University of Urbino Carlo Bo

FRANCESCO VONA
OFCE Sciences-Po and University of Milan

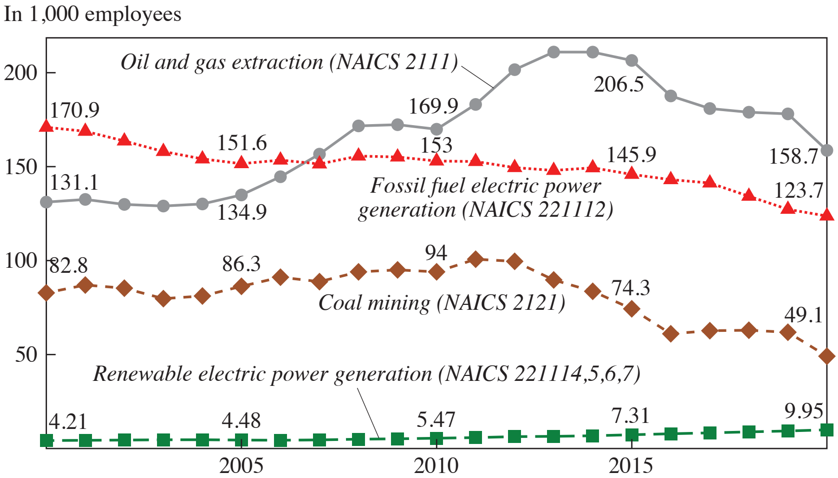
ZIQIAO CHEN
Syracuse University

The Employment Impact of a Green Fiscal Push: Evidence from the American Recovery and Reinvestment Act

ABSTRACT Investments in the green economy are used for both environmental goals and fiscal stimulus. The success of these investments depends, at least in part, on whether they create new jobs and whether such jobs are available to workers hurt by a green transition. We evaluate the employment effect of green investments from the American Recovery and Reinvestment Act (ARRA). Most job creation from green ARRA investments is permanent and emerged in the post-ARRA period, but the plausible range of estimates is extremely wide (zero to twenty-five jobs per $1 million). Such large uncertainty on aggregate effects masks substantial heterogeneity across communities. The green stimulus mostly benefited areas with a greater prevalence of preexisting green skills that created 40 percent additional jobs than average communities. New jobs are primarily manual labor and in occupations performing green tasks, especially in renewable energy. However, manual labor wages do not increase. Descriptive evidence suggests that the skill gap between green energy and fossil fuel workers is modest, but green jobs require significantly more training. Because the spatial distribution of skills and jobs matters, using green stimuli can help reshape the economy in the long run but may also exacerbate regional inequities associated with the green energy transition.

Conflict of Interest Disclosure: This project was supported in part through the Smart Prosperity Institute Research Network and its Greening Growth Partnership, which is supported by a Social Sciences and Humanities Research Council of Canada Partnership Grant (no. 895-2017-1018), as well as by Environment and Climate Change Canada's Economics and Environmental Policy Research Network (EEPRN). Other than the aforementioned, the authors did not receive financial support from any firm or person for this article or from any firm or person with a financial or political interest in this article. They are currently not an officer, director, or board member of any organization with an interest in this article.

Figure 1. US Energy Industry Employment over Time



Source: Quarterly Census on Employment and Wages, Bureau of Labor Statistics (QCEW-BLS).
Note: Figure shows employment (full-time equivalent, FTE) by industry.

There is growing interest in green fiscal stimuli. Investing in the green economy has been identified as a strategic area of intervention as a response both to the climate crisis and to the economic crisis induced by the COVID-19 pandemic (Helm 2020; Agrawala, Dussaux, and Monti 2020). President Biden's original American Jobs Plan, unveiled in March 2021, includes more than $500 billion in green investments such as electric vehicle charging stations, modernizing the electricity grid, and improving climate resilience (White House 2021a). In Europe, the European Commission's European Green Deal, first proposed prior to the COVID-19 pandemic in December 2019, puts a green fiscal stimulus at the center of the European Union's growth strategy to achieve social, economic, and environmental goals.[1]

Among the goals of most green fiscal stimuli is creating new green jobs for workers potentially displaced by a green transition. Figure 1 shows recent US employment trends in energy industries. Employment in coal mining fell from a peak of just over 100,000 in 2011 to around 49,000 in

1. European Commission, "A European Green Deal: Striving to Be the First Climate-Neutral Continent," https://ec.europa.eu/info/strategy/priorities-2019-2024/european-green-deal_en.

2020. Employment in fossil fuel electric power generation has also fallen. Driven by the boom of the shale gas revolution, employment in oil and gas extraction thrived in the same time period, growing from just over 131,000 workers in 2000 to nearly 211,000 by 2013. However, employment in the sector has fallen each year since. While employment in renewable electric power production has doubled over the last decade, these workers remain a small share of jobs in the energy sector, with around 9,950 workers employed in 2020.

In the long run, the acceleration in renewable energy investments triggered by both a green stimulus package and climate policy more generally will pose a significant threat not only to coal communities but to the prosperity of communities depending heavily on oil and gas. The threats faced by these communities are a barrier to political support for carbon pricing and climate policy in the United States and elsewhere (Tomer, Kane, and George 2021; Weber 2020; Vona 2019). To address these concerns, the American Jobs Plan specifically targets hard-hit mining communities, proposing investments such as plugging orphan oil and gas wells and cleaning abandoned mines to create jobs while improving local environmental conditions. Similarly, the European Green Deal includes €17.5 billion to aid regions and workers most affected by a green energy transition.

More generally, the success of green fiscal stimuli depends, at least in part, on whether these investments create new jobs and whether such jobs are available to workers for whom a green transition has a negative impact. Three sets of questions help inform the potential role of green fiscal stimuli as part of a green energy transition.

First, what does the existing literature say about the effect of environmental policies on employment? Will the transition to clean energy create winners and losers among workers with different sets of skills? As we show in section I, while the net effects on employment may be small, recent studies suggest more nuanced results, with low-skilled manual labor workers bearing the largest burden of energy price increases.

Second, what are the employment options for workers in polluting industries with declining job prospects? What must we know to determine their ability to be reemployed? Labor economics research shows that reallocation costs are proportional to the skill differences between origin and destination jobs. To assess whether the skills of displaced workers are likely to be needed in a green economy, in section II we provide descriptive evidence on the skill similarity between green and brown workers.

Third, to what extent can government investments, such as the American Jobs Plan or European Green Deal, be used to create new jobs? And to what extent are any resulting job gains heterogeneous across regions and occupations? To answer this question, our paper uses the US experience from the 2009 American Recovery and Reinvestment Act (ARRA) to assess the potential employment impacts of green fiscal stimuli as part of a green transition.

Our paper provides the first rigorous assessment of the employment effects of ARRA's green investments by exploiting the cross-sectional variation of green ARRA spending across regions. The full stimulus package included over $500 billion of direct government spending, and an additional $290 billion in tax reductions (Council of Economic Advisers 2014). We focus on the direct spending targeted at green investments, which constituted approximately 19 percent of all direct government spending in ARRA (online appendix figure A1). Because a large share of green spending was devoted to public investments, green ARRA may have a cumulative effect stretching beyond the stimulus period (Council of Economic Advisers 2013, 2014). We thus differentiate between the short- and long-term effect of green ARRA. Overall, we find that the effect of green ARRA on job creation emerges primarily in the long run. However, the plausible range of long-term effects is very wide (ranging from zero to twenty-five jobs per $1 million spent), as regions receiving more green spending were more resilient to the Great Recession. The timing of green ARRA's impact differs from previous studies of other ARRA investments, which generally find larger short-term effects.

Importantly, the impact of green ARRA becomes much clearer when we explore several dimensions of heterogeneity. First, green ARRA creates more jobs in commuting zones with a greater prevalence of preexisting green skills. Roughly speaking, green ARRA spending creates up to 70 percent more jobs in areas in the top quartile of the green skills distribution than in the median commuting zone. As the presence of green skills in a community is also strongly correlated with the allocation of green ARRA subsidies, our results provide evidence of the green stimulus as a successful example of picking winners.

Second, looking at specific sectors of the economy, we see the potential of a green stimulus to reshape an economy and have important distributional effects. Most new jobs are manual labor positions, with much growth in the green and construction sectors. These new manual labor positions are permanent jobs, suggesting that green spending can help improve labor market conditions for unskilled workers. However, manual labor wages did not increase. Our research suggests that there may be a suitable path for reallocating manual workers displaced by carbon pricing policies in energy-intensive and fossil fuel industries into green jobs in construction and waste management. However, these green jobs require substantially more on-the-job training than brown jobs, so reallocation costs will not be negligible. Our analysis indicates that job training investments should be a crucial part of any green (energy) transition seeking to minimize labor market distributional effects.

Finally, we make a number of distinct contributions to the empirical literature on fiscal multipliers by looking specifically at investments in the green economy, which are likely to become increasingly important in the future. Our findings are directly comparable with those of the broader literature estimating the effects of ARRA.[2] But the wide range of plausible values of the job creation effect does not allow us to reach firm conclusions on whether green spending is more effective than other types of spending in creating jobs. In the spirit of recent contributions seeking to isolate the microeconomic mechanisms of the local multiplier (Moretti 2010; Garin 2019; Dupor and McCrory 2018; Auerbach, Gorodnichenko, and Murphy 2020), we study the time profile of the effect, the role of key mediating factors, distributional effects across workers, and some mechanisms through which the green stimuli have an impact on the local economy. Results become much clearer when these additional dimensions are added to the analysis. Thus, our paper presents new evidence on the reshaping effect of a green fiscal push rather than providing a precise estimate of the aggregate effect.

Aggregate effects of a green fiscal stimulus are more difficult to identify than the effect of other types of ARRA spending. For other ARRA spending, endogeneity concerns primarily result from the fact that ARRA spending was focused on areas hardest hit by the Great Recession. To identify the causal effects of ARRA, previous literature isolates the exogenous component of the geographical allocation of the fiscal stimulus, and thus a causal effect, using preexisting formulas to allocate federal funds (Wilson 2012; Chodorow-Reich and others 2012; Nakamura and Steinsson 2014). Identifying the causal effect of the green stimulus presents an additional challenge, as the allocation of green ARRA spending depends on structural characteristics of the economy, such as greater technological expertise in green communities, that are positively correlated with employment growth. While we discuss these issues extensively in section IV, we anticipate that these solutions do not completely remove pre-trends between

2. See Chodorow-Reich (2019) for a survey of this literature.

overall employment growth and green ARRA investments. However, this violation of a parallel trend assumption matters only for total employment. When looking at specific sectors or occupations we find no evidence of pre-trends, providing us with confidence that these results are more credible and easier to interpret.

I. Understanding the Employment Effects of Environmental Policies

Besides contributing to the literature on fiscal stimulus, our research is informed by previous work on the employment effects of various environmental policies. Here we present key findings from this literature and discuss our contributions. The effect of environmental policy on employment is still hotly debated and polarized, with advocates on both sides ignoring or exaggerating the labor market costs and benefits of environmental regulations.[3] Advocates of stronger environmental policies argue that such policies create high-paying "green jobs," while critics point to the job losses in energy-intensive industries and mining activities that they are sure will follow. Previous literature finds that the net effect of environmental policies on employment is small, especially when general equilibrium effects and offsetting mechanisms are accounted for (Morgenstern, Pizer, and Shih 2002; Hafstead and Williams 2018; Metcalf and Stock 2020). Moreover, a larger pool of workers with the skills required to perform green tasks reduces mobility frictions and reallocation costs, thus improving the aggregate effect of environmental policies (Castellanos and Heutel 2019). However, recent studies find more nuanced results when looking at specific sectors or workers, with job losses concentrated in polluting industries and among unskilled workers (Yip 2018; Marin and Vona 2019), while workers with technical and engineering skills experience increased employment (Vona and others 2018).

Addressing effects across industries, Kahn and Mansur (2013) compare employment at the county level for adjoining counties, one of which is in attainment with Clean Air Act air quality standards and one which is not. Counties not in attainment face more stringent air pollution regulations, and using neighboring counties as controls helps control for other factors likely to affect employment. Kahn and Mansur find that non-attainment status leads to job losses in specific industries that are intensive in electricity,

3. See, for instance, the survey in Vona (2019).

labor, and pollution. Examples of such industries include petroleum products, paper, primary metals, and transportation equipment. The effect is equivalent to the job losses that would result from a 33 percent increase in electricity prices in attainment counties.

Yip (2018, 2020) uses a difference-in-differences approach to identify the effect of the British Columbia carbon tax on workers using a rich individual-level data set. His main finding is that the tax disproportionately harms workers with middle and low levels of education, both in terms of increases in unemployment rates and decreases in wages. Marin and Vona (2019) examine the effect of long-term increases in energy prices on the relative demand of coarse occupational groups (managers, professionals, technicians, and manual workers) for EU countries and industrial sectors over the period 1995–2011.[4] In their preferred specification, which controls for endogeneity and intervening factors such as import penetration and investments in information and communication technology, the large historical increase in energy prices explains about 13.5 percent of the concomitant increase in the share of technicians, but just 5 percent of the decline in the share of manual workers. Adverse impacts on manual workers are in general small, but they are of particular concern for the political acceptability of green policies since they amplify the secular deterioration of their labor market conditions driven by automation and globalization (Autor, Levy, and Murnane 2003; Autor, Dorn, and Hanson 2013).

In one of the rare studies directly evaluating transitional costs using individual-level data, Walker (2013) shows that foregone lifelong earnings for workers displaced by the US Clean Air Act are larger for workers who change sector. More generally, labor research shows that reallocation costs are proportional to the skill proximity between origin and destination jobs (Kambourov and Manovskii 2009; Gathmann and Schönberg 2010). Thus, the job creation effect of a green stimulus may depend on the availability of workers with the appropriate skills. The distributional effects are expected to be smaller if displaced workers (e.g., coal miners) possess skills that are important to perform the tasks required by the new green jobs (e.g., solar photovoltaic installers). We shed light on the first issue by letting the effect of green spending vary depending on the green skills available in the

4. Historical variation in energy prices has been used as a proxy to evaluate the effects of carbon prices in previous papers (Aldy and Pizer 2015; Cullen and Mansur 2017; Marin and Vona 2021). The reliability of such a proxy is clearly stronger when it is possible to estimate the long-term effect of energy prices (Marin and Vona 2021).

local economy (Vona and others 2018), while we tackle the second issue by comparing the skill and training requirement of workers in the green and brown occupations.

While much work evaluates the effect of policies imposing a cost of pollution (either through standards or prices) on labor markets, almost no work considers the potential of green subsidies opening up new employment opportunities in the so-called green economy. The only exception is the related paper by Vona, Marin, and Consoli (2019), which uses similar data. Following Moretti (2010), they estimate the additional number of jobs indirectly created in the local economy by a new green job. We extend their work by estimating the direct effect of green subsidies, its time profile, and the heterogeneous effects across workers, sectors, and communities.

The effects of a green fiscal push and of carbon taxation (and energy prices) are similar on potential job losers, as both accelerate job destruction in fossil fuel–intensive sectors, possibly creating inequities across regions, sectors, and workers. Regional effects of greening the economy are a politically sensitive issue, especially in the United States, where the fossil fuel industry provides geographically concentrated jobs and drives the economic growth of many local communities (Tomer, Kane, and George 2021). Fearing losses of income and employment, these local communities are reluctant to support any transition without a clear alternative, which is a factor in low political support for carbon pricing and climate policy overall in the United States (Tomer, Kane, and George 2021; Weber 2020). Thus, advocates for a "just transition" argue that carbon pricing alone is unlikely to succeed for both ethical and practical reasons, and a more comprehensive approach is needed to achieve the equity goals (Konisky and Carley 2021), including consideration of the skills and characteristics of occupations needed for a green economy (Muro and others 2019). Despite the challenges to meet the broad equity goals, there can be much potential for crafting policy solutions that bring to these communities more jobs in the clean energy industry, as the geographic distribution of clean energy resources largely aligns with that of fossil fuel resources in the United States (Tomer, Kane, and George 2021).

II. Evidence on Green Skills and Employment

As our empirical analysis will show, the potential for green investments to create jobs depends, at least in part, on a good match between the skills of workers and the jobs being created. Thus, if green fiscal stimuli are to help smooth the employment transition for fossil fuel workers, it is important to compare the skills of these workers to those jobs likely created by green investments. Using data from the Department of Labor's Occupational Information Network (O*NET) to construct green general skills (GGS) indexes, as in Vona and others (2018), we compare the characteristics of workers in brown and green sectors of the economy. Green general skills are skills potentially used in all occupations but that are particularly important for green occupations (Vona and others 2018). However, not all jobs using these green skills are "green jobs." Green general skills are also important in occupations such as physicians, mining machine operators, and some transportation workers. The key point is that workers in these jobs have the skills necessary to do the work required of green occupations, making retraining costs associated with job-to-job mobility lower.

In table 1, we report descriptive statistics comparing both low-skilled (LS) and high-skilled (HS) workers in green and brown occupations. We include data on green skills, training requirements, and other characteristics. Both are also compared to a benchmark of all other occupations in a Standard Occupational Classification (SOC) two-digit group containing at least one green or brown occupation. We use definitions of green and brown occupations by Vona and others (2018), which we further divide into energy and non-energy green and brown occupations.[5] Green energy occupations include jobs related to wind and solar energy, as these are expected to be the main beneficiaries of green stimulus investments around the world. The importance of green skills for each task is normalized to vary between zero and one, and is presented for four macro groups of green skills: engineering and technical, operation management, monitoring, and science. Further details on the construction of all data presented here, including the measurement of green skills, are presented in online appendix A2.

The first section of table 1 compares basic descriptive characteristics of each occupation. Brown fossil fuel occupations stand out in terms of hourly wages, especially for HS workers (row 1). Notably, these jobs, which focus on extraction and production of fossil fuels, are more geographically concentrated than comparable jobs (row 2). For low-skilled workers, green renewable occupations have the highest wages, followed by fossil fuel workers. However, the high wages found for renewable energy workers are primarily due to the wages reported for solar energy sales representatives and installation managers. Wages for installers and service technicians are similar to those of comparable fossil fuel energy workers (tables A5 and A6

5. Online appendix A2 summarizes the definitions of green and brown occupations.

Table 1. Characteristics of Different Green and Brown Occupational Groups

	Brown fossil fuel occupations		*Other brown occupations*		*Green renewable energy occupations*		*Other green occupations*		*Benchmark*	
	LS	*HS*	*LS*	*HS*	*LS*	*HS*	*LS*	*HS*	*LS*	*HS*
1. Hourly wage (BLS)	25.80	70.73	22.22	37.54	37.51	49.26	24.35	53.33	19.49	44.52
2. Gini locational coefficient (ACS)	0.73	0.79	0.57	0.66	0.31	0.44	0.38	0.48	0.34	0.47
3. Age (ACS)	38.86	40.82	41.67	40.86	44.08	41.76	41.03	43.29	39.05	42.02
4. Share of male (ACS)	0.97	0.89	0.78	0.62	0.88	0.84	0.90	0.75	0.52	0.50
5. Educational attainment (yrs.) (ACS)	12.06	15.70	12.04	15.36	12.75	15.73	12.31	15.06	12.67	15.13
6. Required months on-the-job training (O*NET)	8.98	22.30	9.36	7.91	12.62	13.60	13.94	16.74	6.32	12.79
7. GGS: engineering and technical (O*NET)	0.43	0.54	0.43	0.39	0.68	0.69	0.44	0.55	0.24	0.27
8. GGS: operation management (O*NET)	0.42	0.71	0.42	0.60	0.55	0.60	0.46	0.63	0.38	0.61
9. GGS: science (O*NET)	0.25	0.41	0.19	0.36	0.26	0.40	0.21	0.37	0.09	0.15
10. GGS: monitoring (O*NET)	0.47	0.58	0.42	0.56	0.52	0.59	0.46	0.57	0.41	0.61

Sources: Bureau of Labor Statistics, Occupational Employment Statistics (BLS); American Community Survey (ACS); Occupational Information Network database (O*NET).

Note: Macro occupational groups are defined in table A4 in online appendix A2. Low-skill (LS) occupations belong to SOC two-digit major groups from 31 to 53; high-skill (HS) occupations belong to SOC two-digit major groups from 11 to 29. The benchmark is defined as all nongreen and nonbrown occupations in SOC two-digit major groups with at least one green or brown occupation. The following SOC two-digit major groups are excluded from the benchmark: 21, 23, 25, 29, 31, 33, 35, 37, 39. Statistics report averages weighted by occupational employment (from BLS) in 2019. Occupational employment for green occupations is further reweighted for the greenness of the occupation, as presented in online appendix A2. The Gini locational coefficient (see Gabe and Abel 2012) is based on data by occupation and commuting zone from the American Community Survey (1 percent sample, 2019). O*NET data refer to the latest release of O*NET (25.3). Green general skills (GGS) scores are based on Vona and others (2018).

in online appendix A2). Other green occupations are, on average, paid wages greater than in benchmark jobs. While ages of workers are similar across occupations (row 3), a striking difference emerges in terms of gender orientation. The share of males is significantly higher in brown fossil fuel occupations than in other sectors (row 4), suggesting males are more likely to experience negative employment shocks in the transition to a green economy.

Differences in the skill and training requirements represent potential barriers to reemploying brown workers into green jobs. Table 1 illustrates both key similarities and differences. First, the educational requirements of low-skilled brown jobs are slightly lower than both green jobs and the benchmark occupations (row 5). Second, while high-skilled fossil fuel jobs require more months of on-the-job training than other categories (row 6), for low-skilled workers green jobs require substantially more training (at least 12 months) than either the benchmark (6.5 months) or brown occupations (9 months).[6] Third, while green low-skilled occupations require more training, the skills data suggest that green and brown occupations have closer skill sets than the green and benchmark occupations (rows 7–10). This similarity is particularly notable between brown energy jobs and green non-energy jobs. The important difference is that green renewable energy occupations require more engineering and operations management skills than fossil fuel brown occupations. Tables A5 and A6 in the online appendix show that this is true for nearly every possible combination of green energy and brown energy jobs. The role played by the endowment of green skills in the local labor market will be analyzed also in the econometric evaluation of the green ARRA program in section V.

III. The American Recovery and Reinvestment Act

We use data on green investments in the 2009 stimulus package to estimate the impact of green investments on employment. In response to the Great Recession, the American Recovery and Reinvestment Act (ARRA) of 2009, commonly known as the stimulus package, invested over $800 billion in the forms of tax incentives and federal spending programs to stimulate the US economy (Council of Economic Advisers 2014). Through ARRA

6. Notable exceptions shown in table A5 of the online appendix are solar photovoltaic installers and wind turbine service technicians, which require similar levels of training to fossil fuel workers. However, these jobs also require greater engineering and operations management skills, as discussed below.

spending programs, federal agencies partnered with state and local governments and nonprofit and private entities to help "put Americans back to work." Naturally, much of the spending funded projects that provide immediate job opportunities, such as highway construction, or filled state budget shortfalls to bail out school systems and save the jobs of teachers and school staff.

While the primary goal of ARRA was to stimulate macroeconomic growth and provide job opportunities, part of the funds were invested in "transportation, environmental protection, and other infrastructure that will provide long-term economic benefits" (American Recovery and Reinvestment Act of 2009, 2). These include both direct spending intended for immediate job creation, such as Department of Energy (DOE) spending for renewable energy and energy efficiency retrofits and Environmental Protection Agency (EPA) grants for brownfield redevelopment, as well as tax breaks and loan guarantees for renewable energy. Our work focuses on the impact of direct spending intended for job creation, asking both whether these green investments stimulated employment and what types of workers may benefit from a green stimulus.

Among the key principles motivating infrastructure investments in ARRA was that facilitating the transition to an energy-efficient and clean energy economy would lay the foundation for long-term economic growth (US Office of the Vice President 2010). As a result, ARRA included more than \$90 billion for clean energy activities, including DOE contracts and grants to support projects such as energy efficiency retrofits, the development of renewable energy resources, public transportation and clean vehicles, and modernizing the electric grid (Aldy 2013). To meet the Obama administration's target of doubling renewable energy generation by 2012, the DOE provided assistance for a large number of projects related to renewable energy. For example, the Clean Energy Technology Center in Massachusetts received \$24.8 million to design, construct, and operate a wind turbine blade testing facility (US Department of Energy 2010). Moreover, \$3.4 billion in cost-shared grants supported the deployment of smart grid technology, generating more than \$4.5 billion of co-investment (Aldy 2013). ARRA funding also supported the expansion of the Weatherization Assistance Program, which supports low-income families for energy efficiency improvements (Fowlie, Greenstone, and Wolfram 2018).

The EPA oversaw most ARRA programs designated for environmental protection. The largest of these programs was \$6.4 billion for Clean Water and Drinking Water State Revolving Funds, which are among the programs analyzed in Dupor and McCrory (2018). An additional \$600 million was set aside for the EPA's Superfund program to clean up contaminated sites such as New Bedford Harbor in Massachusetts, to which the EPA allocated $30 million (US Office of the Vice President 2010).[7] Another $200 million was invested in the Leaking Underground Storage Tank Trust Fund for the prevention and cleanup of leakage from underground storage tanks.[8] Other EPA funds were allocated to improvements of infrastructure such as wastewater treatment facilities and diesel emissions reduction (Environmental Protection Agency 2009). Different from other ARRA programs, which were allocated according to statutory formulas based on exogenous factors such as the number of highway lane miles in a state or the youth share of its population (Wilson 2012), much green ARRA funding does not follow the same rules.

III.A. Data on ARRA Awards

Our analysis covers the universe of contracts, grants, and loans awarded under the ARRA between 2009 and 2012. Recipients of ARRA funding are required to submit reports through FederalReporting.gov which include information on the amount of expenses and the description of projects.[9] We retrieved data from FedSpending.org on these records derived from reports submitted by nonfederal entities who received ARRA funding.

In line with most recent evaluations of ARRA (Dupor and Mehkari 2016; Dupor and McCrory 2018), our unit of analysis is the local labor market, that is, the so-called commuting zone (CZ). We aggregate county-level data into 709 commuting zones based on the official CZ definitions from the 2000 Decennial Census. As in Dupor and Mehkari (2016), we exclude 122 commuting zones with less than 25,000 inhabitants in 2008, which represent less than 0.5 percent of the US population and employment. We also drop the commuting zone pertaining to New Orleans, as its employment and population data are heavily influenced by the damages and recovery from Hurricane Katrina. Our primary estimation sample thus contains 587 commuting zones. As the entities known as prime recipients who

7. Information on active and archived Superfund sites is available at United States Environmental Protection Agency, "Search Superfund Site Information," https://cumulis.epa.gov/supercpad/cursites/srchsites.cfm.

8. EPA's Web Archive, EPA Information Related to the American Recovery and Reinvestment Act of 2009, "Leaking Underground Storage Tank Program Implements the Recovery Act," https://archive.epa.gov/oust/eparecovery/web/html/index.html.

9. This website is no longer in use, but archived data are available at National Bureau of Economic Research, "American Recovery and Reinvestment Act (ARRA) Federal Spending Detail 2009–2012," https://data.nber.org/data/ARRA/.

received funding directly from the federal government may make subcontracts to other entities, we use the reported place of performance of prime and subprime recipients to allocate the dollar amount of awards to commuting zones based on the zip code. Our ARRA data are time-invariant and include the total amount awarded between 2009 and 2012. As noted in Wilson (2012), nearly 90 percent of expected ARRA spending had been obligated by 2010.[10]

Nearly all DOE and EPA projects relate to the green economy.[11] Thus, our measure of green ARRA includes all ARRA projects from the DOE and EPA and their subordinate agencies, such as various national laboratories. All other ARRA spending is coded as nongreen ARRA.[12] Table A1 in online appendix A1 provides descriptive data on both green and nongreen ARRA. Overall, the stimulus package included over $61 billion on green investments and almost $262 billion on nongreen investments. Of these green investments, $52 billion come from the DOE, while just $9 billion come from the EPA. Roughly 10 percent of green ARRA spending supported research and development (R&D). A small $228 million supported job training for green occupations.

The mean values of green ARRA and nongreen ARRA per commuting zone in our sample are approximately $103 million and $440 million, respectively. The per capita levels of green ARRA and nongreen ARRA are $260 and $985, respectively, based on population in 2008. We highlight the skewed distribution of both green and nongreen ARRA, as the median commuting zone received only $105 and $819 per capita of green and nongreen ARRA awards.

10. Unlike other evaluations of ARRA, we do not consider the location of vendors when allocating funds. Our goal is to ascertain the effectiveness of green ARRA given the "greenness" of the local economy. If a recipient must use vendors from outside the local commuting zone to satisfy a need of the project due to a lack of qualified suppliers in the commuting zone, the funding has been less effective for stimulating local employment.

11. To verify this, we checked projects with the terms *oil*, *gas*, or *coal* in the description. None of these projects related to discovery of new sources. More commonly, they referenced reducing consumption, clean coal, carbon sequestration, or biofuels as a substitute.

12. In addition to the EPA and DOE, a few other agencies funded investments that were plausibly green. The Department of Labor supported four small job training programs (totaling just $496 million) that focused on energy efficiency and the renewable energy industry. Including these investments as green ARRA does not change our results. While the Department of Housing and Urban Development (HUD) also supported green building retrofits, we did not include these programs in our analysis. These do not fall under a single green program, and thus must be identified manually. In our attempt to label HUD investments as "green," we found that many of the green HUD grants were trivial—for example, installing LED lightbulbs in a building—and should have little to no impact on green employment.

Figures A2, A3, and A4 in online appendix A1 illustrate the geographic distribution of green ARRA and nongreen ARRA. We do not observe any apparent, systematic patterns across geographic areas, as both areas receiving high per capita amounts (figures A2 and A3) and areas receiving large shares of green stimulus (figure A4) are spread throughout the country (see table A2 for a list of commuting zones that received the largest ARRA awards). Large infrastructure projects play an important role in communities receiving the most green ARRA, whereas projects to improve energy efficiency or promote renewable energy are distributed more widely (online appendix table A2). Online appendix figure A5 shows the correlation between green (y axis) and nongreen (x axis) ARRA expenditure per capita for commuting zones with at least 25,000 inhabitants. The bivariate correlation between the two components of ARRA is positive and somewhat strong (0.393). As such, controlling for nongreen stimulus spending is important to accurately estimate the impact of green stimulus spending. We discuss our technique for doing so in section IV.

IV. Empirical Strategy

Our empirical strategy addresses two challenges unique to identifying the causal effect of the green stimulus. First, the green stimulus is small relative to the nongreen stimulus. Therefore, controlling for nongreen ARRA expenditures is essential since the recovery plan targeted markets hardest hit by the Great Recession. Second, the allocation of green investments may depend on structural characteristics of the local economy. We include several control variables designed to mitigate these threats to identification. Some controls describe each commuting zone's potential exposure and resilience to the Great Recession. Others capture the stringency of environmental policies in the local labor market as well as the relative importance of green versus nongreen employment in the local economy. Online appendix A2 describes these variables in more detail. However, areas receiving more green ARRA experienced higher employment growth before the Great Recession, even conditioning on these intervening factors. We address both of these issues in this section; IV.A introduces the main endogeneity issues to estimate the effect of green ARRA on employment, and IV.B discusses our approach to tackle them.

IV.A. Illustrating Endogeneity Issues

ARRA spending has been primarily designed to mitigate the effects of the Great Recession on local labor markets. Thus, it targets areas hardest hit by the recession and is endogenous by construction. Controlling for nongreen ARRA expenditures is essential but potentially introduces another endogenous variable complicating the identification of the green ARRA effect (Angrist and Pischke 2008). The trade-off is between an error of misspecification from not including nongreen ARRA and a bias in estimating the green ARRA effect for including a bad control (nongreen ARRA) correlated with the error term. We address this by using a series of dummy variables for nongreen ARRA spending, which allows us to compare the effects of green ARRA in communities that received similar levels of nongreen ARRA investments.

To illustrate the difference in the allocation of green and nongreen ARRA as well as the source of data variation used for identification, we examine the distribution of the two types of spending along the nongreen ARRA distribution. Figure A6 in online appendix A1 reports the deviations from the mean and the standard deviation of green and nongreen ARRA spending per capita relative to the national mean for each vigintile of nongreen ARRA spending per capita. Since nongreen ARRA has been directed to areas hardest hit by the recession, the figure illustrates the extent to which green ARRA has been allocated following a different criterion. The left panel of figure A6 shows that the positive correlation between green and nongreen ARRA masks substantial variation across vigintiles as we observe commuting zones with low nongreen ARRA and high green ARRA or vice versa. In addition, the right panel suggests that the standard deviation of green ARRA within each vigintile is very similar across vigintiles with the exception of the first and last vigintile of nongreen ARRA spending. In our econometric analysis, we will use twenty dummies for nongreen ARRA vigintile to make sure that the effect of green ARRA is not capturing that of other ARRA programs. This particular functional form to treat nongreen ARRA allows testing the robustness of our results to the exclusion of vigintiles in which the dispersion of green ARRA spending is very high or low or the correlation with nongreen ARRA very high.

For green ARRA, identification is complicated by the presence of an additional source of endogeneity. Given the significant share of green ARRA spending devoted to long-term investments and research, the allocation of such spending may have followed criteria related to other structural features of the local economy such as the presence of a federal R&D laboratory or high-tech manufacturing. Thus, we directly explore the observable characteristics of a commuting zone that are correlated with green ARRA spending. Strong unbalances in the observable characteristics of commuting zones receiving different amounts of green ARRA are a red spy of an unbalanced distribution also in unobservables (Altonji, Elder, and Taber 2005). We consider the association between the log of green ARRA spending per capita and two sets of covariates that will be used also as controls in our econometric model presented in the next section. The first set captures the economic conditions in commuting zone *i* before the Great Recession and are quite standard in the literature evaluating the ARRA (Wilson 2012; Chodorow-Reich and others 2012; Chodorow-Reich 2019).[13] The second set of variables are more specific to the green economy, such as the stringency of environmental regulation in the local area (Greenstone 2002), wind and solar energy potential (Aldy 2013), and an index of local green general skills (Vona and others 2018).[14] We also consider two alternatives to model regional fixed effects: year-varying census division dummies and state dummies. The choice of the way of modeling time-varying regional effects is nontrivial. Using census division dummies is a popular choice of previous ARRA evaluations, thus it allows us to compare our findings with previous literature (Dupor and Mehkari 2016). Using state fixed effects better accounts for state-specific policies important

13. We consider both the level and the pre-trends (2005–2007) in several variables such as total employment, unemployment, and employment in different sectors. As in Wilson (2012), we include the pre-sample level (average 2006–2008) and long pre-trends (2000–2007) for the following variables: total employment, employment in health and education, employment in the public sector, employment in manufacturing, construction, and extraction, unemployment. We also add other confounders of local labor market conditions such as pre-sample income per capita, a dummy equal one for commuting zones with positive shale gas production and import penetration. See online appendix A2 for details on data sources and construction of these variables.

14. As in Greenstone (2002), we use changes in the attainment status to National Ambient Air Quality Standards (NAAQS) for the six criteria air pollutants defined by the US Clean Air Act (CAA). We classify as nonattainment commuting zones in which at least one-third of the population resides in nonattainment counties. We also add a dummy variable to identify areas with nonattainment status for at least one of the NAAQS in 2006 and that therefore were already exposed to stringent CAA regulation. Since wind and solar energy received other types of support from the federal and state governments, including tax credits and loan guarantees as part of ARRA (Aldy 2013), we add proxies for the wind and solar potential interacted by year fixed effects. We include a dummy equal one for areas hosting a public R&D lab and the log of local population, as Vona, Marin, and Consoli (2019) show that is highly correlated with the size of the green economy in metropolitan areas. Since some green ARRA subsidies were allocated to state governments to be used throughout the state, we include a dummy variable indicating if the commuting zone includes a state capital. Finally, to proxy for the green capabilities of each commuting zone, we include the share of employment before the Great Recession (e.g., in 2006) in each commuting zone in occupations above the 75th percentile of the national distribution of GGS requirements, that is, skills most relevant in green jobs; see Vona and others (2018) and online appendix A2 for details on the green skill measures. See online appendix A2 for details on data sources and construction of these variables.

to a green economy, such as renewable portfolio standards, as well as for unobserved shocks that are geographically concentrated.

Online appendix table B1 shows that the inclusion of the vigintiles of nongreen ARRA is not enough to eliminate differences in observable characteristics that are significantly correlated with the intensity of green ARRA spending per capita. The table also highlights the different potential sources of endogeneity in the allocation of green ARRA: commuting zones receiving more green subsidies are both stronger in terms of technological expertise (workforce skills for the green economy, higher share of manufacturing employment, and the presence of a federal R&D lab) and somewhat more vulnerable to the Great Recession (i.e., higher share of employment in construction, which was particularly badly hit by the Great Recession). Areas receiving more green ARRA also have a larger share of employment in the public sector. However, in section V we confirm that our results are not driven by public sector employment.

The last diagnostic concerns violations of the parallel trend assumption. While untestable, the presence of pre-trends is typically used as a reliable diagnostic to assess the plausibility of this assumption. In our context, we test the possibility that employment growth before the Great Recession differs depending on the level of green ARRA received using an event study framework by including observations from 2000 to 2007. Since per capita green ARRA is correlated with the structural characteristics of the areas that are usually associated with sustained employment growth, we include controls for the observable commuting zone characteristics and vigintiles of nongreen ARRA described above. Observing that green ARRA went disproportionately to areas growing faster before the Great Recession conditional on these covariates indicates the presence of unobserved variables that are correlated with both the allocation of green ARRA and employment dynamics.

In sum, while the role of unbalances in the covariates can be mitigated by directly testing the robustness of the results to the exclusion of specific areas (i.e., those with R&D labs), the presence of pre-trends in some cases requires greater care to provide an accurate estimate of the effect of green ARRA on employment. We discuss the possible solution to this problem in the next section.

IV.B. Estimating Equation and Addressing Pre-trends

Our main econometric model is an event study model that jointly estimates the effects of green ARRA for years before and after the crisis. It can be seen as a straightforward extension of the econometric model used in the papers reviewed by Chodorow-Reich (2019) that primarily exploits the cross-sectional variation of fiscal spending to identify local multiplier effects. The first main advantage of this approach is that we can explicitly tackle the potential pre-trends discussed above. The second advantage is being able to assess whether the effect of green ARRA lasts beyond the stimulus period, possibly generating a virtuous circle of (green) investments. Our dependent variable is the long difference between our measures of per capita employment in year t relative to our base year of 2008.[15] We estimate the following equation for a balanced panel of 587 commuting zones:

$$\text{(1)} \qquad \Delta \ln\left(y_{it}\right) = \alpha + \sum\nolimits_{\tau} \beta_{\tau} \ln\left(\frac{GreenARRA_i}{pop_{i,2008}}\right) \times D_{\{t=\tau\}} + \sum\nolimits_{\tau} X'_{it_0} \varphi_t \times D_{\{t=\tau\}} + \sum\nolimits_{\tau} \mathrm{G}'_{it_0} \vartheta_t \times D_{\{t=\tau\}} + \mu_{i \in v,t} + \eta_{i \in c,t} + \epsilon_{it},$$

$$\tau = T_0, \ldots, 2006, \ldots, 2017$$

where $\epsilon_{i,t}$ is an error term, G'_{it_0} is a matrix of control variables specific to the green economy, and X'_{it_0} is a matrix of control variables used in previous ARRA evaluations (see footnotes 11 and 12 for details); $\mu_{i \in v,t}$ are year-specific dummy variables for the vigintiles of nongreen ARRA spending and $\eta_{i \in c,t}$ are year-specific region fixed effects (FE) at either the census division or state level. The dummy variables $D_{\{t=\tau\}}$ allow us to estimate separate coefficients for each year. The initial year T_0 is 2000 for total employment and 2005 for employment in different occupations and sectors.[16]

The main variable of interest is green ARRA spending, also rescaled by total population in 2008 in the commuting zone. While effective green spending spanned several years between 2009 and 2012, nearly all outlays were announced in 2009 (Wilson 2012). Because it is difficult to disentangle the announcement effect from the real spending effect, we build a time invariant measure of green spending as the total spending across those four years. We take a log transformation for both our dependent and main explanatory variable to account for the skewness in their respective

15. Employment is either green employment, total employment, or employment in a particular sector (construction, manufacturing, etc.) or occupation (managers, manual workers, etc.). See online appendix A2 for more details on data sources and measurement of our dependent variables.

16. American Community Survey micro data from the Integrated Public Use Microdata Series for the years 2001 to 2004 are only geo-localized at the state level, preventing us from building CZ-level indicators of different types of employment in these years.

distributions.[17] Therefore, our estimated coefficient $\hat{\beta}_\tau$ provides estimates of the number of jobs created by green ARRA in a given year.[18]

In all regressions, we cluster standard errors at the state level, using the state of the main county in each commuting zone. We cluster at the state level because the boundaries of a local labor market can be larger than the commuting zone perimeter, especially in post-recession times when workers are forced to search for a job in a larger area. Finally, we weight observations using the population level in 2008.

For ease of interpretation, we also present an alternative specification where we allow the coefficient of green ARRA and of all the other covariates, including region fixed effects and the vigintiles for nongreen ARRA, to vary only among four symmetrical periods: early pre-ARRA (2000–2003), late pre-ARRA (2004–2007), the short run (2009–2012), and the long run (2013–2016).[19] For samples beginning in 2005, only one pre-period is included. We estimate:

$$\text{(2)} \qquad \Delta \ln(y_{it}) = \alpha + \sum\nolimits_\tau \beta_\tau \ln\left(\frac{GreenARRA_i}{pop_{i,2008}}\right) \times D_{\{t=\tau\}} + \sum\nolimits_\tau X'_{it_0}\varphi_t \times D_{\{t=\tau\}} + \sum\nolimits_\tau G'_{it_0}\vartheta_t \times D_{\{t=\tau\}} + \mu_{i\in v,t} + \eta_{i\in c,t} + \epsilon_{it},$$

where τ = early pre-ARRA, late pre-ARRA, short run, long run.

Here $\hat{\beta}_\tau$ indicates the average number of job-years created by green ARRA in each of these four periods. So that the value can always be interpreted as growth in employment relative to 2008, in these models we define the dependent variable as follows:

$$\Delta \ln(y_{i,t}) = \ln\left(\frac{y_{i,2008}}{pop_{i,2008}}\right) - \ln\left(\frac{y_{i,t}}{pop_{i,2008}}\right) = \ln\left(\frac{y_{i,2008}}{y_{i,t}}\right) \qquad \text{if } t < 2008$$

$$\Delta \ln(y_{i,t}) = \ln\left(\frac{y_{i,t}}{pop_{i,2008}}\right) - \ln\left(\frac{y_{i,2008}}{pop_{i,2008}}\right) = \ln\left(\frac{y_{i,t}}{y_{i,2008}}\right) \qquad \text{if } t > 2008$$

17. As show in online appendix table B2, using logs reduces sensitivity to outliers due to the skewed distribution of green ARRA. In the robustness checks, we show that the log-log results do not change when removing outliers. In contrast, if levels of all variables are used, we only estimate a positive effect of green ARRA on employment if these outliers are dropped from the sample.

18. Because of the log specification, the quantification of the number of jobs created is not straightforward as in related papers. In online appendix C we report the arithmetic to translate the estimated coefficients into number of jobs created.

19. In this specification, we drop 2017 to make the length of each time period equal.

A further advantage of this specification is that it reduces the number of coefficients to be estimated, which is important for assessing the role of mediating factors of green ARRA effects. In section V, we consider whether the existing skill composition in each commuting zone changes the effectiveness of green ARRA, focusing on the mediating effect of a preexisting pool of workers with a high level of green skills. In doing so, we add to equation (2) a full set of interactions between the green skill index and the ARRA spending in the four periods.

Constraining the coefficients to remain constant within each subperiod also provides us one strategy to address possible pre-trends. Recall that, given the unbalances in the covariates discussed in the previous section and the possible presence of pre-trends discussed earlier, we cannot assume that the allocation of green ARRA spending to commuting zones is quasi random, even after including our rich set of controls. The pre-trend effect $\hat{\beta}_{pre}$ reflects the presence of unobserved variables that are correlated with both the allocation of green ARRA and the outcome variables. When pre-trends are present (i.e., $\hat{\beta}_{pre} > 0$), we compute the long- and short-term effect of green ARRA by subtracting its effect before 2008 in a period that is equally distant to the benchmark year as, by construction, effects will get closer to zero as we approach the base year of 2008 when pre-trends are present. Thus, $\hat{\beta}_{short} - \hat{\beta}_{pre2004\text{–}07}$ and $\hat{\beta}_{long} - \hat{\beta}_{pre2000\text{–}03}$ can be interpreted as the net effect of green ARRA on total jobs created per year in the short or long run, respectively. As will be extensively discussed in section V, the credibility of these net effect estimates rests upon an untestable assumption regarding the functional form of the relationship between employment and green ARRA before the Great Recession.

IV.C. An Alternative Instrumental Variable Strategy

As an alternative identification strategy, we exploit the well-known fact that ARRA spending was allocated according to formulas that were in use before the passage of the act (Chodorow-Reich 2019).[20] Importantly, the

20. According to Conley and Dupor (2013), two-thirds of ARRA spending was allocated using such a formulaic approach to privilege shovel-ready projects that have an immediate impact on the economy. For instance, spending in road construction, education, and health were allocated by the act using the formulas in place before the act (Wilson 2012; Garin 2019). An example for green ARRA are Energy Efficiency and Conservation Block Grants. This program was created by the Energy Independence and Security Act of 2007, which provided specific guidelines for distribution of funds. ARRA provided additional funding for this program and stipulated that the same formulas for eligibility in the 2007 act be used (American Recovery and Reinvestment Act of 2009). However, many DOE ARRA projects supported new infrastructure, such as grid modernization, and do not appear to have been allocated formulaically.

formulaic instrument has a typical shift-share structure used in the seminal literature on cross-sectional multipliers (Nakamura and Steinsson 2014). In previous studies, such an instrument satisfied the exclusion restriction of affecting total employment only through ARRA spending because the main source of endogeneity was the local effect of the Great Recession.

Following these studies, we use an instrument that combines the initial "share" of EPA plus DOE spending in the commuting zone (over total DOE and EPA spending) with the green ARRA "shift." Such an instrument adds an exogenous shock in green expenditures to areas that were already receiving a larger amount of green spending before ARRA.[21] Unfortunately, endogeneity of green ARRA is also related to the persistent effect of pre-ARRA green investments by both private and public institutions. Thus, this instrumental variable strategy is less effective in our case. Because such an instrument adds an exogenous shock in green expenditures to areas that were already receiving larger green investments before ARRA, we face a problem similar to that put forward by Jaeger, Ruist, and Stuhler (2018), who note that a shift-share instrument conflates short- and long-term effects. We follow their suggestion and take a share far in the past (i.e., an average share of DOE plus EPA spending between 2003 and 2004), under the assumption that the effect of past spending gradually fades away and thus is excludable from the second stage. Note that having a reliable measure of pre-ARRA green government spending would be the ideal solution to distinguish the additional contribution of green ARRA from that of past trends associated with pre-ARRA green spending. However, as explained in online appendix D, building an accurate measure of pre-ARRA green spending is difficult due to the lack of details in public spending data pre-ARRA. Summing up, while the instrumental variable (IV) mitigates endogeneity related to nonrandom assignment of green ARRA subsidies, it captures the effect of past and present green ARRA on areas that were already on a green path and thus it is not well suited to mitigate violations of the nonparallel trend assumption mentioned above.

21. The instrument of green ARRA reads as $IV_i = \frac{DoE\ Pre{-}ARRA_{i,2003-04}}{DoE\ Pre{-}ARRA_{2003-04}} \times \frac{Green\ ARRA\ DoE}{Pop_{2008}} + \frac{EPA\ Pre{-}ARRA_{i,2003-04}}{EPA\ Pre{-}ARRA_{2003-04}} \times \frac{Green\ ARRA\ EPA}{Pop_{2008}}$, where total green ARRA EPA and DOE per capita is reallocated to commuting zones depending on their respective pre-ARRA shares of spending over the national total, that is, $\frac{DoE\ Pre{-}ARRA_{i,2003-04}}{DoE\ Pre{-}ARRA_{2003-04}}$ and $\frac{EPA\ Pre{-}ARRA_{i,2003-04}}{EPA\ Pre{-}ARRA_{2003-04}}$. See online appendix D for further details.

We directly test this conjecture by running the two-stage least squared counterpart of equation (2) using the instrument described above. The detailed results are illustrated in online appendix D for sake of space. It is worth noting first that the predictive power of the shift-share instrument is poor, with an *F*-test of the excluded instrument just above the usual cutoff of 10 (for census dummies) and just below that cutoff (for state dummies; see table D1). The weak instrument problem is consistent with the fact that DOE spending (the bulk of green spending) was redirected toward green programs. Second, compared to the ordinary least squares (OLS) estimator, the IV largely overstates both the pre-trends for total employment ($\hat{\beta}_{pre}$; see table D2) and the long-term effect of green ARRA per capita ($\hat{\beta}_{long}$). This latter result is consistent with previous studies on fiscal multipliers that found a larger job creation effect when a credible instrument is used (Nakamura and Steinsson 2014). Although the IV results suggest that the effect of green ARRA is highly heterogeneous and much stronger on compliers, they also exacerbate the source of endogeneity associated with the presence of pre-trends.[22] The OLS estimate is probably more conservative (being the average of the exogenous shock on green compliers and the endogenous shock on noncompliers) but also more reliable as less likely to conflate the effect of green ARRA with that of past green policies. Therefore, in the remainder of this paper, we choose OLS as the preferred estimator.

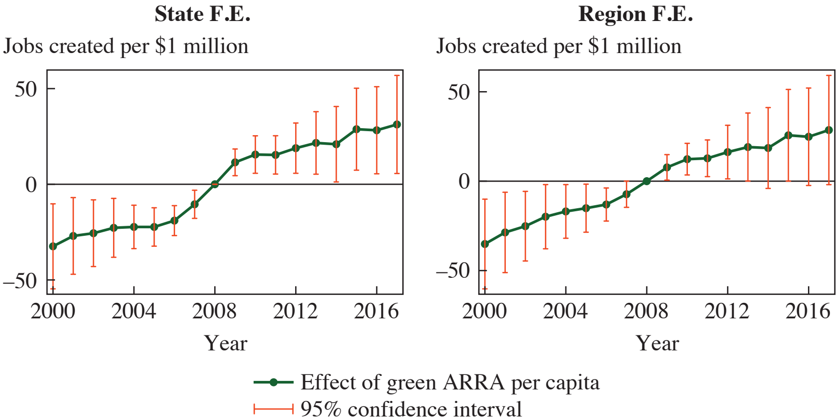
V. Results

This section presents the main results of the paper. We begin with total employment, including a discussion of the time profile of employment trends and the mediating effects of green skills. We then explore green ARRA restructured labor markets by looking at different occupations and sectors.

Figure 2 plots the year-by-year effects of green ARRA using both state and regional fixed effects (FE). The time profiles of both are similar, except that the pre-trends are nearly constant during the early pre-ARRA period (2000–2003) using state fixed effects, which also provide more precise estimates of the yearly job creation. Because state fixed effects also more effectively control for other green policies and unobserved characteristics correlated with employment growth, we consider the state fixed effect

22. Indeed, the IV may capture the effect of past and present green ARRA on areas that were already on a green path, that is, compliers in a local average treatment effect (LATE) interpretation (Imbens and Angrist 1994).

Figure 2. Total Employment: Jobs per Year Created by $1 Million Green ARRA



Source: Authors' calculations.

specification as our preferred one. In both cases, we see early job creation that continues through our sample period, leveling off at the end. By the end of the sample, an additional $1 million green ARRA creates just over thirty-two jobs per year.

While these results are suggestive of permanent job creation, they must be interpreted carefully because of the violation of the parallel trend assumption. We turn to the model estimating average effects for each of four four-year periods to illustrate how the presence of preexisting employment trends affects the interpretation of our results. The estimates ($\hat{\beta}_{short}$ and $\hat{\beta}_{long}$) provide the *gross* average short-run and long-run effects. Using the specification of equation (2), we can estimate the net average jobs per year created by subtracting a pre-trend effect constrained to be constant within two subperiods (i.e., 2000–2003 and 2004–2007). Before discussing these results in table 2, we use figure 2 to gain insights on the implicit assumption that pre-trend effects change mostly between (rather than within) subperiods. In figure 2, the slope connecting two neighboring years represents the annual growth of per capita employment for a community receiving an extra $1 million green ARRA. Consistent with the fact that state fixed effects do a better job controlling for unobserved characteristics correlated with pre-trends, this slope is flat until 2005, and it is primarily between 2006 and 2008 that communities receiving more green

Table 2. Estimates for Total Employment

Change in log employment per capita compared to 2008	*State FE*	*Census division FE*
Green ARRA per capita (log) × D2000–2003	0.0051***	0.0052**
	(0.0017)	(0.0020)
Green ARRA per capita (log) × D2004–2007	0.0034***	0.0025**
	(0.0007)	(0.0009)
Green ARRA per capita (log) × D2009–2012	0.0029***	0.0023**
	(0.0008)	(0.0009)
Green ARRA per capita (log) × D2013–2016	0.0045***	0.0039*
	(0.0017)	(0.0020)
Jobs per year created, $1 million green ARRA		
Pre-ARRA (2000–2003)	27.15***	27.65**
	(8.88)	(10.47)
Pre-ARRA (2004–2007)	18.88***	13.52**
	(3.95)	(5.21)
Short run (2009–2012)	15.3***	12.32**
	(4.31)	(4.62)
Long run (2013–2016)	25.52***	22.26*
	(9.41)	(11.49)
Short (2009–2012) to Pre (2004–2007)	–3.03	–0.82
	(3.72)	(4.50)
Long (2009–2012) to Pre (2000–2003)	–3.31	–7.1
	(7.43)	(9.84)
R^2	0.7688	0.7032
Observations	9979	9979

Source: Authors' calculations.

Note: Regressions weighted by CZ population in 2008. Sample: 587 commuting zones with at least 25,000 residents in 2008. Year fixed effects and state (or census division) times period fixed effects included. Additional control variables (interacted with D2000–2003, D2004–2007, D2009–2012, and D2013–2016 dummies): vigintiles of nongreen ARRA per capita, share of employment in occupations with GGS > p75 (2006), population 2008 (log), income per capita (2005), import penetration (year 2005), pre-trend (2000–2007) employment manufacturing / population, pre-trend (2000–2007) total employment / population, pre-trend (2000–2007) employment construction / population, pre-trend (2000–2007) employment extractive / population, pre-trend (2000–2007) employment public sector / population, pre-trend (2000–2007) unemployed / population, pre-trend (2000–2007) employment education and health / population, total employment (average 2006–2008) / population, employment manufacturing (average 2006–2008) / population, employment construction (average 2006–2008) / population, employment extractive (average 2006–2008) / population, employment public sector (average 2006–2008) / population, unemployed (average 2006–2008) / population, employment education and health (average 2006–2008) / population, shale gas extraction in commuting zone interacted with year dummies, potential for wind energy interacted with year dummies, potential for photovoltaic energy interacted with year dummies, federal R&D lab, commuting zone hosts the state capital, nonattainment CAA old standards, nonattainment CAA new standards. Data on total employment and employment share by industry come from BLS-QCEW. See online appendix A2 for details. Standard errors clustered by state in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

ARRA experienced faster employment growth.[23] Since green spending was allocated to areas more resilient to the Great Recession, we can say very little on short-term effects either subtracting the pre-trends or not. The absence of a net short-term effect can either reflect a fast convergence to a higher precrisis steady state (so it should be interpreted as evidence supporting the use of green spending to restart the economy) or the greater resilience of greener areas (so it should be interpreted as evidence of lack of additionality).

In turn, our analysis allows us to set credible bounds to the long-term effect. The flat job-year effect in the early precrisis period indicates that $\hat{\beta}_{pre2000\text{–}03}$ reflects the steady-state level of the employment gap in favor of communities receiving more green ARRA that results from greater resilience to the recession afterward. This assumes that this greater resilience continued through the post-ARRA period. Consequently, the difference between $\hat{\beta}_{long}$ and $\hat{\beta}_{pre2000\text{–}03}$ is the lower bound of the employment effect.[24] For the upper bound, we use the gross job creation, $\hat{\beta}_{long}$. This upper bound is plausible for at least two reasons. First, previous literature shows that the OLS estimates of local job multipliers are smaller than the IV estimates. This finding is further corroborated when we let the impact of green ARRA vary depending on the endowment of green skills in a commuting zone. Second, with an accommodating monetary policy and spillovers across regions, a local spending effect typically underestimates the aggregated effect (Chodorow-Reich 2020; Dupor and McCrory 2018).

Table 2 presents these results. Both the gross average short-run and long-run effects ($\hat{\beta}_{short}$ and $\hat{\beta}_{long}$) are positive and statistically different from zero. In terms of gross job creation, $1 million of green spending adds between 12.3 (with census FE) and 15.3 (with state FE) new jobs per year in the short term and 22.3 (with census FE) and 25.5 (with state FE) jobs per year in the long term. Using census division fixed effects for comparability, the short-term estimates are in the lower range of estimates of

23. These results are confirmed by using the first difference of employment as the dependent variable, allowing us to explicitly test for changes in the annual growth rate in employment. We also check the resilience of different commuting zones using monthly data near the peak of the Great Recession. Results confirm that greener areas were more resilient to the crisis. Both results are available upon request from the authors.

24. Note that $\hat{\beta}_{pre2000\text{–}03}$ is greater than $\hat{\beta}_{pre2004\text{–}07}$ even if pre-trend accelerates in the latter period. The reason is that the $\hat{\beta}_{\tau}$ is forced to be zero in 2008. Thus, subtracting $\hat{\beta}_{pre2000\text{–}03}$ allows us to retrieve a true lower bound of the net effect.

papers evaluating other programs of ARRA (Chodorow-Reich 2019).[25] For the long-term estimates, there is no clear benchmark in the literature using the cross-sectional approach to estimate local multipliers. An exception is Garin (2019), who finds no long-term effect of construction spending under ARRA. Green spending may have a larger and more persistent long-term effect on job creation than other types of infrastructural investment.

However, this interpretation is complicated by the fact that the net average effect (our lower bound) is statistically indistinguishable from zero. Unlike in Garin (2019), where pre-trends were not an issue, the presence of pre-trends produces a plausible estimation range between zero and a statistically significant estimate of 25.5 jobs per year. The large range of estimates for the long-term green spending multiplier does not allow us to confidently support the statement that green spending is a driver of permanent jobs. At a minimum, the lower bound indicates that green spending helped areas that were relatively better off before the Great Recession maintain their precrisis advantage. To lend support to the interpretation that green ARRA picked winners, we examine next the mediating effect of green skills.

V.A. The Mediating Effect of Green Skills

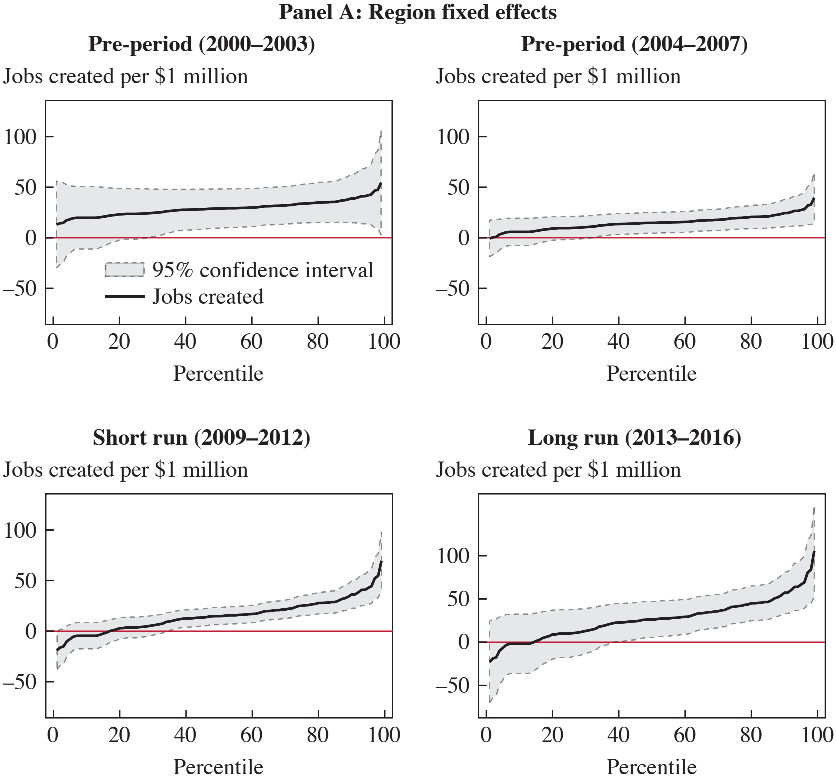
The large uncertainty on the aggregate effect may mask substantial heterogeneity across communities with different levels of green competences. Commuting zones with a workforce more prepared to perform green tasks are more likely to experience larger gains in both the short and long run. Looking at the heterogeneous effect with respect to the existing skill base of the workforce allows us also to shed light on the large gap between the OLS and IV estimates, improving the interpretation of our results. Because the IV results highlight much larger effects on compliers, that is, commuting zones already investing in the green economy, this result reinforces our expectation that the green stimulus would be more effective in areas with a higher concentration of green skills. Recall, indeed, that the initial concentration of green skills in a region is positively associated with the allocation of green ARRA spending.

25. Note that other papers estimate gross job creation effects, while we privilege the hyperconservative estimation given by the net short-term effect. As discussed in section IV, other papers also use a formulaic IV that identifies the effect on compliers, which is found to be generally larger than the effect on the entire population.

In table 1, we showed that the types of skills workers need to work in green jobs are different than the skills needed in the rest of the economy, requiring more on-the-job training as well as engineering and technical competences. We use the data on green skills described in section II to identify the share of employment in each commuting zone in occupations with green general skill (GGS) importance in the 75th percentile or higher in 2006 (i.e., prior to the recession). This includes 113 occupations, listed in table A7 in online appendix A2. While these jobs need not themselves be green, this captures the local endowment of the types of skills in high demand in a green economy.

We augment the model constraining the effects across four periods by interacting our green ARRA variables (early-pre, late-pre, short, and long) with the share of employment in occupations with GGS importance in the 75th percentile or higher. Note that all models already control for the initial concentration of green skills in a region and allow the effect of the concentration of green skills to vary across periods. Figure 3 shows the marginal effect of green ARRA at different levels of initial green skills for the specification with both state and census division dummies. Complete regression results are given in table B3 of online appendix B. The results show, as expected, the importance of the initial skill base. Gross job creation increases with the level of green skills. Comparing communities at the median and 75th percentiles of green skills, 40 to 70 percent more jobs are created in communities with high green skills in both the short and long run. Using the preferred specification with state fixed effects, short-run gross job creation becomes significant when the share of workers with high green skills reaches the 20th percentile of all communities, or 23.4 percent (17th percentile, or 22.3 percent, with regional fixed effect). Long-run gross job creation becomes significant when the share of workers with high green skills reaches the 32nd percentile of all communities, or 24.0 percent (39th percentile, or 24.9 percent, with regional fixed effects). Importantly, while we still observe pre-trends, the relationship between pre-trends and green skills appears weaker, particularly in the model using regional fixed effects. The magnitude of the interaction coefficient between green skills and green ARRA is between two and three times larger in the post-ARRA period than in the pre-ARRA period (online appendix table B3). Thus, green spending enhances net job creation as well. Because of the added noise when subtracting pre-trends, estimates of net job creation are imprecise. Short-run net job creation becomes positive at the 73rd percentile of all communities, but never statistically significant (46th percentile with regional fixed effects, but not statistically significant until reaching the

Figure 3. Variation in the Effect of Green ARRA on Employment by Initial Green Skills



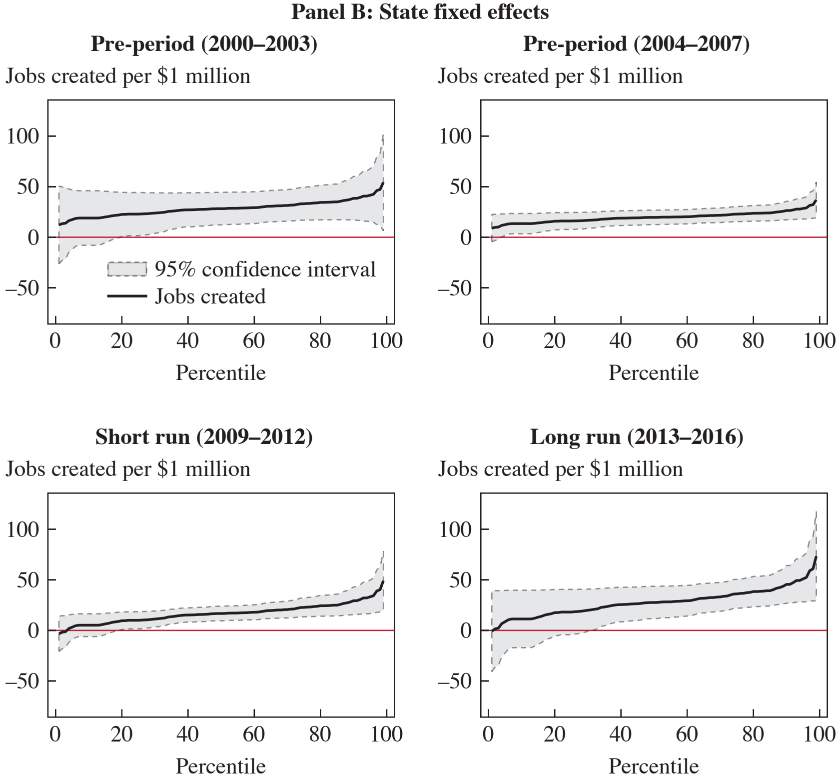
(*continued on next page*)

97th percentile). In the long run, the net effect of jobs created becomes positive in the 72nd percentile (64th with regional fixed effects) but is never statistically significant. Interestingly, by allowing an easier match between green tasks and skills, the availability of green skills increases the short-run effectiveness of green spending more than the long-run effectiveness.[26]

These results are even more remarkable when noting that the initial share of occupations in the upper quartile of GGS importance itself is a

26. To verify that this effect is not simply driven by the fact that communities with more green skills are richer, in online appendix table B4 we conduct a falsification test by interacting green ARRA with per capita income in 2005, rather than green skills. The interaction is never significant, and the estimates of jobs created hardly vary across different income levels.

Figure 3. Variation in the Effect of Green ARRA on Employment by Initial Green Skills (*Continued*)



Source: Authors' calculations based on estimates from online appendix table B3.

good predictor of future employment growth, with an effect that increased after the crisis (online appendix table B3). Indeed, in the most conservative specification with state fixed effects, a one standard deviation in the green skills share (0.027) accounts for a 1.1 percent difference in employment growth in the early precrisis period that increases up to 2.0 percent in the short term and 2.3 percent in the long run (although with a p-value of 0.101).[27] Online appendix table B1 shows that the initial share of

27. With regional fixed effects, the acceleration is much more pronounced: a standard deviation in the share of green skills explains only 1.4 percent difference in employment growth in the early precrisis period, while it accounts for a differential employment growth of 3.3 percent in the short run and 4.1 percent in the long run (p-value = 0.013).

occupations in the upper quartile of GGS importance is also strongly correlated with the allocation of green ARRA subsidies. In combination, these results reinforce our interpretation of the green stimulus as a successful example of picking the winners. The main policy lesson is that increasing the green skills in a community, such as through job training focused on mid-level technical and engineering skills, should represent a key part of a successful policy package for the green transition.

V.B. Reshaping the Economy: Heterogeneous Effects of Green ARRA

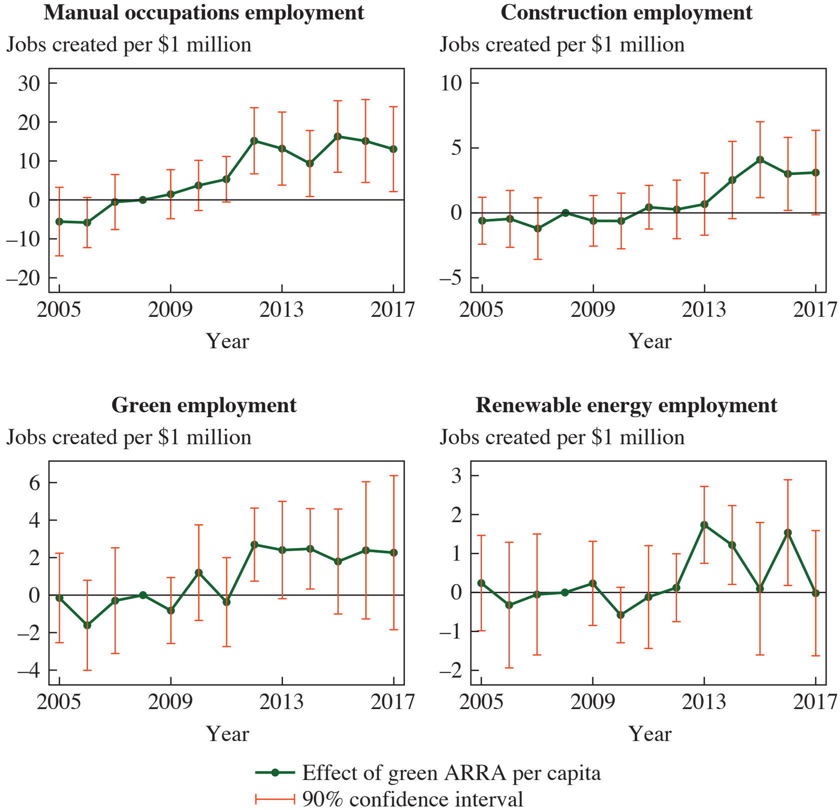
To summarize our results on total employment, we find evidence of gross job creation that is strongest in communities with more preexisting green skills. However, the presence of pre-trends in the total employment regressions complicates the interpretation of these results. That is not the case when looking at specific types of workers, where, as will be shown, we find no evidence of pre-trends complicating the interpretation. Here, we show that green ARRA plays an important role in *reshaping* the economy. We present results for all manual labor, construction, overall green employment, and renewable energy employment. We concentrate on results using the preferred specification with state fixed effects.

The choice of these four categories of jobs is consistent with the objectives of the green ARRA stimulus. Clearly, the creation of green and renewable energy jobs is the main channel through which the effect of green ARRA spending should take place (Vona, Marin, and Consoli 2019).[28] As noted by Garin (2019), a necessary condition for a positive effect of specific government spending is that it should create jobs in the sectors most likely affected by such spending. We then focus on manual labor and construction employment, both because green spending includes investments in infrastructure and construction (such as improving building energy efficiency) and for the importance of these sectors in the debate on the distributional effects of trade and technology shocks (Autor, Dorn, and Hanson 2013; Acemoglu and Restrepo 2020) and of the rise of populism in the United States (Autor and others 2020).

Figure 4 shows year-by-year results for specific employment types, while table 3 complements these results by reporting the point estimates of the green ARRA coefficients for the pre-ARRA period ($\hat{\beta}_{pre}$), the short

28. Green employment is measured by reweighing occupational employment by the share of specific tasks in each occupation that O*NET defines as green; see online appendix A2 and Vona, Marin, and Consoli (2019).

Figure 4. Jobs per Year Created by $1 Million Green ARRA



Source: Authors' calculations.
Note: All models estimated using state fixed effects.

term ($\hat{\beta}_{short}$), and the long term ($\hat{\beta}_{long}$). The table also reports the number of jobs per year created per millions of dollars spent. Since pre-trends are not an issue here, we only include jobs created for the gross effects ($\hat{\beta}_{short}$ and $\hat{\beta}_{long}$).[29]

For manual labor, figure 4 reveals the presence of a slightly upward pre-trend that is, however, never statistically significant.[30] Statistically significant

29. Subtracting insignificant pre-trends simply adds noise to the interpretation without providing new information.

30. Moreover, the results for manual labor are robust to using state or region fixed effects, and there is clearly no evidence of a pre-trend using regional fixed effects (online appendix table B1).

Table 3. Reshaping Results (State Fixed Effects)

Change in log employment (by type) per capita compared to 2008	*Manual occupations*	*Construction employment*	*Green employment*	*Renewable employment*
Green ARRA per capita (log) × D2005–2007	0.0028	0.0023	0.0028	0.0003
	(0.0023)	(0.0034)	(0.0043)	(0.0083)
Green ARRA per capita (log) × D2009–2012	0.0051**	–0.0004	0.0027	–0.0013
	(0.0023)	(0.0043)	(0.0041)	(0.0061)
Green ARRA per capita (log) × D2013–2016	0.0102***	0.0100**	0.0086*	0.0164**
	(0.0036)	(0.0045)	(0.0051)	(0.0076)
Jobs per year created, $1 million green ARRA				
Pre-ARRA (2005–2007)	3.97	0.71	0.71	0.03
	(3.26)	(1.03)	(1.08)	(0.69)
Short-run (2009–2012)	6.17**	–0.1	0.65	–0.09
	(2.75)	(1.00)	(0.98)	(0.42)
Long-run (2013–2016)	13.4***	2.54**	2.33*	1.19**
	(4.75)	(1.15)	(1.37)	(0.56)
R^2	0.5849	0.7177	0.3864	0.2786
Observations	7044	7044	7044	7044

Source: Authors' calculations.

Note: Regressions weighted by CZ population in 2008. Sample: 587 commuting zones with at least 25,000 residents in 2008. Year fixed effects and state (or census division) times period fixed effects included. Additional control variables (interacted with D2000–2003, D2004–2007, D2009–2012, and D2013–2016 dummies): vigintiles of nongreen ARRA per capita, share of employment in occupations with GGS > p75 (2006), population 2008 (log), income per capita (2005), import penetration (year 2005), pre-trend (2000–2007) employment manufacturing / population, pre-trend (2000–2007) total employment / population, pre-trend (2000–2007) employment construction / population, pre-trend (2000–2007) employment extractive / population, pre-trend (2000–2007) employment public sector / population, pre-trend (2000–2007) unemployed / population, pre-trend (2000–2007) employment education and health / population, total employment (average 2006–2008) / population, employment manufacturing (average 2006–2008) / population, employment construction (average 2006–2008) / population, employment extractive (average 2006–2008) / population, employment public sector (average 2006–2008) / population, unemployed (average 2006–2008) / population, employment education and health (average 2006–2008) / population, shale gas extraction in commuting zone interacted with year dummies, potential for wind energy interacted with year dummies, potential for photovoltaic energy interacted with year dummies, federal R&D lab, commuting zone hosts the state capital, nonattainment CAA old standards, nonattainment CAA new standards. Employment data calculated by multiplying total employment (BLS-QCEW) by the share of workers in each category, taken from ACS. See online appendix A2 for details. Standard errors clustered by state in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

job creation for manual workers begins in 2012, with 14.9 jobs created. The level of jobs per year created remains steady after 2012, providing evidence of permanent job creation. On average, 13.4 manual labor jobs per year are created per $1 million green ARRA in the long run, compared to only 6.17 in the short run (table 3). Thus, over half of the gross total job creation was in manual labor.

Construction jobs exhibit no pre-trends and a similar time profile of the post-crisis effects, although job creation was delayed until 2015. This further lag in job creation is consistent with the fact that administrative delays tend to be longer for infrastructure spending (Ramey 2020). Compared to Garin's (2019) study of direct construction spending, our results both are larger and suggest permanent job creation, with an average of 2.54 construction jobs per year created in the long run (table 3). While this can be partly explained by fact that Garin's (2019) county-level analysis leaves out positive demand spillovers across counties, further research is required to explore the labor intensity of green infrastructure relative to other infrastructure. For instance, O*NET tasks data suggest that maintenance activities are likely to be particularly important for green jobs, suggesting a possible channel through which jobs are maintained in areas with energy-efficient buildings or renewable energy infrastructure.

For green employment, the results are estimated much less precisely. Still, the absence of pre-trend is very clear, suggesting that areas receiving more green ARRA were not necessarily experiencing a faster green growth before the Great Recession. Significant green job creation begins in 2012, with 2.8 jobs per year, and again persisted until the end of our sample. Note that, as the estimates of overall green employment are imprecise, the estimate of 2.3 jobs created in the long run is only significant at the 10 percent level (table 3). While this effect seems small, it is roughly 10 percent of gross total job creation, whereas green employment is just 4.7 percent of total employment from 2005 to 2017 in our data.[31] For renewable energy jobs, the patterns largely mimic those observed for green employment with two caveats. On the one hand, the year-by-year estimates plotted in figure 4 are very unstable and imprecise. On the other hand, the reshaping effect emerges more clearly as highlighted by the positive and significant long-run effect (table 3). Not surprisingly, the effect is also large relative to the share of renewable energy employment (1.3 percent) with \$1 million green ARRA creating about 1.2 renewable jobs per year in the long run.

To summarize, the reshaping effect of the green fiscal stimulus emerges clearly from our results. Of the gross job creation for total employment, half was in manual labor, while job creation in construction and green occupations each make up about 10 percent.[32] These findings are qualitatively

31. The 4.7 percent estimate is higher than the estimate of 3.1 percent provided by Vona, Marin, and Consoli (2019) for 2014. This is due to an aggregation bias. See online appendix A2 for details.

32. Note that we cannot sum up these figures as these jobs largely overlap.

confirmed in comprehensive robustness checks (see online appendix B), where we exclude areas with unbalanced characteristics, define green ARRA in different ways, and group areas with similar nongreen ARRA spending differently. Moreover, for green jobs our definition of green ARRA is conservative. If we exclude R&D spending and loans and contracts, which are more likely to support large infrastructure projects (leaving only grants), we obtain statistically significant estimates of up to 3.8 green jobs created in the long run (online appendix tables B9 and B10).

Online appendix table B11 provides additional insight to the heterogeneous effects of green ARRA. We look for employment effects in three additional sectors: manufacturing (NAICS 31-33), public administration (NAICS 92), and support services including waste management (NAICS 56). Those sectors are either most likely to receive green subsidies (e.g., waste management) or to employ workers needed to administer and monitor ARRA programs (e.g., public administration). While we observe gross job gains in manufacturing, these gains are offset by pre-trends in the 2005–2007 period. Green ARRA spending reduces the share of employment in the public sector, at least in the short run. This result reassures us that the effect on total employment is not associated with a crowding out of private jobs.

V.C. Distributional Effects on Manual Workers

While the green stimulus reshaped labor markets by increasing the size of the local green economy, the distributional effect of the stimulus among workers is less clear. In online appendix table B12 and figure B2 we estimate separate models for different broad groups of workers following a standard grouping in the literature on task-biased technological change (Acemoglu and Autor 2011): abstract occupations, service workers, clerical occupations, and manual labor (see table A8 in online appendix A2). The important result here is that all job creation from green ARRA occurs in manual labor occupations, while both the net and the gross effects for other occupational groups are far from being significant at conventional levels. Moreover, the results for abstract and clerical workers suggest additional insights into the pre-trend. Both show evidence that areas receiving more green ARRA grew faster right before the Great Recession. However, neither occupation group experiences long-run employment gains. The short-run gains for abstract employment end in 2010. While not definitive, these suggest that any pre-trends that continued past the Great Recession were unlikely to extend more than a couple of years, making the lower bound estimate of total employment appear less plausible. Although the upper bound gross job creation may probably overstate job creation, it seems likely that green ARRA created at least some new jobs in the long run.

Manual workers have been losing in terms of wages and employability for trade (Autor, Dorn, and Hanson 2013), automation (Acemoglu and Restrepo 2020), and, but to a lesser extent, the effect of climate policies (Marin and Vona 2019). It is thus important to provide an in-depth look at how the green stimulus affected manual labor. Table 4 considers the effect of green ARRA on manual labor wages (columns 1–3) and on educational attainment of manual workers. First, column 1 replaces changes in per capita employment as the dependent variable with the average hourly wage of manual workers. Despite increasing demand for manual labor, green ARRA investments did not increase the wages of manual workers.[33] In columns 2 and 3, we see that most of the increase in manual labor jobs occurred in jobs where workers earned less than the US median wage for all manual workers. These missing wage gains highlight the well-known deterioration of the bargaining power of manual workers facing a series of correlated negative shocks. While the manual labor jobs created in the short run were evenly distributed between workers having or not having more than a high school education, by the long run most gains were among workers with less than a high school education (columns 4–5). Overall, public spending in the green economy under ARRA was too small to substantially improve the bargaining power of manual workers. Thus, it remains an open question whether larger green stimuli can revert the long-run decline of the working conditions of manual labor.

VI. Policy Discussion

Our results can inform both the design of future green fiscal stimuli programs and address longer-term concerns about job losses in the transition to a green economy. Our first key finding is the potential for green investments to reshape the economy. Over half of gross job creation was in manual labor, and green jobs also experienced a notable increase. Importantly, these jobs appear permanent, so that green investments offer new opportunities for workers often left behind by changing environmental regulations and by other structural transformations in the labor markets, such as trade and automation. For example, as discussed in section II, the skills

33. This may be explained by the need to comply with prevailing wage laws. Since contractors were required to document that workers were paid prevailing wages, they had little incentive to pay more than the prevailing wage. We thank Joe Aldy for this insight.

Table 4. Focus on Manual Occupations

Dep var: Change in log employment (by category) per capita compared to 2008 (except column 1)	*Average hourly wage of manual workers*	*Manual workers, hourly wage > US med. for manual workers*	*Manual workers, hourly wage < US med. for manual workers*	*Manual workers with education > high school degree*	*Manual workers with high school degree or less*
Green ARRA per capita (log)	0.0080	0.0049	–0.0005	–0.0016	0.0044
× D2005–2007	(0.0056)	(0.0036)	(0.0031)	(0.0044)	(0.0029)
Green ARRA per capita (log)	–0.0045	0.0032	0.0093**	0.0094*	0.0041
× D2009–2012	(0.0048)	(0.0031)	(0.0036)	(0.0049)	(0.0025)
Green ARRA per capita (log)	–0.0010	0.0084*	0.0132***	0.0109**	0.0098**
× D2013–2017	(0.0052)	(0.0044)	(0.0049)	(0.0053)	(0.0042)
Jobs per year created, $1 million green ARRA					
Pre-ARRA (2005–2007)	N/A	3.63	–0.36	–0.59	4.67
		(2.66)	(2.08)	(1.58)	(3.04)
Short-run (2009–2012)	N/A	2.08	5.36**	3.24*	3.54
		(1.99)	(2.06)	(1.72)	(2.17)
Long-run (2013–2017)	N/A	5.92*	8.08***	4.27**	9.06**
		(3.09)	(3.01)	(2.09)	(3.90)
R^2	0.3500	0.4878	0.4707	0.3599	0.5726
Observations	7044	7044	7044	7044	7044

Source: Authors' calculations.

Note: OLS model weighted by CZ population in 2008. Sample: commuting zones with at least 25,000 residents in 2008. Year fixed effects and state times period fixed effects included. Additional control variables (interacted with D2005–2007, D2009–2012, and D2013–2016 dummies) same as table 3. Standard errors clustered by state in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

of low-skilled fossil fuel workers are often a decent match for jobs in the green economy. That these manual labor jobs are permanent offers hope that the larger green stimulus discussed on both sides of the Atlantic will provide new employment opportunities as part of a green energy transition. But because job training requirements are higher for green energy jobs than for comparable positions, any green spending plan intending to create green jobs should include funds for job training to ensure a smooth transition into green jobs for displaced workers in fossil fuel and energy intensive sectors.

A second key finding is that, whether due to administrative delays, skill gaps, or the time needed to build new green infrastructure, ARRA's green investments created jobs more slowly than other ARRA investments. Administrative delays such as buy American guidelines, determining prevailing wages to comply with the Davis-Bacon Act, and complying with local regulations may have slowed the initial impact of spending. For instance, less than one-half of DOE funds allocated had been spent by 2011 (Carley, Nicholson-Crotty, and Fisher 2015; Carley 2016). However, administrative delays seem unlikely to explain the permanence of green jobs created by ARRA. Another potential explanation is that federal investments attracted additional private investments in green sectors (Mundaca and Richter 2015) and generally crowded-in state spending (Leduc and Wilson 2017). Many ARRA programs required matching funds from the private sector, and this was particularly true of DOE projects (Council of Economic Advisers 2010). Transforming to a greener economy was expected to support long-term economic growth (Aldy 2013).[34] Our results on the mediating effect of green skills suggest another possibility, as the importance of skills suggests matching funding to skills may affect the time profile of the green ARRA effect.

Such delays are a feature of other public investments that have an important infrastructure component (Ramey 2021). Garin (2019) finds that the job creation effect of construction infrastructure peaked in 2013, but then started declining until going to zero in 2015. Importantly, while our year-by-year results show that most job creation began in 2012, the effect looks permanent for the case of green ARRA spending, especially so in communities with the appropriate set of skills. Given the permanent nature of

34. For example, the DOE's smart grid program invested $4.5 billion in new smart grid technology, which was matched by $6 billion in private sector funds (Council of Economic Advisers 2010). It is reasonable to expect such new infrastructure investment to provide lasting benefits for green employment.

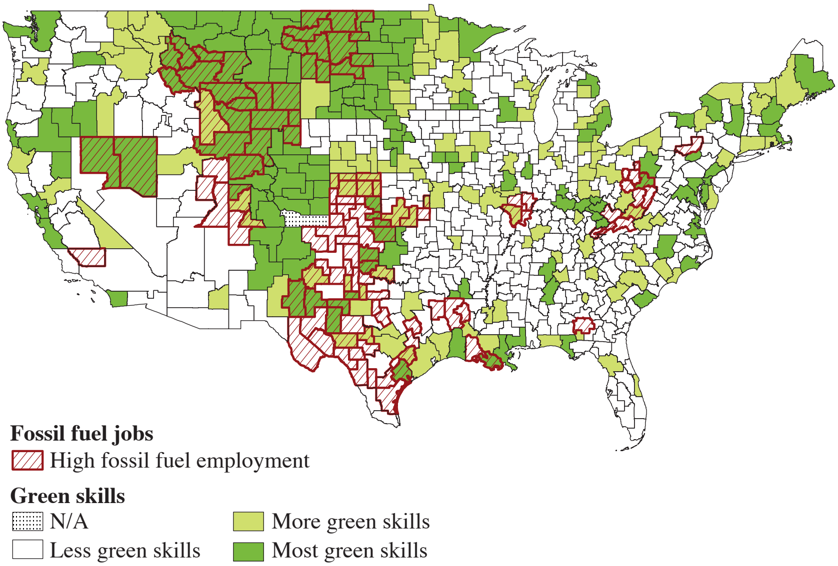
many of the jobs created, green investments can help meet long-run policy goals, such as rebuilding after the pandemic and, more importantly, mitigate the impact of the green energy transition for fossil fuel workers and communities.

Recent proposals for green investments in the United States provide examples of how green fiscal stimuli can serve both roles mentioned above. The Biden administration's $2 trillion American Jobs Plan (AJP) unveiled in spring 2021 includes about $550 billion in green investments (White House 2021a). The bipartisan compromise reached on July 28, 2021, reduces the total investment to just $550 billion but maintains over $200 billion for green investments (White House 2021b). The AJP includes a long-term focus, claiming "this is the moment to reimagine and rebuild a new economy" and promising "to meet the great challenges of our time," including the climate crisis (White House 2021a). To achieve this goal, the AJP includes projects to help workers whose jobs may be at risk as the world transitions away from fossil fuels. Green investments are more appropriate as part of such long-term planning addressing climate change than as short-term economic stimulus. Table A3 of online appendix A1 highlights major areas of green spending in each plan. Examples of green investments include plugging orphan oil and gas wells and cleaning abandoned mines to create jobs for displaced energy workers, developing charging infrastructure for electric vehicles, and improving water infrastructure, such as by replacing lead pipes. While such jobs offer opportunities for displaced energy workers, they also illustrate the challenges of place-based policies to aid distressed energy communities, as jobs such as plugging wells or cleaning abandoned mines are unlikely to be permanent jobs.

Our third key finding is that workers must have the skills needed in green jobs for green fiscal stimuli to be successful. Thus, green spending policies may not work equally well in distressed communities lacking the appropriate green skills. Recall as well that the availability of green skills increases the short-run effectiveness of green spending more than the long-run effectiveness. In the short run, this means that a good match between required skills and local skill endowments is essential for successful fiscal stimuli. In the long-run, distressed energy communities may need to combine green spending with appropriate retraining policies.

Moreover, green investments may create spatial inequities that affect political acceptability and the potential for different regions to benefit from the transition to a greener economy. We draw attention to two dimensions of such inequalities here. Both relate to the geographic distribution of green skills.

Figure 5. Geographic Distribution of Green Skills



Source: Authors' calculations.

Note: Figure shows commuting zones in the top quartile (dark), second quartile (light), and bottom 50th percentile of green skills, using our measure of share of employment in jobs in the top quartile of green skill requirement based on 2019 data. Communities in the top 20 percent of the share of fossil fuel employment are outlined and highlighted with dark stripes. Census data on green skills are missing for two commuting zones in Colorado.

First, it is obvious that communities with a higher share of fossil fuel jobs will experience large negative shocks due to the reduction in demand for fossil fuels. In the United States, many communities dependent on coal have already experienced economic decline, as both lower natural gas prices and the expansion of wind energy reduced demand for coal (Fell and Kaffine 2018; Weber 2020). More stringent emission reduction goals will eventually bring similar declines to communities where oil and gas drilling is prominent. Our results suggest that not all communities with a high share of fossil fuel jobs possess the right engineering and technical skills to attract green activities. Figure 5 illustrates the overlap between the presence of fossil fuel jobs (dark stripes indicating commuting zones in the top 20 percent of the share of fossil fuel employment) and green skill intensity in 2019 (shaded). There is a large heterogeneity in the level of green competences in fossil fuel intensive communities. Areas in the West and Midwest appear well prepared for the low-carbon transition.

Many communities in both Wyoming and North Dakota have high levels of green skills. Although beyond the scope of this paper, that may in part be due to the abundance of wind energy resources in these regions. While there is larger variation in green skills endowments in the fossil fuel intensive regions in the South, these regions mostly specialize in oil and gas, which will still play a role in the transition to a greener energy economy. In contrast, the Appalachian region is facing dramatic decreases in demand for coal and also has several commuting zones with low levels of green skills.

Second, communities with a higher share of green skills are also wealthier, as shown in table B13 of the online appendix. Thus, using large green stimuli as part of a green energy transition has the potential to exacerbate regional inequities. While the AJP attempts to address regional inequities by focusing infrastructure investments such as water infrastructure on disadvantaged communities, communities with the appropriate level of green competences will attract complementary private-sector investments in green enabling sectors, such as producers of wind turbines or electric vehicles, that are generally high-tech and concentrated in wealthier regions (Bontadini and Vona 2020). This may conjure a trade-off between choosing to specialize in the production of green technologies and using green spending to create new opportunities for distressed communities, especially in regions such as Appalachia.

Previous literature on place-based policies shows that investments in vocational and on-the-job training can be particularly effective in distressed regions (Bartik 2020), reinforcing our claim that well-targeted job training investments should be a key part of green fiscal plans to come. Worker-level evidence on the effectiveness of training investments is more mixed, but the recent paper by Hyman (2018) provides somewhat encouraging results on the effect of Trade Adjustment Assistance on earnings and reemployment of displaced workers. However, the lessons of previous spatially localized shocks—that is, the China shock and the decline of coal communities (Autor, Dorn, and Hanson 2021)—indicate that the labor market adjustment can be extremely long and painful for affected workers. It is thus unlikely that in the context of localized shocks, such as those to coal or shale gas communities, training investments alone can be a panacea. Future research should consider the potential of broader policies not just to help those directly affected by energy sector job losses but also to tackle the spillover effects to the rest of the local economy when these jobs move out.

VII. Conclusion

We perform a comprehensive evaluation of the economic effect of green stimulus using the historical experience of the American Recovery and Reinvestment Act, which represents the largest push to the green economy to date. Our results inform both current policy debates and address longer-term concerns about job losses in the transition to a green economy. Currently, Green New Deal programs are seen by some policy advocates as a win-win solution both to relaunch sluggish economic growth in developed countries and to tackle climate change. While the size of the green stimulus of 2009 was small compared to what is proposed as part of a post-COVID-19 recovery, our research highlights interesting features of a green stimulus that can offer guidance to the design of future green stimulus programs, as well as to the broader potential of green investments to ease the employment shocks from a green energy transition.

First, our results suggest green ARRA works more slowly than other stimulus investments. The effect of green ARRA on total employment is ambiguous; while the gross effect is twenty-five jobs per year created per \$1 million of green ARRA, the presence of pre-trends makes it difficult to discern whether these are new jobs or simply a return to pre–Great Recession levels of employment. However, what is clear is that both the changes in total employment and those in specific sectors persist over time. The persistency of the job creation effect is clearly a positive aspect of the green fiscal stimulus and a notable difference from previous studies of other ARRA investments, which generally find short-term effects. In contrast, we do not find evidence of short-run employment gains for green ARRA. Thus, green stimulus investments appear more effective for reshaping an economy than for restarting an economy. While our focus is on the potential employment benefits from green investments, future research should also consider the potential environmental benefits of green stimulus, as the long-run impacts on employment suggest that green investments lead to durable changes in the green economy. However, since these investments do not come with regulatory requirements to reduce emissions, do these long-run changes lead to an improved environment?

Second, the impact of the green stimulus becomes much clearer when we explore several dimensions of heterogeneity. Green ARRA creates more jobs in commuting zones with larger initial shares of occupations that use intensively green skills. In particular, \$1 million of green ARRA spending creates approximately 1.5 as many jobs in areas in the top quartile of the green skills distribution than in the median commuting zone. Our descriptive evidence suggests that the skill gap between green energy and fossil fuel jobs is modest, but green jobs require significantly more on-the-job training than fossil fuel jobs. Moreover, the geographical distribution of green skills may complicate the reallocation process required by the energy transition. On the one hand, the geographic concentration of these skills among fossil fuel dependent communities varies. On the other hand, communities with a higher share of green skills are also wealthier, so that green investments potentially enhance opportunities in communities already in position to support a green economy. Additional investments in vocational and on-the-job training could improve the effectiveness of green stimuli in regions without the required green skills. Evaluation of such training programs is left for future work.

Third, a green stimulus has potential to reshape an economy and thus may have important distributional effects. Green ARRA especially increases the demand for manual laborers. Beyond the direct impacts of a green stimulus, these results also have broader implications for whether governments can help ease labor market transitions in response to environmental policy using place-based policies. Recent studies suggest that environmental regulation may reduce jobs in specific sectors, particularly for manual (Marin and Vona 2019) and unskilled labor (Yip 2018). In contrast, subsidies to green infrastructure can benefit unskilled workers and thus may enhance the political support for other climate policies. However, wage gains did not follow the increase in the demand for manual tasks in areas receiving higher green subsidies. Exploring whether this is due to the fact that green jobs in construction are of low quality compared to similar jobs or to the widespread deterioration of the bargaining power of unskilled workers requires the use of longitudinal worker-level data and is left for future research.

ACKNOWLEDGMENTS This project has been supported in part through the Smart Prosperity Institute Research Network and its Greening Growth Partnership, which is supported by a Social Sciences and Humanities Research Council of Canada Partnership Grant (no. 895-2017-1018), as well as by Environment and Climate Change Canada's Economics and Environmental Policy Research Network (EEPRN). This work was also supported by Horizon 2020 Framework Programme, project INNOPATHS (grant no. 730403). We thank Joe Aldy, James Stock, Gabriel Chodorow-Reich, Valerie Ramey, Carolyn Fischer, Michelle Li, and Michael Chen for useful suggestions and discussions, especially on green ARRA data. For helpful comments, we thank seminar participants at Harvard University, Duke Kunshan University, the London School of Economics, University of Bremen, SPRU at University of Sussex, University of Newcastle, APPAM, CMCC Ca' Foscari, CESifo, the ETH workshop Energy, Innovation and Growth: Theory and Empirics, the Coalition of Finance Ministers for Climate Action workshop on The Political Economy of Carbon Pricing Post Covid-19, the workshop Where and How to Invest the EU Recovery Funds? at Universidad Pontificia Comillas of Madrid, the Resources for the Future workshop Evaluating Climate-Oriented Economic Recovery Programs, and the Greening Growth Partnership and Economics and Environmental Policy Research Network Annual Symposium.

References

Acemoglu, Daron, and David Autor. 2011. "Skills, Tasks and Technologies: Implications for Employment and Earnings." In *Handbook of Labor Economics 4B*, edited by Orley Ashenfelter and David E. Card. Amsterdam: North Holland.

Acemoglu, Daron, and Pascual Restrepo. 2020. "Robots and Jobs: Evidence from US Labor Markets." *Journal of Political Economy* 128, no. 6: 2188–244.

Agrawala, Shardul, Damien Dussaux, and Norbert Monti. 2020. "What Policies for Greening the Crisis Response and Economic Recovery? Lessons Learned from Past Green Stimulus Measures and Implications for the COVID-19 Crisis." Working Paper 164. Paris: Organization for Economic Cooperation and Development. https://www.oecd-ilibrary.org/environment/what-policies-for-greening-the-crisis-response-and-economic-recovery_c50f186f-en.

Aldy, Joseph E. 2013. "Policy Monitor—A Preliminary Assessment of the American Recovery and Reinvestment Act's Clean Energy Package." *Review of Environmental Economics and Policy* 7, no. 1: 136–55.

Aldy, Joseph E., and William A. Pizer. 2015. "The Competitiveness Impacts of Climate Change Mitigation Policies." *Journal of the Association of Environmental and Resource Economists* 2, no. 4: 565–95.

Altonji, Joseph G., Todd E. Elder, and Christopher R. Taber. 2005. "Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools." *Journal of Political Economy* 113, no. 1: 151–84.

American Recovery and Reinvestment Act (ARRA) of 2009, Pub. L. 111-5, 123 Stat. 115, section 3.

Angrist, Joshua D., and Jörn-Steffen Pischke. 2008. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton, N.J.: Princeton University Press.

Auerbach, Alan J., Yuriy Gorodnichenko, and Daniel Murphy. 2020. "Local Fiscal Multipliers and Fiscal Spillovers in the USA." *IMF Economic Review* 68, no. 1: 195–229.

Autor, David, David Dorn, and Gordon H. Hanson. 2013. "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." *American Economic Review* 103, no. 6: 2121–68.

Autor, David, David Dorn, and Gordon H. Hanson. 2021. "On the Persistence of the China Shock." In the present volume of *Brookings Papers on Economic Activity*.

Autor, David, David Dorn, Gordon Hanson, and Kaveh Majlesi. 2020. "Importing Political Polarization? The Electoral Consequences of Rising Trade Exposure." *American Economic Review* 110, no. 10: 3139–83.

Autor, David, Frank Levy, and Richard Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *Quarterly Journal of Economics* 118, no. 4: 1279–333.

Bartik, Timothy J. 2020. "Using Place-Based Jobs Policies to Help Distressed Communities." *Journal of Economic Perspectives* 34, no. 3: 99–127.

Bontadini, Filippo, and Francesco Vona. 2020. “Anatomy of Green Specialization: Evidence from EU Production Data, 1995–2015.” Working paper 21/2020. Paris: Science Po OFCE. https://www.ofce.sciences-po.fr/pdf/dtravail/OFCEWP2020-21.pdf.

Carley, Sanya. 2016. “Energy Programs of the American Recovery and Reinvestment Act of 2009.” *Review of Policy Research* 33, no. 2: 201–23.

Carley, Sanya, Sean Nicholson-Crotty, and Eric J. Fisher. 2015. “Capacity, Guidance and the Implementation of the American Recovery and Reinvestment Act.” *Public Administration Review* 75, no. 1: 113–25.

Castellanos, Kenneth A., and Gareth Heutel. 2019. “Unemployment, Labor Mobility, and Climate Policy.” Working paper 25797. Cambridge, Mass.: National Bureau of Economic Research. https://www.nber.org/papers/w25797.

Chodorow-Reich, Gabriel. 2019. “Geographic Cross-Sectional Fiscal Spending Multipliers: What Have We Learned?” *American Economic Journal: Economic Policy* 11, no. 2: 1–34.

Chodorow-Reich, Gabriel. 2020. “Regional Data in Macroeconomics: Some Advice for Practitioners.” *Journal of Economic Dynamics and Control* 115:103875.

Chodorow-Reich, Gabriel, Laura Feiveson, Zachary Liscow, and William Gui Woolston. 2012. “Does State Fiscal Relief during Recessions Increase Employment? Evidence from the American Recovery and Reinvestment Act.” *American Economic Journal: Economic Policy* 4, no. 3: 118–45.

Conley, Timothy G., and Bill Dupor. 2013. “The American Recovery and Reinvestment Act: Solely a Government Jobs Program?” *Journal of Monetary Economics* 60, no. 5: 535–49.

Council of Economic Advisers. 2010. *The Economic Impact of the American Recovery and Reinvestment Act of 2009, Fourth Quarterly Report*. Washington: Council of Economic Advisers. https://obamawhitehouse.archives.gov/administration/eop/cea/factsheets-reports/economic-impact-arra-4th-quarterly-report/summary.

Council of Economic Advisers. 2013. *The Economic Impact of the American Recovery and Reinvestment Act of 2009, Ninth Quarterly Report*. Washington: Council of Economic Advisers. https://obamawhitehouse.archives.gov/sites/default/files/docs/cea_9th_arra_report_final_pdf.pdf.

Council of Economic Advisers. 2014. “The Economic Impact of the American Recovery and Reinvestment Act Five Years Later.” In *Economic Report of the President*. Washington: United States Government Printing Office.

Cullen, Joseph A., and Erin T. Mansur. 2017. “Inferring Carbon Abatement Costs in Electricity Markets: A Revealed Preference Approach Using the Shale Revolution.” *American Economic Journal: Economic Policy* 9, no. 3: 106–33.

Dupor, Bill, and Peter B. McCrory. 2018. “A Cup Runneth Over: Fiscal Policy Spillovers from the 2009 Recovery Act.” *Economic Journal* 128, no. 611: 1476–508.

Dupor, Bill, and M. Salif Mehkari. 2016. “The 2009 Recovery Act: Stimulus at the Extensive and Intensive Labor Margins.” *European Economic Review* 85: 208–28.

Environmental Protection Agency. 2009. American Recovery and Reinvestment Act Funding for the National Clean Diesel Funding Assistance Program: Request for Applications. Washington: Environmental Protection Agency. https://www.epa.gov/sites/default/files/2015-10/documents/recovery-act-national-clean-diesel-rfa.pdf.

Fell, Harrison, and Daniel T. Kaffine. 2018. "The Fall of Coal: Joint Impacts of Fuel Prices and Renewables on Generation and Emissions." *American Economic Journal: Economic Policy* 10, no. 1: 90–116.

Fowlie, Meredith, Michael Greenstone, and Catherine Wolfram. 2018. "Do Energy Efficiency Investments Deliver? Evidence from the Weatherization Assistance Program." *Quarterly Journal of Economics* 133, no. 3: 1597–644.

Gabe, Todd M., and Jaison R. Abel. 2012. "Specialized Knowledge and the Geographic Concentration of Occupations." *Journal of Economic Geography* 12, no. 2: 435–53.

Garin, Andrew. 2019. "Putting America to Work, Where? Evidence on the Effectiveness of Infrastructure Construction as a Locally Targeted Employment Policy." *Journal of Urban Economics* 111:108–31.

Gathmann, Christina, and Uta Schönberg. 2010. "How General Is Human Capital? A Task-Based Approach." *Journal of Labor Economics* 28, no. 1: 1–50.

Greenstone, Michael. 2002. "The Impacts of Environmental Regulations on Industrial Activity: Evidence from the 1970 and 1977 Clean Air Act Amendments and the Census of Manufactures." *Journal of Political Economy* 110, no. 6: 1175–219.

Hafstead, Marc A., and Roberton C. Williams III. 2018. "Unemployment and Environmental Regulation in General Equilibrium." *Journal of Public Economics* 160:50–65.

Helm, Dieter. 2020. "The Environmental Impacts of the Coronavirus." *Environmental and Resource Economics* 76, no. 1: 21–38.

Hyman, Benjamin G. 2018. "Can Displaced Labor Be Retrained? Evidence from Quasi-Random Assignment to Trade Adjustment Assistance." Working Paper. Philadelphia: Mack Institute for Innovation Managment. https://mackinstitute.wharton.upenn.edu/wp-content/uploads/2018/11/FP0385_WP_2018Nov.pdf.

Imbens, Guido, and Joshua Angrist. 1994. "Identification and Estimation of Local Average Treatment Effects." *Econometrica* 62, no. 2: 467–75.

Jaeger, David A., Joakim Ruist, and Jan Stuhler. 2018. "Shift-Share Instruments and the Impact of Immigration." Working Paper 24285. Cambridge, Mass.: National Bureau of Economic Research. https://www.nber.org/papers/w24285.

Kahn, Matthew, and Erin Mansur. 2013. "Do Local Energy Prices and Regulation Affect the Geographic Concentration of Employment?" *Journal of Public Economics* 101:105–14.

Kambourov, Gueorgui, and Iourii Manovskii. 2009. "Occupational Specificity of Human Capital." *International Economic Review* 50, no. 1: 63–115.

Konisky, David M., and Sanya Carley. 2021. "What We Can Learn from the Green New Deal about the Importance of Equity in National Climate Policy." *Journal of Policy Analysis and Management* 40, no. 3: 996–1002.

Leduc, Sylvain, and Daniel J. Wilson. 2017. "Are State Governments Roadblocks to Federal Stimulus? Evidence on the Flypaper Effect of Highway Grants in the 2009 Recovery Act." *American Economic Journal: Economic Policy* 9, no. 2: 253–92.

Marin, Giovanni, and Francesco Vona. 2019. "Climate Policies and Skill-Biased Employment Dynamics: Evidence from EU Countries." *Journal of Environmental Economics and Management* 98:102253.

Marin, Giovanni, and Francesco Vona. 2021. "The Impact of Energy Prices on Socioeconomic and Environmental Performance: Evidence from French Manufacturing Establishments, 1997–2015." *European Economic Review* 135:103739.

Metcalf, Gilbert E., and James H. Stock. 2020. "Measuring the Macroeconomic Impact of Carbon Taxes." In *American Economic Association Papers and Proceedings*, vol. 110. Pittsburgh, Pa.: AEA Publications.

Moretti, Enrico. 2010. "Local Multipliers." *American Economic Review* 100, no. 2: 373–77.

Morgenstern, Richard, William Pizer, and Jhih-Shyang Shih. 2002. "Jobs versus the Environment: An Industry-Level Perspective." *Journal of Environmental Economics and Management* 43, no. 3: 412–36.

Mundaca, Luis, and Jessika Luth Richter. 2015. "Assessing 'Green Energy Economy' Stimulus Packages: Evidence from the U.S. Programs Targeting Renewable Energy." *Renewable and Sustainable Energy Reviews* 42:1174–86.

Muro, Mark, Adie Tomer, Ranjitha Shivaram, and Joseph Kane. 2019. "Advancing Inclusion through Clean Energy Jobs." Washington: Brookings Institution, Metropolitan Policy Program. https://www.brookings.edu/research/advancing-inclusion-through-clean-energy-jobs/.

Nakamura, Emi, and Jón Steinsson. 2014. "Fiscal Stimulus in a Monetary Union: Evidence from US Regions." *American Economic Review* 104, no. 3: 753–92.

Ramey, Valerie A. 2021. "The Macroeconomic Consequences of Infrastructure Investment." In *Economic Analysis and Infrastructure Investment*, edited by Edward L. Glaeser and James M. Poterba. Chicago: University of Chicago Press.

Tomer, Adie, Joseph W. Kane, and Caroline George. 2021. "How Renewable Energy Jobs Can Uplift Fossil Fuel Communities and Remake Climate Politics." Washington: Brookings Institution, Metropolitan Policy Program. https://www.brookings.edu/research/how-renewable-energy-jobs-can-uplift-fossil-fuel-communities-and-remake-climate-politics/.

US Department of Energy. 2010. "Recovery Act State Memos: Massachusetts." Washington: Department of Energy. https://www.energy.gov/downloads/massachusetts-recovery-act-state-memo.

US Office of the Vice President. 2010. "100 Recovery Act Projects That Are Changing America." Washington: Environmental Protection Agency. https://archive.epa.gov/recovery/web/pdf/100-recovery-act-projects-changing-america-report.pdf.

Vona, Francesco. 2019. "Job Losses and the Political Acceptability of Climate Policies: Why the 'Job-Killing' Argument Is So Persistent and How to Overturn It." *Climate Policy* 19, no. 4: 524–32.

Vona, Francesco, Giovanni Marin, and Davide Consoli. 2019. "Measures, Drivers and Effects of Green Employment: Evidence from US Metropolitan and Non-Metropolitan Areas, 2006–2014." *Journal of Economic Geography* 19, no. 5: 1021–48.

Vona, Francesco, Giovanni Marin, Davide Consoli, and David Popp. 2018. "Environmental Regulation and Green Skills: An Empirical Exploration." *Journal of the Association of Environmental and Resource Economists* 5, no. 4: 713–53.

Walker, W. Reed. 2013. "The Transitional Costs of Sectoral Reallocation: Evidence from the Clean Air Act and the Workforce." *Quarterly Journal of Economics* 128:1787–835.

Weber, Jeremy G. 2020. "How Should We Think about Environmental Policy and Jobs? An Analogy with Trade Policy and an Illustration from US Coal Mining." *Review of Environmental Economics and Policy* 14, no. 1: 44–66.

White House. 2021a. "Fact Sheet: The American Jobs Plan." March 31. https://www.whitehouse.gov/briefing-room/statements-releases/2021/03/31/fact-sheet-the-american-jobs-plan/.

White House. 2021b. "Fact Sheet: Historic Bipartisan Infrastructure Deal." July 28. https://www.whitehouse.gov/briefing-room/statements-releases/2021/07/28/fact-sheet-historic-bipartisan-infrastructure-deal/.

Wilson, Daniel J. 2012. "Fiscal Spending Jobs Multipliers: Evidence from the 2009 American Recovery and Reinvestment Act." *American Economic Journal: Economic Policy* 4, no. 3: 251–82.

Yip, Chi Man. 2018. "On the Labor Market Consequences of Environmental Taxes." *Journal of Environmental Economics and Management* 89:136–52.

Yip, Chi Man. 2020. "The Ins and Outs of Employment: Labor Market Adjustments to Carbon Taxes." Working Paper. https://arts.ucalgary.ca/sites/default/files/teams/27/chi-man-yip-jmp-ins-and-out-employment-labor-market-adjustments-carbon-taxescompressed.pdf.

*** **APPENDICES FOR ON-LINE PUBLICATION ONLY** ***

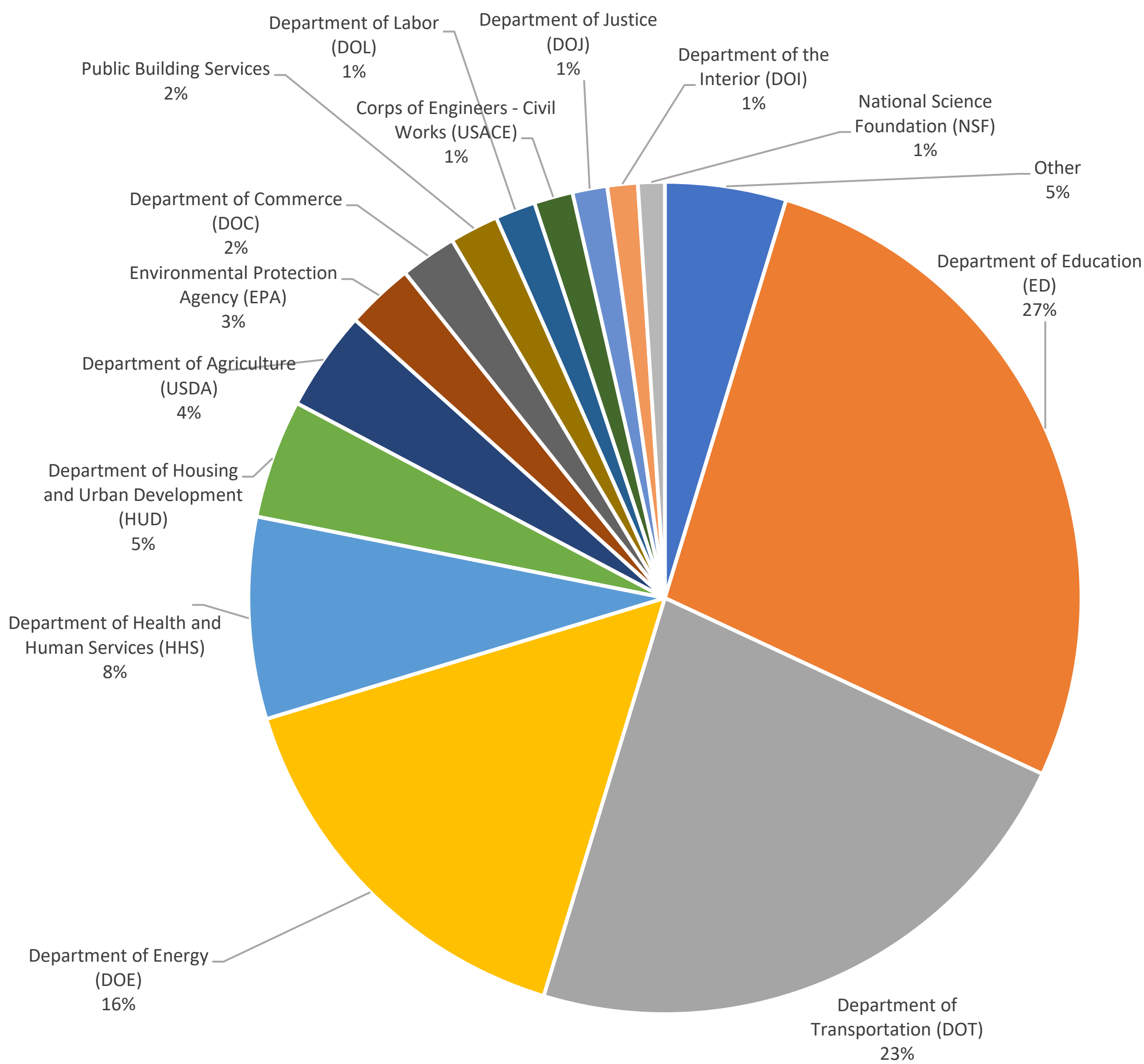
The Employment Impact of a Green Fiscal Push: Evidence from the American Recovery and Reinvestment Act

David Popp, Francesco Vona, Giovanni Marin, and Ziqiao Chen

Appendix A - Data Appendix

A1 – Background on Green ARRA investments

Figure A1 – ARRA spending by awarding Department / Agency



Notes: own elaboration based on Recovery.gov data from NBER data repository.

Table A1 – Descriptive statistics for green and non-green ARRA

	Non-green ARRA	Green ARRA	DOE ARRA	EPA ARRA	Green research ARRA	Green training ARRA
Total, million $	211,065	49,293	42,269	7,023	4,901	187
By commuting zone, million $						
mean	354.71	83.21	71.41	11.80	8.35	0.32
s.d.	883.56	266.56	253.35	24.83	54.89	1.15
min	1.59	0.00	0.00	0.00	0.00	0.00
median	97.51	12.80	7.23	4.21	0.00	0.00
max	9,406.82	3,579.14	3,506.34	279.47	969.47	10.92
By commuting zone, per capita						
mean	705.71	181.02	147.50	33.52	19.22	0.52
s.d.	476.20	718.54	715.50	44.22	260.55	3.22
min	8.65	0.00	0.00	0.00	0.00	0.00
median	591.35	72.96	43.20	19.24	0.00	0.00
max	5,513.08	13,117.54	13,067.59	371.92	6,146.42	63.05

Notes: data by 587 commuting zone includes only CZ with at least 25000 inhabitants. ARRA for years 2009-2012 divided by population in 2008 (dollars per capita).

Table A2 – Top 10 areas in terms of green and non-green ARRA per capita

Panel A: Green ARRA

Main county of the CZ	Top 10 CZ by green ARRA per capita Green ARRA per capita	Non-green ARRA per capita	Population in 2008	Examples of largest ARRA projects
Morgan County, IL	13118	627	55090	• Over $700 million for construction of Future Gen • Multiple $1 million EPA subcontracts to different communities
Orangeburg County, SC	6894	656	157729	• Nearly $1 billion for cleanup of Savannah River Nuclear Site
Elko County, NV	5693	1095	59144	• Over $300 million loan for construction of electric transmission line • $2.7 million subaward from Weatherization Assistance program • $2 million to study feasibility of waste heat power generation
Benton County, WA	5537	490	298566	• Multiple $100+ million DOE contracts for waste remediation for closure of Hanford facility
Alamosa County, CO	2253	1016	45845	• $86 million loan for cogeneration project • $17 million EPA grant for Superfund remediation
Frederick County, MD	2191	793	709225	• Multiple $500 million sub-awards to Betchel Group for projects developing new solar energy resources • Multiple $1+ EPA subcontracts to different communities
Santa Barbara County, CA	2050	654	682217	• $1.3 billion subcontract to Sunpower Corp. to develop a solar PV plant • $14 million research award to UC Santa Barbara • Multiple $2+ DOE grants
Malheur County, OR	1514	607	64024	• $93 million to USG Oregon LLC to develop geothermal power technology
Santa Fe County, NM	1424	1875	232103	• Multiple $100+ million awards to Los Alamos National Security for waste remediation • $10 billion research award to Los Alamos
Larimer County, CO	1384	1095	291650	• $370 million loan to Abound Solar Manufacturing • $17 million grant to UQM Technologies for producing EV and hybrid vehicle propulsion systems

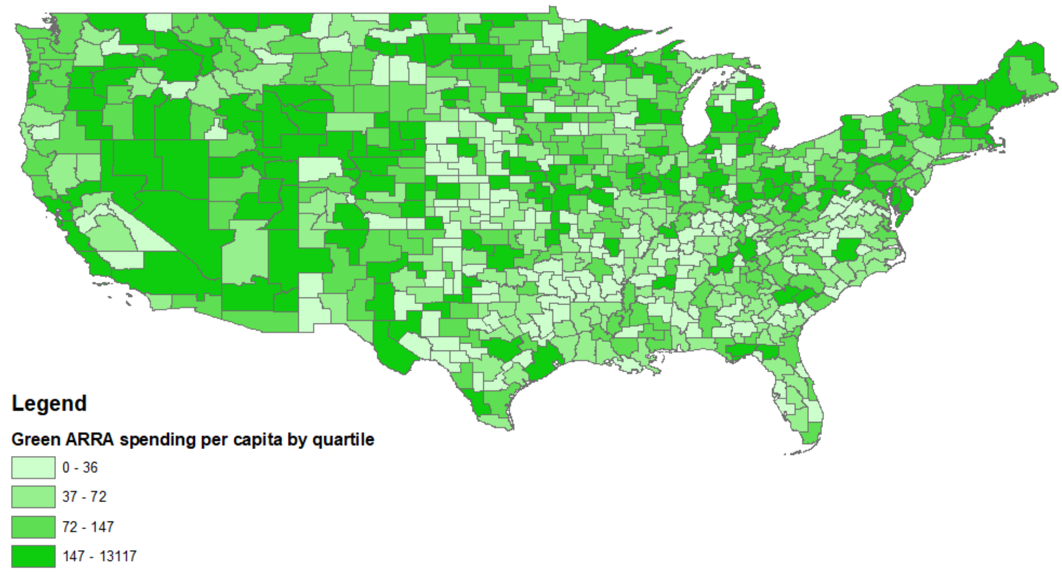
Notes: only CZ with at least 25000 inhabitants. ARRA for years 2009-2012 divided by population in 2008 (dollars per capita). Main county of the CZ identified as the county with the largest population level

Panel B: Non-green ARRA

Main county of the CZ	Top 10 CZ by non-green ARRA per capita Green ARRA per capita	Non-green ARRA per capita	Population in 2008	Examples of largest ARRA projects
Sangamon County, IL	226.78	5513.08	321216	• $13 million subaward to help local governments improve energy efficiency • $11 million DOE grant to improve energy efficiency in low-income family homes
Fairbanks North Star Borough, AK	184.56	4904.81	101940	• $4.2 million research award to Univ. of Alaska for geothermal research • multiple $1 million EPA sub-awards to local communities to improve wastewater infrastructure
Leon County, FL	379.26	3354.22	383912	• $49 million state grant for renewable energy • $8 million to the City of Tallahassee for smart grid infrastructure
Juneau Borough/city, AK	425.53	2684.93	43943	• multiple DOE and EPA subcontracts between $2-$10 million
Thurston County, WA	113.97	2605.99	379016	• $9 million EPA subcontract • $4.6 million to the City of Tacoma for dam improvements
Clarke County, IA	254.48	2522.96	33184	• 3 $1 million + subawards made by DOE and EPA
Sacramento County, CA	252.15	2503.45	2196308	• $109 million to Sacramento Municipal Utility for smart grid development • $24 million grant to Clean Energy Systems, Inc to develop clean power turbines • Recipient of multiple DOE awards to be distributed statewide
Bell County, TX	44.81	2304.20	398202	• $9.8 million EPA subcontract to improve water infrastructure • $4.9 million DOE subcontract for weatherization assistance
Genesee County, MI	158.10	2231.88	968243	• $27 million subcontract to Michigan Saves • $17 million EPA subcontract to the city of Lansing for a green project
Stutsman County, ND	433.50	2210.92	34258	• 3 $3-4 million EPA subcontracts to local communities

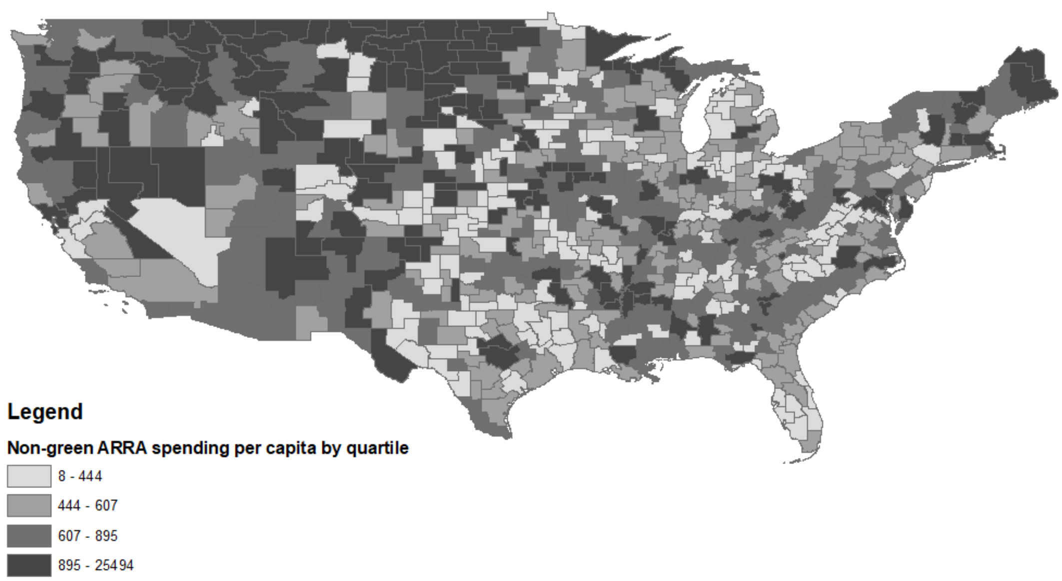
Notes: only CZ with at least 25000 inhabitants. ARRA for years 2009-2012 divided by population in 2008 (dollars per capita). Main county of the CZ identified as the county with the largest population level

Figure A2 – Green ARRA spending per capita by Commuting Zone



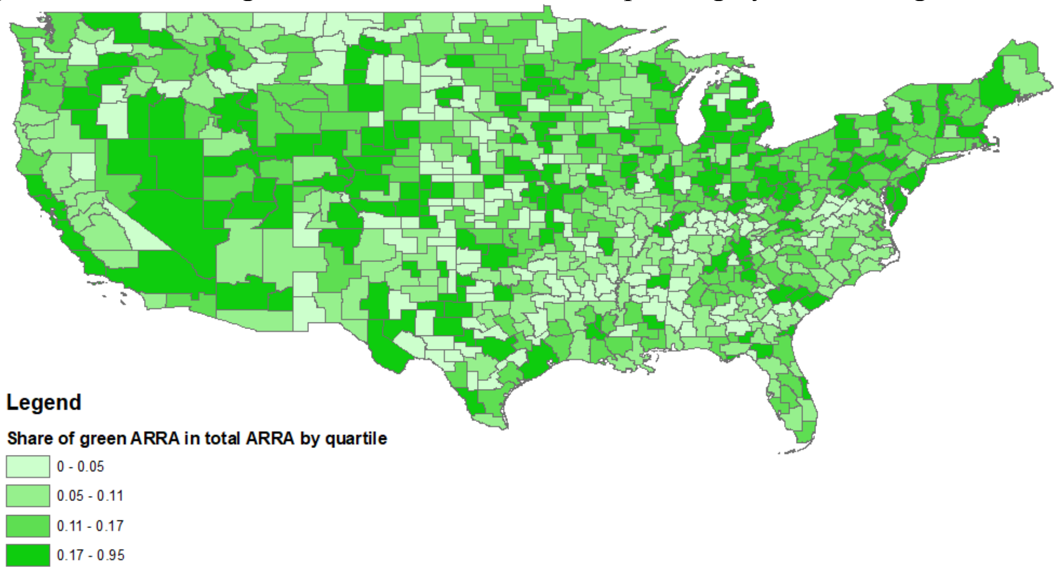
Notes: own elaboration based on Recovery.gov data from NBER data repository. Green ARRA is defined as ARRA spending awarded by DOE and EPA broken down by quartiles. Per capita analysis based on the population of each commuting zone prior to the recession, in 2008. Alaska and Hawaii not shown.

Figure A3 – Non-green ARRA spending per capita by Commuting Zone



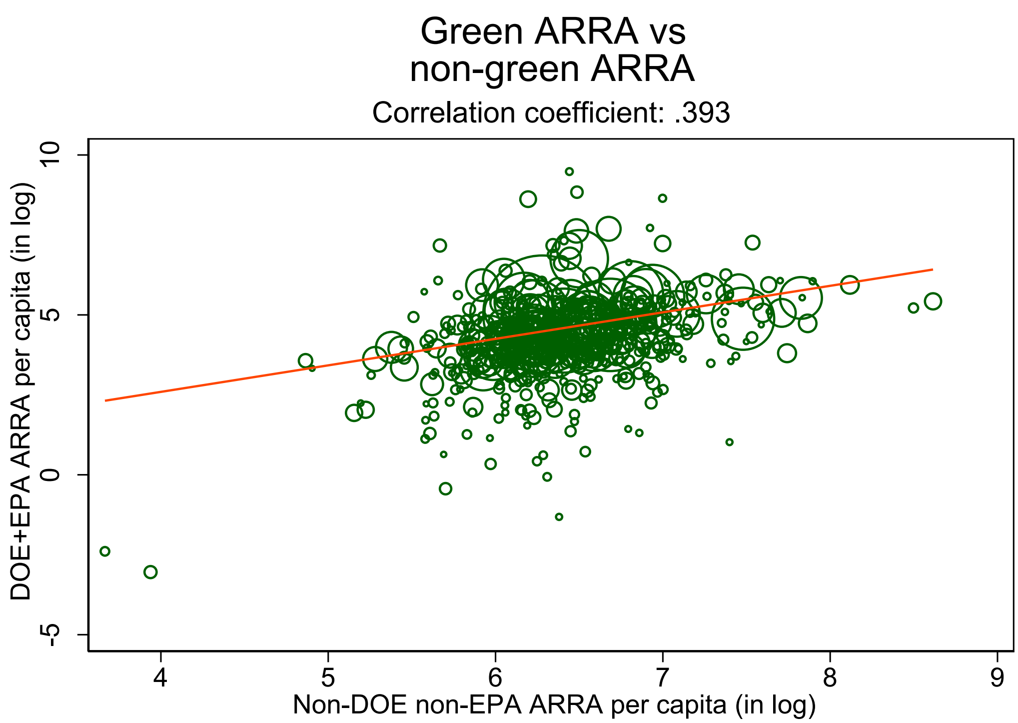
Notes: own elaboration based on Recovery.gov data from NBER data repository. Non-green ARRA is defined as ARRA spending awarded by all agencies except DOE and EPA broken down by quartiles. Per capita analysis based on the population of each commuting zone prior to the recession, in 2008. Alaska and Hawaii not shown.

Figure A4 – Share of green ARRA in total ARRA spending by Commuting Zone



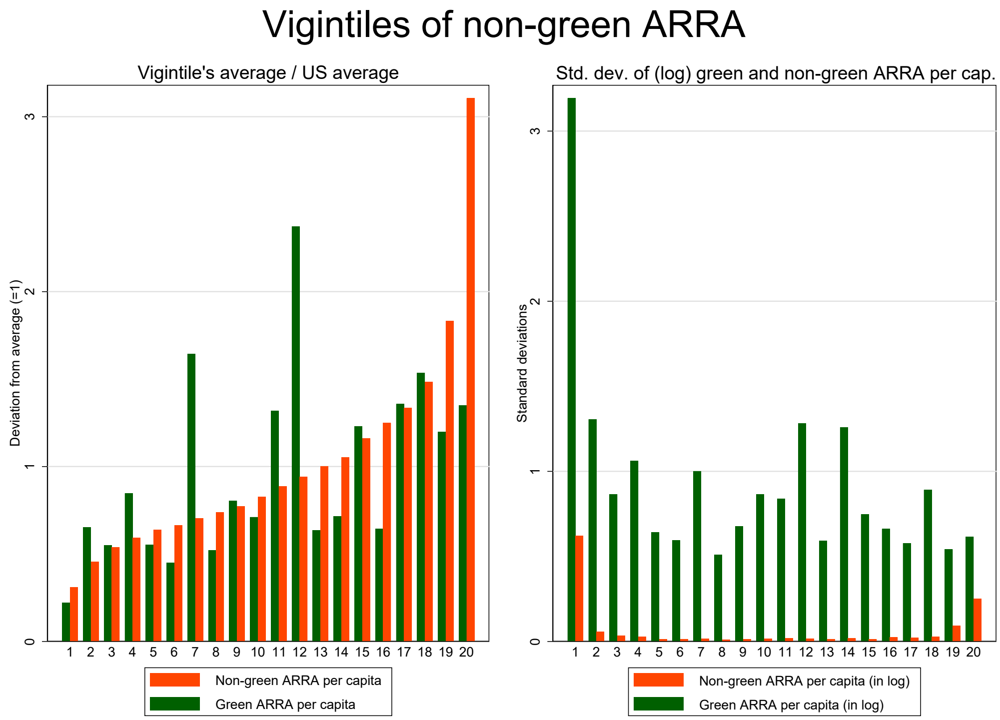
Notes: own calculation based on Recovery.gov data from NBER data repository. Green ARRA is defined as ARRA spending awarded by the DOE and EPA. Each shade represents a different quartile. Alaska and Hawaii not shown.

Figure A5 – Correlation between green and non-green ARRA per capita



Notes: per capita analysis based on the population of each commuting zone prior to the recession, in 2008. Linear fit and correlation coefficient weighted by CZ population in 2008. Sample: CZ with at least 25000 inhabitants.

Figure A6. Green ARRA per capita (average & SD) by vigintile of non-green ARRA per capita



Notes: unweighted vigintiles of non-green ARRA per capita across all CZ. Within-vigintiles average and SD is weighted by CZ population in 2008.

Table A3 -- Green investments in 2021 infrastructure proposals

	American Jobs Plan (billions)	Bipartisan Infrastructure Framework (billions)
Power infrastructure incl. envi. remediation	$100	$94
Electrifying vehicles and EV infrastructure	$174	$15
Water infrastructure	$111	$55
Climate science, innovation, and R&D	$35	N/A
Clean energy manufacturing	$46	N/A
Resilience projects	N/A	$50
Workforce development (not all green)	*$100*	*N/A*
Total (excl. workforce development)	$466	$214
Total (incl. workforce development)	$566	$214

Notes: The Bipartisan Infrastructure Framework regrouped parts of the original American Jobs Plan into a new category of resilience projects. Thus, the total amount of green investments in American Jobs Plan may not be exhaustive.

Sources: AJP: "FACT SHEET: The American Jobs Plan." The White House. March 31, 2021. https://www.whitehouse.gov/briefing-room/statements-releases/2021/03/31/fact-sheet-the-american-jobs-plan/, last accessed July 17, 2021.

Bipartisan plan: "FACT SHEET: Historic Bipartisan Infrastructure Deal." July 28, 2021. https://www.whitehouse.gov/briefing-room/statements-releases/2021/07/28/fact-sheet-historic-bipartisan-infrastructure-deal/, last accessed August 24, 2021.

A2 – Other data: definitions and data sources

i. Green occupations and green employment

Our measures of green employment and green skills are based on Vona et al. (2018) and inspired by the task approach of labor markets (Acemoglu and Autor, 2011). For each occupation, the O*NET database provides the tasks expected of workers and the skills needed to complete these tasks. Tasks are further divided into 'general' tasks, which are common to all occupations, and 'specific' tasks that are unique to individual occupations. The *greenness* of each occupation is the share of specific tasks that are green (see also Dierdorff et al., 2009, and Vona et al., 2019). Computing the average of occupational greenness (weighted by sampling weights and annual hours worked) for each commuting zone provides the number of full time equivalent green workers in each commuting zone. The green occupations summarized in Table 1 are any occupation with a greenness greater than 0. We further divide these green occupations into renewable and non-renewable energy jobs, where renewable energy jobs focus on occupations specific to wind or solar energy.

Our measure of green employment by commuting zone, used as a dependent variable in Table 3, is calculated as:

$$GreenEmp_{it} = TotEmp_{it}\left(\sum_{o} Greenness_o \times Share\_h\_worked_{ito}\right)$$

where:

- $Greenness_o$ is computed as the importance-weighted share of green specific tasks over total specific tasks (source: O*NET, version 18.0) in occupation *o* as in Vona et al. (2019);

- $Share\_h\_worked_{ito}$ is the share of hours worked by employees in SOC occupation *o* in CZ *i* and year *t* (source: IPUMS-ACS);
- $TotEmp_{it}$ is total employment in CZ *i* and year *t* (source: BLS-QCEW).

Our estimate of green employment is found to be, on average, an upper-bound compared to recent figures due to possible aggregation bias at the occupational level and to the fact that we consider three additional years (2015-2016-2017). Our benchmark is Vona et al. (2019), who estimate green employment using data on 'pure' 6-digit SOC occupational classification (775 occupations) from BLS-OES at the metropolitan and nonmetropolitan area level. According to their estimate, green employment accounts for 3% of total US employment in 2006-2014. Our estimates here, which use 450 occupations in IPUMS-ACS data by commuting zone, suggest that green employment is 4.7% of total US employment over a similar but slightly longer timeframe.

An example to illustrate the possible aggregation bias is the following. In ACS the occupation "17-3020 Engineering Technicians, Except Drafters" is not broken down into its 8 6-digit occupations. While the average greenness of 17-3020 is 0.16, it includes both 6-digit occupations with zero greenness (e.g. "17-3021 Aerospace Engineering and Operations Technicians") and occupations with greenness equal to one (e.g. "17-3025 Environmental Engineering Technicians"). Clearly, taking the unweighted average, as we did here, over-estimate the weight given to green occupations that taking the weighted average, as in Vona et al. (2019) whereby BLS data are available at a more disaggregated level from BLS-OES at the metropolitan and nonmetropolitan area level. The simple reason for this is that the relative size of green occupations within a broad category such as "17-3020 Engineering Technicians, Except Drafters" is smaller than the uniform weights that one would attribute in absence of employment statistics at a more disaggregated level. We refer the interested reader to Vona et al. (2019) for further evidence and discussions of the aggregation bias associated with the use of too coarse occupation-based measure of green employment. Table A4 provides the full list of green and brown occupations used in Table 1.

Table A4 – List of green and brown occupations (SOC 2018 classification) used for macro-occupational groups in Table 1

SOC code	Occupation title
	Brown 'fossil' occupations (HS)
17-2151	Mining and Geological Engineers, Including Mining Safety Engineers
17-2171	Petroleum Engineers
	Brown 'fossil' occupations (LS)
47-5011	Derrick Operators, Oil and Gas
47-5012	Rotary Drill Operators, Oil and Gas
47-5013	Service Unit Operators, Oil and Gas
47-5041	Continuous Mining Machine Operators
47-5043	Roof Bolters, Mining
47-5044	Loading and Moving Machine Operators, Underground Mining
47-5071	Roustabouts, Oil and Gas
47-5081	Helpers--Extraction Workers
51-8092	Gas Plant Operators
51-8093	Petroleum Pump System Operators, Refinery Operators, and Gaugers
53-7072	Pump Operators, Except Wellhead Pumpers
53-7073	Wellhead Pumpers
	Brown ''other' occupations (HS)
17-2041	Chemical Engineers
19-1012	Food Scientists and Technologists
19-2031	Chemists
19-4031	Chemical Technicians
	Brown ''other' occupations (LS)
43-5041	Meter Readers, Utilities
45-4023	Log Graders and Scalers
47-4071	Septic Tank Servicers and Sewer Pipe Cleaners
47-5022	Excavating and Loading Machine and Dragline Operators, Surface Mining
47-5023	Earth Drillers, Except Oil and Gas
47-5032	Explosives Workers, Ordnance Handling Experts, and Blasters
47-5051	Rock Splitters, Quarry
49-2095	Electrical and Electronics Repairers, Powerhouse, Substation, and Relay
49-9012	Control and Valve Installers and Repairers, Except Mechanical Door
49-9041	Industrial Machinery Mechanics
49-9043	Maintenance Workers, Machinery
49-9045	Refractory Materials Repairers, Except Brickmasons
49-9051	Electrical Power-Line Installers and Repairers
51-1011	First-Line Supervisors of Production and Operating Workers
51-2051	Fiberglass Laminators and Fabricators
51-3091	Food and Tobacco Roasting, Baking, and Drying Machine Operators and Tenders
51-3092	Food Batchmakers
51-3093	Food Cooking Machine Operators and Tenders
51-4021	Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic
51-4022	Forging Machine Setters, Operators, and Tenders, Metal and Plastic
51-4023	Rolling Machine Setters, Operators, and Tenders, Metal and Plastic
51-4033	Grinding, Lapping, Polishing, and Buffing Machine Tool Setters, Operators, and Tenders, Metal and Plastic
51-4051	Metal-Refining Furnace Operators and Tenders

SOC code	Occupation title	
51-4052	Pourers and Casters, Metal	
51-4062	Patternmakers, Metal and Plastic	
51-4071	Foundry Mold and Coremakers	
51-4191	Heat Treating Equipment Setters, Operators, and Tenders, Metal and Plastic	
51-4192	Layout Workers, Metal and Plastic	
51-4193	Plating Machine Setters, Operators, and Tenders, Metal and Plastic	
51-4194	Tool Grinders, Filers, and Sharpeners	
51-6061	Textile Bleaching and Dyeing Machine Operators and Tenders	
51-6063	Textile Knitting and Weaving Machine Setters, Operators, and Tenders	
51-6064	Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders	
51-6091	Extruding and Forming Machine Setters, Operators, and Tenders, Synthetic and Glass Fibers	
51-6093	Upholsterers	
51-7011	Cabinetmakers and Bench Carpenters	
51-7021	Furniture Finishers	
51-7031	Model Makers, Wood	
51-7032	Patternmakers, Wood	
51-7041	Sawing Machine Setters, Operators, and Tenders, Wood	
51-7042	Woodworking Machine Setters, Operators, and Tenders, Except Sawing	
51-8012	Power Distributors and Dispatchers	
51-8091	Chemical Plant and System Operators	
51-9011	Chemical Equipment Operators and Tenders	
51-9012	Separating, Filtering, Clarifying, Precipitating, and Still Machine Setters, Operators, and Tenders	
51-9021	Crushing, Grinding, and Polishing Machine Setters, Operators, and Tenders	
51-9022	Grinding and Polishing Workers, Hand	
51-9023	Mixing and Blending Machine Setters, Operators, and Tenders	
51-9031	Cutters and Trimmers, Hand	
51-9032	Cutting and Slicing Machine Setters, Operators, and Tenders	
51-9041	Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders	
51-9051	Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders	
51-9111	Packaging and Filling Machine Operators and Tenders	
51-9124	Coating, Painting, and Spraying Machine Setters, Operators, and Tenders	
51-9191	Adhesive Bonding Machine Operators and Tenders	
51-9192	Cleaning, Washing, and Metal Pickling Equipment Operators and Tenders	
51-9193	Cooling and Freezing Equipment Operators and Tenders	
51-9195	Molders, Shapers, and Casters, Except Metal and Plastic	
51-9196	Paper Goods Machine Setters, Operators, and Tenders	
51-9197	Tire Builders	
53-4013	Rail Yard Engineers, Dinkey Operators, and Hostlers	
53-7031	Dredge Operators	
53-7041	Hoist and Winch Operators	
53-7063	Machine Feeders and Offbearers	
53-7071	Gas Compressor and Gas Pumping Station Operators	
	Green 'renewable' occupations (HS):	Greenness
17-2199.10	Wind Energy Engineers	1
17-2199.11	Solar Energy Systems Engineers	1
	Green 'renewable' occupations (LS):	Greenness
41-4011.07	Solar Sales Representatives and Assessors	1
47-1011.03	Solar Energy Installation Managers	1
47-2231.00	Solar Photovoltaic Installers	1
49-9081.00	Wind Turbine Service Technicians	1
	Green ''other' occupations (HS):	Greenness
11-1011.03	Chief Sustainability Officers	1
11-1021.00	General and Operations Managers	0.1133
11-2011.00	Advertising and Promotions Managers	1
11-2021.00	Marketing Managers	0.1720
11-3051.00	Industrial Production Managers	1
11-3051.02	Geothermal Production Managers	1
11-3051.03	Biofuels Production Managers	1

SOC code	Occupation title	
11-3051.04	Biomass Power Plant Managers	1
11-3051.06	Hydroelectric Production Managers	1
11-3071.00	Transportation, Storage, and Distribution Managers	0.2437
11-9013.00	Farmers, Ranchers, and Other Agricultural Managers	0.1444
11-9021.00	Construction Managers	0.2510
11-9041.00	Architectural and Engineering Managers	0.1780
11-9041.01	Biofuels/Biodiesel Technology and Product Development Managers	1
11-9121.02	Water Resource Specialists	1
13-1041.07	Regulatory Affairs Specialists	0.1438
13-1081.01	Logistics Engineers	0.3310
13-1081.02	Logistics Analysts	0.1626
13-1151.00	Training and Development Specialists	0.0862
13-2052.00	Personal Financial Advisors	0.1168
17-1011.00	Architects, Except Landscape and Naval	0.2683
17-1012.00	Landscape Architects	0.2601
17-2011.00	Aerospace Engineers	0.4607
17-2031.00	Bioengineers and Biomedical Engineers	0.3255
17-2051.00	Civil Engineers	0.4516
17-2051.01	Transportation Engineers	0.1794
17-2071.00	Electrical Engineers	0.1607
17-2072.00	Electronics Engineers, Except Computer	0.1967
17-2081.00	Environmental Engineers	1
17-2141.00	Mechanical Engineers	0.2774
17-2141.01	Fuel Cell Engineers	1
17-2141.02	Automotive Engineers	0.2979
17-2161.00	Nuclear Engineers	0.3308
17-2199.03	Energy Engineers, Except Wind and Solar	0.9526
17-2199.05	Mechatronics Engineers	0.1149
17-2199.06	Microsystems Engineers	0.1935
17-2199.07	Photonics Engineers	0.1174
17-2199.08	Robotics Engineers	0.0615
17-2199.09	Nanosystems Engineers	0.3014
17-3023.00	Electrical and Electronic Engineering Technologists and Technicians	0.2125
17-3024.00	Electro-Mechanical and Mechatronics Technologists and Technicians	0.2235
17-3024.01	Robotics Technicians	0.0687
17-3025.00	Environmental Engineering Technologists and Technicians	1
17-3026.00	Industrial Engineering Technologists and Technicians	0.1912
17-3027.00	Mechanical Engineering Technologists and Technicians	0.1249
17-3027.01	Automotive Engineering Technicians	0.2777
19-1013.00	Soil and Plant Scientists	0.6218
19-1031.00	Conservation Scientists	1
19-2021.00	Atmospheric and Space Scientists	0.4624
19-2041.01	Climate Change Policy Analysts	1
19-2041.02	Environmental Restoration Planners	1
19-2041.03	Industrial Ecologists	1
19-2099.01	Remote Sensing Scientists and Technologists	0.0716
19-3011.01	Environmental Economists	1
19-3051.00	Urban and Regional Planners	0.3604
19-3099.01	Transportation Planners	0.1259
19-4051.00	Nuclear Technicians	0.3837101
19-4099.03	Remote Sensing Technicians	0.1156
23-1022.00	Arbitrators, Mediators, and Conciliators	0.0283
27-3031.00	Public Relations Specialists	0.21
	Green 'other' occupations (LS):	Greenness
41-3031.00	Securities, Commodities, and Financial Services Sales Agents	0.2993
41-4011.00	Sales Representatives, Wholesale and Manufacturing, Technical and Scientific Products	0.1125
43-5011.01	Freight Forwarders	0.1686
43-5071.00	Shipping, Receiving, and Inventory Clerks	0.0734
47-2061.00	Construction Laborers	0.1585
47-2152.00	Plumbers, Pipefitters, and Steamfitters	0.2412

SOC code	Occupation title	
47-2181.00	Roofers	0.3009
47-2211.00	Sheet Metal Workers	0.2141
47-4011.00	Construction and Building Inspectors	0.2642
47-4041.00	Hazardous Materials Removal Workers	1
49-3023.00	Automotive Service Technicians and Mechanics	0.4401
49-3031.00	Bus and Truck Mechanics and Diesel Engine Specialists	0.1508
49-9021.00	Heating, Air Conditioning, and Refrigeration Mechanics and Installers	0.1315
49-9071.00	Maintenance and Repair Workers, General	0.1348
49-9099.01	Geothermal Technicians	1
51-2011.00	Aircraft Structure, Surfaces, Rigging, and Systems Assemblers	0.1295
51-4041.00	Machinists	0.0658
51-8011.00	Nuclear Power Reactor Operators	0.2752
51-8099.01	Biofuels Processing Technicians	1
51-9061.00	Inspectors, Testers, Sorters, Samplers, and Weighers	0.0584
53-3032.00	Heavy and Tractor-Trailer Truck Drivers	0.0856
53-6051.07	Transportation Vehicle, Equipment and Systems Inspectors, Except Aviation	0.4355
53-7081.00	Refuse and Recyclable Material Collectors	1

ii. Brown occupations

The brown ‘fossil fuel’ and brown ‘other’ jobs summarized in Table 1 are identified based on the relevance of their occupational employment in specific selected industries. Brown ‘fossil fuel’ jobs are occupations that are specifically employed in fossil-fuel related industries, according to BLS-OES data for 2019. Fossil-fuel related industries are Oil and Gas Extraction (NAICS 2111), Coal Mining (NAICS 2121), Support Activities for Mining (NAICS 2131), Fossil Fuel Electric Power Generation (NAICS 221112), Petroleum and Coal Products Manufacturing (NAICS 3241), and Pipeline Transportation of Crude Oil (NAICS 4861). We rank occupations based on the share of total occupational employment that is employed in these fossil-fuel related industries and select as brown ‘fossil’ jobs the ones contributing to at least 1/3 of the total employment in these industries. For brown ‘other’ jobs, we rely on the definition used in Vona et al. (2018), where a similar approach was used but considering the exposure of sectors to air pollution regulations.[1]

[1] The occupations for which an overlap was found between the two definitions were identified as brown ‘fossil fuel’. Similarly, occupations overlapping between green and brown were included as brown jobs.

Table A5 -- Wages, training and skill requirement of Green Renewable Occupations in details

O*NET SOC Code	Occupation Title	Hourly wage (BLS)	Required on-the-job training (months)	GGS: engineering & technical	GGS: operation management	GGS: science	GGS: monitoring
17-2199.10	Wind Energy Engineers	49.26	15.66	0.71	0.64	0.48	0.60
17-2199.11	Solar Energy Systems Engineers	49.26	11.55	0.68	0.57	0.32	0.59
41-4011.07	Solar Sales Representatives and Assessors	44.70	5.13	0.55	0.54	0.25	0.49
47-1011.03	Solar Energy Installation Managers	34.35	16.40	0.75	0.56	0.26	0.53
47-2231.00	Solar Photovoltaic Installers	22.52	8.45	0.64	0.49	0.20	0.51
49-9081.00	Wind Turbine Service Technicians	27.26	9.24	0.60	0.53	0.38	0.51

Notes: data from O*NET 25.3, except hourly wages (from OES-BLS). High-skilled workers on top, low-skilled workers below the dashed line. Data refer to year 2019.

Table A6 -- Wages, training and skill requirement of Brown 'Fossil Fuel' Occupations in details

O*NET SOC Code	Occupation Title	Hourly wage (BLS)	Required on-the-job training (months)	GGS: engineering & technical	GGS: operation management	GGS: science	GGS: monitoring
17-2151	Mining and Geological Engineers	46.63	25.38	0.59	0.71	0.38	0.63
17-2171	Petroleum Engineers	75.37	21.71	0.53	0.71	0.41	0.57
47-5011	Derrick Operators, Oil and Gas	23.09	4.91	0.38	0.38	0.24	0.38
47-5012	Rotary Drill Operators, Oil and Gas	27.44	32.18	0.43	0.41	0.22	0.48
47-5013	Service Unit Operators, Oil and Gas	24.71	7.14	0.56	0.53	0.30	0.43
47-5041	Continuous Mining Machine Operators	27.18	6.48	0.45	0.39	0.20	0.62
47-5043	Roof Bolters, Mining	28.63	3.83	0.39	0.42	0.12	0.55
47-5044	Loading and Moving Machine Operators	25.83	12.12	0.39	0.16	0.17	0.46
47-5071	Roustabouts, Oil and Gas	19.85	3.37	0.37	0.31	0.30	0.42
47-5081	Helpers--Extraction Workers	18.46	3.53	0.49	0.42	0.25	0.57
51-8092	Gas Plant Operators	34.16	13.81	0.40	0.40	0.27	0.49
51-8093	Petroleum Pump System Operators	35.49	10.51	0.38	0.50	0.19	0.47
53-7072	Pump Operators, Except Wellhead Pumpers	23.61	7.08	0.40	0.40	0.20	0.60
53-7073	Wellhead Pumpers	26.48	9.36	0.45	0.38	0.28	0.51

Notes: data from O*NET 25.3, except hourly wages (from OES-BLS). High-skilled workers on top, low-skilled workers below the dashed line. Data refer to year 2019.

iii. Green General Skills

Using O*NET data on the importance of general skills to each occupation, Vona et al. (2018) identify a set of *green general skills* (GGS, hereafter "green skills") that are potentially used in all occupations, but are particularly important for occupations with high greenness. They aggregate this set of selected green skills into 4 macro-groups: Engineering and Technical, Operation Management, Monitoring, and Science.[2] Tables A5 and A6 present details of the descriptive data shown in Table 1 for each brown fossil and green energy job.

To assess the existing base of green skills in each commuting zone, for all 450 SOC-based occupations we compute for years 2000 (Decennial Census) and 2005 (ACS) the average importance score of Green General Skills (GGS, see Vona et al., 2018) using data on tasks and skills from the O*NET (Occupational Information Network) database (version: 18.0). Then, using the distribution (weighted by hours worked) of green skills across different (450) occupations in 2000 (IPUMS 5% sample of the Decennial Census), we identify the occupations with green skills importance in the 75th percentile or higher across all US workers. This includes 113 occupations, which are listed in Table A7. Consistent with the types of skills included in Green General Skills, these occupations include many scientific and engineering occupations. However, not all jobs using Green General Skills are "green jobs." Green General Skills are also important in occupations such as physicians, mining machine operators, and some transportation workers. The key point is that workers in these jobs have the skills necessary to do the work required of green occupations. We compute the local green skills base in each commuting zone using microdata

[2] These four macro groups contain the following skills represented in the O*NET database: **GGS engineering & technical** – engineering and technology (2C3b); design (2C3c); building and construction (2C3d); mechanical (2C3e); drafting, laying out, and specifying technical devices, parts, and equipment (4A3b2); estimating the quantifiable characteristics of products, events, or information (4A1b3);**GGS operation management** – systems analysis (2B4g); systems evaluation (2B4h); updating and using relevant knowledge (4A2b3); provide consultation and advice to others (4A4b6); **GGS monitoring** – law and government (2C8b); evaluating information to determine compliance with standards (4A2a3); **GGS science** – physics (2C4b); biology (2C4d).

from the annual American Community Survey (ACS, years 2005-2017, 1% sample of the US population) from IPUMS. For each commuting zone and year, we calculate the share of total employees (weighted by sampling weights and annual hours worked) in jobs at the top quartile of green skills importance.

Table A7 -- List of occupations in the top quartile of GGS (definitions for SOC codes can be found at https://usa.ipums.org/usa-action/variables/OCCSOC#codes_section)

SOC code	Occupation title
111021	General and Operations Managers
1110XX	Chief Executives and Legislators
113021	Computer and Information Systems Managers
113051	Industrial Production Managers
113061	Purchasing Managers
119013	Farmers, Ranchers, and Other Agricultural Managers
119021	Constructions Managers
119030	Education Administrators
119041	Engineering Managers
119081	Lodging Managers
119111	Medical and Health Services Managers
119121	Natural Science Managers
119151	Social and Community Service Managers
119199	Managers, All Other
119XXX	Miscellaneous Managers, Including Funeral Service Managers and Postmasters and Mail Superintendents
131021	Buyers and Purchasing Agents, Farm Products
131023	Purchasing Agents, Except Wholesale, Retail, and Farm Products
131041	Compliance Officers, Except Agriculture, Construction, Health and Safety, and Transportation
131051	Cost Estimators
131081	Logisticians
131111	Management Analysts
132021	Appraisers and Assessors of Real Estate
132099	Financial Specialists, All Other
151111	Computer And Information Research Scientists
151121	Computer Systems Analysts
151122	Information Security Analysts
151143	Computer Network Architects
151199	Computer Occupations, All Other
152011	Actuaries
171010	Architects, Except Naval
171020	Surveyors, Cartographers, and Photogrammetrists
172011	Aerospace Engineers
172041	Chemical Engineers
172051	Civil Engineers
172061	Computer Hardware Engineers
172070	Electrical and Electronics Engineers
172081	Environmental Engineers
1720XX	Biomedical and Agricultural Engineers
172110	Industrial Engineers, including Health and Safety
172121	Marine Engineers and Naval Architects

SOC code	Occupation title
172131	Materials Engineers
172141	Mechanical Engineers
1721XX	Petroleum, mining and geological engineers, including mining safety engineers
1721YY	Miscellaneous engineeers, including nuclear engineers
173010	Drafters
173020	Engineering Technicians, Except Drafters
173031	Surveying and Mapping Technicians
191010	Agricultural and Food Scientists
191020	Biological Scientists
191030	Conservation Scientists and Foresters
1910XX	Medical Scientists, and Life Scientists, All Other
192010	Astronomers and Physicists
192021	Atmospheric and Space Scientists
192030	Chemists and Materials Scientists
192040	Environmental Scientists and Geoscientists
192099	Physical Scientists, All Other
193051	Urban and Regional Planners
1930XX	Miscellaneous social scientists including sociologists
194011	Agricultural And Food Science Technicians
194021	Biological Technicians
194031	Chemical Technicians
1940YY	Miscellaneous Life, Physical, and Social Science Technicians, Including Social Science Research Assistants
2310XX	Lawyers, and judges, magistrates, and other judicial workers
2590XX	Other Education, Training, and Library Workers
291011	Chiropractors
291020	Dentists
291031	Dieticians and Nutritionists
291041	Optometrists
291051	Pharmacists
291060	Physicians and Surgeons
291071	Physician Assistants
291081	Podiatrists
291123	Physical Therapists
291124	Radiation Therapists
291126	Respiratory Therapists
29112X	Other Therapists, Including Exercise Physiologists
291131	Veterinarians
291181	Audiologists
292010	Clinical Laboratory Technologists and Technicians
292021	Dental Hygienists
292030	Diagnostic Related Technologists and Technicians
292041	Emergency Medical Technicians and Paramedics
292061	Licensed Practical and Licensed Vocational Nurses
292081	Opticians, Dispensing
299000	Other Healthcare Practitioners and Technical Occupations
331012	First-Line Supervisors of Police and Detectives
331021	First-Line Supervisors of Fire Fighting and Prevention Workers
331099	First-Line Supervisors of Protective Service Workers, All Other
332011	Firefighters
332020	Fire Inspectors
333021	Detectives and Criminal Investigators
333050	Police Officers
371012	First-Line Supervisors of Landscaping, Lawn Service, and Groundskeeping Workers
372021	Pest Control Workers
419031	Sales Engineers
451011	First-Line Supervisors of farming, fishing, and forestry workers

SOC code	Occupation title
452011	Agricultural Inspectors
454011	Forest and Conservation Workers
471011	First-Line Supervisors of Construction Trades and Extraction Workers
472011	Boilermakers
472050	Cement Masons, Concrete Finishers, and Terrazzo Workers
472111	Electricians
472150	Pipelayers, Plumbers, Pipefitters, and Steamfitters
472211	Sheet Metal Workers
472XXX	Structural Iron and Steel Workers
474011	Construction and Building Inspectors
474021	Elevator Installers and Repairers
474041	Hazardous Materials Removal Workers
474051	Highway Maintenance Workers
475031	Explosives Workers, Ordnance Handling Experts, and Blasters
475040	Mining Machine Operators
4750XX	Other extraction workers
47XXXX	Miscellaneous construction workers including solar Photovaltaic Installers, and septic tank servicers and sewer pipe cleaners
491011	First-Line Supervisors of Mechanics, Installers, and Repairers
492020	Radio and Telecommunications Equipment Installers and Repairers
492091	Avionics Technicians
492096	Electronic Equipment Installers and Repairers, Motor Vehicles
492097	Electronic Home Entertainment Equipment Installers and Repairers
49209X	Electrical and electronics repairers, industrial and utility
493011	Aircraft Mechanics and Service Technicians
493023	Automotive Service Technicians and Mechanics
493031	Bus and Truck Mechanics and Diesel Engine Specialists
499021	Heating, Air Conditioning, and Refrigeration Mechanics and Installers
499043	Maintenance Workers, Machinery
499044	Millwrights
49904X	Industrial and Refractory Machinery Mechanic
499051	Electrical Power-Line Installers and Repairers
499060	Precision Instrument and Equipment Repairers
499094	Locksmiths and Safe Repairers
49909X	Other Installation, Maintenance, and Repair Workers
514010	Computer Control Programmers and Operators
514111	Tool and Die Makers
518010	Power Plant Operators, Distributors, and Dispatchers
518021	Stationary Engineers and Boiler Operators
518031	Water and Wastewater Treatment Plant and System Operators
518090	Miscellaneous Plant and System Operators
532010	Aircraft Pilots and Flight Engineers
536051	Transportation Inspectors
5360XX	Other transportation workers
537070	Pumping Station Operators
5370XX	Conveyor operators and tenders, and hoist and winch operators
537XXX	Miscellaneous material moving workers including shuttle car operators, and tank car, truck, and ship loaders

iv. Dependent variables: employment

Our main dependent variable is the change in various measures of employment per capita (using population in 2008) compared to the base year 2008. Data on average annual employment level by county is retrieved from the BLS-QCEW (Quarterly Census of Employment and Wages of the Bureau of Labor Statistics), which reports average annual employment by US county and by industry. County-level data are then aggregated up at the CZ level. We also use BLS-QCEW to estimate employment by industry (Table 3 and Appendix Table B11). In all regressions, we account for the base-year (2008) level of CZ employment per capita by industry as well as the growth in CZ employment per capita (population in 2008) by industry and total over the period 2000-2007 (pre-trends).

Data on occupations and skills are based on microdata from the Decennial Census (5% sample, year 2000) and the American Community Survey (ACS, 1% sample of the US population, years 2005-2017) available at IPUMS (Integrated Public Use Microdata Series, Ruggles et al., 2020). We just consider working-age (16-64) employed persons. We allocate worker-level information to CZs based on the worker's place of work (county place of work: 59.2% of workers; PUMA place of work: 32.5% of workers) and, when not available, county of residence (8.3% of workers). Based on the definition of commuting zone, most of these residual workers should be employed within the same CZ where they reside.

Occupational groups (Table 3 and Appendix Table B12) are identified following the definition provided by Acemoglu and Autor (2011). The list of SOC occupations (ACS definition) by each macro occupational group is reported in Table A8. Similarly to the measure of greenness, we compute the share of hours worked (weighted by sampling weights) by employees in each macro-occupational group and CZ over the total hours worked in the CZ using data from IPUMS-ACS. The number of employees by occupational group is then computed as the product between the share of hours worked in CZ and the total number of employees (BLS-QCEW).

In our focus on manual occupations (Table 4), we identify sub-categories of manual workers based on data from IPUMS-ACS. We compute the hourly wage (column 1) as the ratio between total wages received and total annual hours worked. In column 2 and 3 we use, respectively, the share of manual workers with hourly wage above or below US-median hourly wage in the US. Finally, in columns 4 and 5 we consider the educational attainment of manual workers using information on educational attainment from IPUMS-ACS: we define manual workers with high school degree or more as those manual workers that completed at least the 12th grade. Table A9 provides descriptive statistics on our dependent variables.

Table A8 – Macro-occupational groups based on Acemoglu and Autor (2011) (definitions for SOC codes can be found at https://usa.ipums.org/usa-action/variables/OCCSOC#codes_section)

Macro-occupational group	SOC codes
Abstract occupations	111021, 1110XX, 112011, 112020, 112031, 113011, 113021, 113031, 113040, 113051, 113061, 119013, 119021, 119030, 119041, 119051, 119071, 119081, 119111, 119121, 119141, 119151, 119199, 119XXX, 131011, 131021, 131022, 131023, 131041, 131051, 131070, 131081, 131111, 131121, 131XXX, 132011, 132031, 132041, 132051, 132052, 132053, 132061, 132070, 132081, 132082, 132099, 151111, 151121, 151122, 151131, 151134, 15113X, 151141, 151142, 151143, 151150, 151199, 152011, 152031, 1520XX, 171010, 171020, 172011, 172041, 172051, 172061, 172070, 172081 ,1720XX, 172110, 172121, 172131, 172141, 1721XX, 1721YY, 173010, 173020, 173031, 191010, 191020, 191030, 1910XX, 192010, 192021, 192030, 192040, 192099, 193011, 193030, 193051, 1930XX, 194011, 194021, 194031, 1940YY, 2310XX, 232011, 232090, 251000, 252010, 252020, 252030, 252050, 253000, 254010, 254021, 259041, 2590XX, 271010, 271020, 272011, 272012, 272020, 272030, 272040, 272099, 273010, 273020, 273031, 273041, 273042, 273043, 273090, 274021, 274030, 2740XX, 291011, 291020, 291031, 291041, 291051, 291060, 291071, 291081, 291122, 291123, 291124, 291125, 291126, 291127, 29112X, 291131, 291181, 291199, 292010, 292021, 292030, 292041, 292050, 292061, 292071, 292081, 292090, 299000, 312010, 312020, 33909X, 391010, 519080, 532010, 532020
Manual occupations	471011, 472011, 472031, 472040, 472050, 472061, 472071, 47207X, 472080, 472111, 472121, 472130, 472140, 472150, 472161, 472181, 472211, 472XXX, 473010, 474011, 474021, 474031, 474041, 474051, 474061, 475021, 475031, 475040, 4750XX, 4750YY, 47XXXX, 491011, 492011, 492020, 492091, 492092, 492096, 492097, 492098, 49209X, 493011, 493021, 493022, 493023, 493031, 493040, 493050, 493090, 499010, 499021, 499031, 499043, 499044, 49904X, 499051, 499052, 499060, 499071, 499091, 499094, 499096, 499098, 49909X, 511011, 512011, 512020, 512031, 512041, 512090, 513011, 513020, 513091, 513092, 513093, 514010, 514021, 514022, 514023, 514030, 514041, 514050, 5140XX, 514111, 514120, 514XXX, 515111, 515112, 515113, 516011, 516021, 516031, 516040, 516050, 516063, 516064, 51606X, 516093, 51609X, 517011, 517021, 517041, 517042, 5170XX, 518010, 518021, 518031, 518090, 519010, 519020, 519030, 519041, 519051, 519061, 519071, 519111, 519120, 519151, 519191, 519194, 519195, 519196, 519197, 519198, 5191XX, 531000, 533011, 533020, 533030, 533041, 5330XX, 534010, 534031, 5340XX, 535020, 5350XX, 536021, 536031, 5360XX, 537021, 537030, 537051, 537061, 537062, 537063, 537064, 537070, 537081, 5370XX
Service occupations	211010, 211020, 21109X, 212011, 212021, 212099, 311010, 319011, 319091, 31909X, 331011, 331012, 331021, 331099, 332011, 332020, 333010, 333021, 333050, 3330XX, 339011, 339021, 339030, 339091, 33909X, 351011, 351012, 352010, 352021, 353011, 353021, 353022, 353031, 353041, 359021, 359031, 3590XX, 371011, 371012, 372012, 37201X, 372021, 373010, 391021, 392021, 393010, 393021, 393031, 393090, 394000, 395011, 395012, 395090, 396010, 396030, 397010, 399011, 399021, 399030, 399041, 399099, 536051, 537XXX
Clerical occupations	113071, 131030, 132021, 254031, 411011, 411012, 412010, 412021, 412022, 412031, 413011, 413021, 413031, 413041, 413099, 414010, 419010, 419020, 419031, 419041, 419091, 419099, 431011, 432011, 432021, 432099, 433011, 433021, 433031, 433041, 433051, 433061, 433071, 434011, 434031, 434041, 434051, 434061, 434071, 434081, 434111, 434121, 434131, 434141, 434161, 434171, 434181, 434199, 434XXX, 435011, 435021, 435030, 435041, 435051, 435052, 435053, 435061, 435071, 435081, 435111, 436010, 439011, 439021, 439022, 439041, 439051, 439061, 439071, 439081, 439111, 439XXX

Table A9 – Descriptive statistics of dependent variables

Variable	mean	s.d.	min	median	max
Total employment / pop	0.4239	0.0658	0.0141	0.431	0.9562
Employment in abstract occ / pop	0.1549	0.0419	0.0038	0.1536	0.3265
Employment in manual occ / pop	0.0957	0.0226	0.0032	0.0938	0.348
Employment in service occ / pop	0.0717	0.0125	0.0021	0.0717	0.1543
Employment in clerical occ / pop	0.1024	0.0186	0.0029	0.1043	0.1734
Green employment / pop	0.020	0.0047	0.0007	0.0201	0.0557
Green renewable energy employment / pop	0.0056	0.0016	0.0001	0.0056	0.0276
Employment in manufacturing / pop	0.0436	0.0236	0.0003	0.0399	0.2152
Employment in construction / pop	0.0206	0.0067	0.0004	0.0198	0.0982
Employment in public administration/pop	0.0217	0.0114	0.0001	0.0195	0.1828
Employment in waste management / pop	0.0245	0.0092	0	0.0252	0.1262
Average h. wage of manual workers	18.39	3.11	10.09	18.21	102.96
Manual workers with h wage > US-median for manual / pop	0.0533	0.0138	0.0015	0.0523	0.238
Manual workers with h wage < US-median for manual / pop	0.0425	0.0131	0.0014	0.0412	0.1227
Manual workers with > high school degree / pop	0.0277	0.0073	0.0007	0.0269	0.1352
Manual workers with high school degree or less / pop	0.068	0.0179	0.0023	0.066	0.2128

Notes: data by commuting zone includes only CZ with at least 25000 inhabitants. Statistics weighted by population in 2008.

v. Control variables

In addition to initial levels of employment for the various categories described above, data for the control variables in our regressions come from the following sources.

Data on unemployed persons is obtained from the BLS-LAUS Local Unemployment Statistics database while data on county-level population and personal income per capita is retrieved from the database maintained by the Bureau of Economic Analysis.

To calculate import penetration, we begin with data at the US-level. We compute sector-specific (4-digit NAICS) import penetration as the ratio between total import of manufactured products of each sector and total 'domestic use' of products of the same sector (import + domestic output – export). Data on import and export by sector are retrieved from Schott (2008), while domestic output is retrieved from the NBER-CES database. We then estimate CZ-level import penetration as the weighted average of sector-specific (4-digit NAICS) national import penetration, using employment by CZ and 4-digit NAICS sector as weights (source: County Business Patterns database).

To account for the presence of shale gas extraction, we obtained geospatial data on shale gas and oil play boundaries from the US Energy Information Administration.[3] We use GIS to compute a dummy variable equal to 1 if the CZ overlaps any of the shale oil and gas resources. Thus, the indicator represents the *potential* for shale oil or gas activity. To avoid endogeneity, we do not include actual drilling activity.

Indicators of wind and photovoltaic energy potential are based on detailed information from the National Renewable Energy Laboratory.[4] For wind, this information includes speed and variability of winds at different heights and for the presence of obstacles. For solar, this information considers the intensity and slope of solar radiation and for obstacles and terrain slope. We attribute to each CZ the average indicator of potential for wind and photovoltaic energy generation, ranging from 1 (low potential) to 7 (high potential).

We compute two dummy variables to account for the presence of local stringent environmental regulation to limit air pollution within the Clean Air Act. The dummy variable NA CAA old standard is set to one if at least 1/3 of the CZ resides in counties that were designed as nonattainment according to National Ambient Air Quality Standards (NAAQS) set in the pre-sample period: carbon oxide (1971), lead (1978), NO2 (1971), ozone (1979; 1997), particulate matter <10 micron (1987), particulate matter <2.5 micron (1997), SO2 (1971). The dummy variable NA CAA new standards, instead, considers recently approved more stringent NAAQS: lead (2008), ozone (2008), particulate matter <2.5 micron (2006), SO2 (2010).

Finally, we manually detect the presence of Federal R&D laboratories and state capitals in each CZ and create two dummy variables.

---

[3] https://www.eia.gov/maps/maps.htm, last accessed May 27, 2020.
[4] https://www.nrel.gov/gis/index.html, last accessed May 27, 2020.

Table A10 reports descriptive statistics, weighted by population in 2008, for all our control variables.

Table A10 – Descriptive statistics of control variables

Variable	mean	s.d.	min	median	max
Share of empl with GGS>p75 (year 2006)	0.254	0.027	0.173	0.253	0.372
Population 2008 (log)	14.197	1.423	10.136	14.377	16.685
Income per capita (2005)	38.149	8.067	18.229	37.815	77.863
Import penetration (year 2005)	0.008	0.005	0.001	0.006	0.051
Pre trend (2000-2007) employment tot / pop	-0.01	0.02	-0.092	-0.01	0.112
Pre trend (2000-2007) empl manufacturing / pop	-0.015	0.01	-0.09	-0.015	0.031
Pre trend (2000-2007) empl constr / pop	0.002	0.004	-0.013	0.001	0.027
Pre trend (2000-2007) empl extractive / pop	0.001	0.003	-0.009	0	0.101
Pre trend (2000-2007) empl public sect / pop	0	0.004	-0.046	0	0.057
Pre trend (2000-2007) unempl / pop	0.003	0.005	-0.016	0.003	0.021
Pre trend (2000-2007) empl edu health / pop	0.012	0.01	-0.039	0.011	0.068
Empl total (average 2006-2008) / pop	0.430	0.060	0.016	0.436	0.614
Empl manuf (average 2006-2008) / pop	0.045	0.023	0	0.044	0.173
Empl constr (average 2006-2008) / pop	0.023	0.007	0.001	0.022	0.088
Empl extractive (average 2006-2008) / pop	0.002	0.006	0	0	0.148
Empl public sect (average 2006-2008) / pop	0.022	0.011	0	0.02	0.138
Empl edu health (average 2006-2008) / pop	0.072	0.022	0.001	0.071	0.169
Unempl (average 2006-2008) / pop	0.025	0.005	0.001	0.025	0.071
Shale gas extraction in CZ	0.343	0.475	0	0	1
Potential for wind energy	1.62	0.639	1	2	5
Potential for photovoltaic energy	5.083	0.832	4	5	7
Federal R&D lab	0.258	0.438	0	0	1
CZ hosts the state capital	0.222	0.415	0	0	1
Nonattainment CAA old standards	0.694	0.461	0	1	1
Nonattainment CAA new standards	0.365	0.481	0	0	1

Notes: data by commuting zone includes only CZ with at least 25000 inhabitants. Statistics weighted by population in 2008.

Appendix B – Supplementary Results and Robustness Checks

In this Appendix we present some supplementary results and a series of robustness checks that address critical aspects of our identification strategy or our definition of green ARRA. First, Table B1 shows the drivers of the allocation of green ARRA spending. As noted in the main text, the results in this table highlight potential sources of endogeneity in the allocation of green ARRA across commuting zones.

Tables B2 to B10 present additional results and robustness checks for the main regressions in section V. For each set of robustness checks, we present results using both state or Census region fixed effects. When our robustness checks change the set of commuting zones included or definition of non-green ARRA, we also recalculate the vigintiles of non-green ARRA. To allow each set of tables to fit on a single page, we omit coefficient estimates and instead present just the calculations for jobs created per $1 million green ARRA.

Table B2 justifies our use of a log-log model, as it handles outliers in green ARRA spending better than a linear model. While much of the existing literature evaluating ARRA spending uses models in levels, the distribution of green ARRA is particularly skewed. According to our data, the skewness (kurtosis) of non-green ARRA per capita in levels is 4.24 (35.06), while the skewness (kurtosis) of green ARRA per capita in levels is 16.46 (415.5).[5] In columns 1 and 4 we present models with all variables in levels for all CZs with at least 25000 inhabitants. This corresponds to the sample in Table 2 of the main text. With a linear model, the results are very noisy, with very small coefficients and large standard errors. However, a careful inspection of the variable on green ARRA identifies several outliers. While the mean (median) green ARRA per

[5] These statistics are calculated on the subset of commuting zones with at least 25000 inhabitants and are weighted for population in 2008.

capita is \$162 (\$99 per capita median), seven CZs with a level of green ARRA per capita greater than \$2000. However, if we exclude these seven outliers (columns 3 and 6) the estimated jobs created are very similar to the ones shown in Table 2. In contrast, the log-log model is not sensitive to the effect outliers, as shown in columns 5 and 6. Here, excluding these seven outliers from the log-log estimation leads to results that are almost identical to Table 2. The log transformation is thus very effective in mitigating the risk that outliers drive our results.

Next, Table B3 shows detailed results of the estimation interacting green skills with green ARRA, presented in Figure 3 in the main text. Of particular note here is that, not only are the interactions statistically significant, but so are the levels of the initial share of occupations in the upper quartile of GGS importance themselves, and this effect is trending upward over time. Indeed, in the most conservative specification with state fixed effects, a one standard deviation in the green skills share (0.027) accounts for a 1.1% difference in employment growth in the early pre-crisis period that increases up to 2.0% in the short-term and 2.3% in the long-run (although with a p-value of 0.101).[6] Recall from Table B1 that the initial share of occupations in the upper quartile of GGS importance is also strongly correlated with the allocation of green ARRA subsidies. In combination, these results reinforce our interpretation of the green stimulus as a successful example of picking the winners.

Table B4 presents the falsification test using the initial income per capita rather than green skills as mediating factor of the green ARRA effect. The interaction is never significant, and the estimates of jobs created hardly vary across different income levels. This rules out the possibility that the mediating effect of green competences is capturing unobserved demand factors associated

[6] With regional fixed effects, the acceleration is much more pronounced: a standard deviation in the share of green skills explains only 1.4% difference in employment growth in the early pre-crisis period, while it accounts for a differential employment growth of 3.3% in the short-run and 4.1% in the long-run (p-value = 0.013).

with the preferences of the local population, such as non-homothetic preferences for green goods and services.

Tables B5 and B6 consider the importance of particular observations that potentially drive our results. Column (1) repeats the results from Table 2 in the text. In column (2) we drop observations from 2009. While ARRA spending was announced in 2009, much of the money was not allocated until 2010 (Wilson, 2012). Thus, including 2009 in our data may artificially reduce the short-run estimates of job creation. Although we see slightly larger short-run estimates of job creation for total and manual employment when excluding data from 2009, the differences are small. In column (3) we exclude commuting zones in the highest and lowest vigintiles of non-green ARRA spending, as the standard deviation in per capita non-green ARRA is much higher for these two groups, and again observe only small changes in the results. Column (4) excludes commuting zones hosting federal R&D laboratories, which was a key covariate with unbalanced characteristics in Table B1, leading to just slightly larger long-run estimates of green employment. Finally, in column (5) we show that our results are robust to including small commuting zones (e.g. < 25,000 residents).

Continuing our check of the robustness of our results, Tables B7 and B8 re-run our results using different groupings of non-ARRA spending. In addition to the vigintiles used in the main text (column 4), we consider quintiles of non-green ARRA (column 1), deciles of non-green ARRA (column 2) or 15 groups of non-ARRA spending (column 3). Our results are not sensitive to the choice of groupings and the estimates of jobs created are nearly identical in all columns.

Tables B9 and B10 consider alternative definitions of our ARRA variables, seeking to understand which type of green spending is most effective in stimulating job creation. Column (1) repeats the results from Tables 2 and 3 in the text. In column (2) we add spending on the four

Department of Labor training programs mentioned in footnote 8, which provided training for energy efficiency and renewable energy jobs. The four programs are Pathways Out of Poverty, the Energy Training Partnership, Green Capacity Building Grants, and the State Energy Sector Partnership. A total of $496 million was spent on these four programs. Consistently with the fact that green training programs were small, we do not observe notable differences in our estimated coefficients.

Roughly ten percent of green ARRA supported R&D efforts, primarily for clean energy. One might expect such investments to have little job creation impact as energy R&D usually takes long to become commercially viable (Popp 2016). Consistent with that, our estimates of jobs created slightly increase in the long-run when dropping green R&D from the ARRA data (column 3), except for construction employment. However, the short-run results remain similar. Overall, the expected slow job creation of R&D spending does not clearly emerge with our data, but again detecting significant differences for small variation in green spending is difficult in our empirical setup.

Our ARRA data includes three types of support: grants, contracts, and loans. In column 4 we remove funds for the Department of Energy Loan Guarantee Program. This program supported 23 clean energy projects with loans totaling $7.9 billion – over 18% of all DOE ARRA investments. Most were for solar or wind (including the controversial loan to Solyndra), although other projects such as energy storage and biomass were also granted loans through this program. Because these loans required payback from the private sector, including such loans could cause our estimates to underestimate the effectiveness of public sector investments. Nearly 2 years after funds were first allocated, the DOE had closed on only 8 of the projects eventually funded. Consistent with these arguments, the effect of green ARRA on employment is slightly larger for manual employment, but not for total or green employment. For total employment higher estimated long-run coefficients are offset by higher pre-trends with Census division fixed effects, while with state fixed effects we do not observe a detectable increase of the long-term effect..

In column (5) we drop all ARRA loans, including those from other agencies, so that we are comparing similar types of spending across all agencies. This leads us to re-calculate the vigintiles of non-green ARRA to reflect the different data. Loans were less important for other agencies, with just 2.2 percent of non-green ARRA granted as loans. Thus, not surprisingly, results are similar to omitting the DOE Loan Guarantee program only. For green jobs our definition of green ARRA is conservative. If we exclude R&D spending and/or loans and contracts, which are more likely to support large infrastructure projects (leaving only grants), we obtain statistically significant estimates of up to 3.8 green jobs created in the long-run.

In column (6) we omit contracts from the ARRA data. Just 17 percent of green ARRA and 15 percent of non-green ARRA was awarded as contracts. While many green ARRA contracts were for green services, such as EPA contracts for remediating hazardous waste, some contracts are for administrative work, such as program evaluation and support, that might not be considered green. Consistent with these tasks not being green, in our preferred specification with state fixed effects, removing contracts leads to larger long-run estimates of green jobs created, and little change for other occupations. Finally, only including ARRA grants (e.g., omitting both loans and contracts, column 7) slightly increase the short-term effect for total and manual employment and long-run green employment. Overall, while some differences emerge in exploring the effect of different types of green ARRA spending, the small size of total green spending makes it difficult to definitively identify advantages of one type of spending over the other.

Table B11 and Table B12 report the results for alternative sectors and occupations, respectively. As noted in the text, the reshaping effect of green spending is not observable for other sectors (Table B11) or occupations (Table B12). Table B11 suggests gross job creation in manufacturing, but the presence of pre-trend does not allow to reach firm conclusion regarding a sort of green reindustrialization induced by green spending. Figure B1 plots the year-by-year effects for our main occupations using Census region fixed effects. The time paths are similar, but the estimates are less precise. Figure B2 shows the year-by-year results referenced in the main text for the four occupation groups: manual, abstract, clerical, and service. In both Table B12 and Figure B2, we observe a detectable pre-trend for abstract and clerical occupations, but neither occupation group experiences long-run employment gains. As discussed in the main text, this result provides suggestive evidence to the lack of persistence of the pre-trends.

Table B13 presents our final supplementary result. This table shows the relationship between different community characteristics and green skills. The results are expected from the analysis of the drivers of green spending of Table B1. The commuting zones with more employment in GGS-intensive occupations are wealthier, less populated, with lower unemployment rates and are more likely to host a federal R&D lab. Quite interesting, these communities are not "greener". Indeed, they have a higher share of employment in the extraction section and lower solar energy potential. This finding suggests that, on average, the skill base of fossil-fuel regions is ready to be used in greener activities, although Figure 5 in the main text highlights a substantial heterogeneity across communities.

Table B1 – Drivers of green ARRA

Dep var: Green (EPA+DoE) ARRA per capita (in log)	(1)	(2)	(3)	(4)
Share of empl with GGS>p75 (year 2006)	5.859**	4.212**	5.049**	3.635*
	(2.414)	(1.974)	(2.304)	(2.002)
Population 2008 (log)	0.0700	0.0501	0.0434	0.0162
	(0.0995)	(0.0841)	(0.144)	(0.112)
Income per capita (2005)	-0.0309**	-0.0261**	-0.0141	-0.00907
	(0.0141)	(0.0129)	(0.0190)	(0.0165)
Import penetration (year 2005)	10.56	-3.447	1.915	-6.080
	(16.47)	(14.59)	(15.86)	(16.03)
Pre trend (2000-2007) employment tot / pop	1.380	2.303	0.873	3.597
	(4.661)	(4.711)	(6.839)	(6.144)
Pre trend (2000-2007) empl manufacturing / pop	-4.365	-3.987	-1.648	-3.594
	(7.918)	(7.757)	(11.06)	(10.54)
Pre trend (2000-2007) empl constr / pop	-4.301	-7.000	9.692	-4.267
	(17.38)	(16.49)	(25.69)	(23.06)
Pre trend (2000-2007) empl extractive / pop	-1.530	-1.270	-4.947	-0.0447
	(13.07)	(14.00)	(15.08)	(14.14)
Pre trend (2000-2007) empl public sect / pop	3.332	-1.960	3.866	-5.430
	(10.94)	(9.909)	(12.41)	(9.387)
Pre trend (2000-2007) unempl / pop	6.106	14.39	-6.149	7.942
	(15.74)	(13.83)	(24.46)	(22.39)
Pre trend (2000-2007) empl edu health / pop	4.963	2.579	3.617	0.0269
	(5.203)	(5.280)	(6.940)	(5.544)
Empl total 2008 / pop	4.846	3.797	5.028	3.885
	(2.908)	(2.496)	(3.509)	(2.729)
Empl manuf 2008 / pop	-2.273	2.371	0.696	4.310
	(2.838)	(3.071)	(3.168)	(3.482)
Empl constr 2008 / pop	30.90**	36.14***	25.72*	26.41**
	(12.00)	(12.59)	(13.89)	(12.81)
Empl extractive 2008 / pop	0.181	1.150	-1.672	-2.074
	(10.27)	(9.764)	(9.411)	(8.629)
Empl public sect 2008 / pop	11.06**	0.259	15.52**	5.640
	(5.126)	(4.775)	(6.223)	(5.685)
Unempl 2008 / pop	21.13	20.78	13.58	21.03
	(20.25)	(15.99)	(26.11)	(22.58)
Empl edu health 2008 / pop	-1.753	-1.858	-2.448	0.355
	(3.344)	(3.145)	(3.726)	(3.277)
Shale gas extraction in CZ	0.131	0.231	-0.0405	0.121
	(0.169)	(0.150)	(0.200)	(0.173)
Potential for wind energy	-0.0533	-0.0498	-0.103	-0.0361
	(0.113)	(0.123)	(0.151)	(0.149)
Potential for photovoltaic energy	0.0906	0.184**	-0.0241	0.147
	(0.101)	(0.0888)	(0.176)	(0.175)
Federal R&D lab	0.382*	0.241	0.343	0.169
	(0.215)	(0.163)	(0.260)	(0.208)
CZ hosts the state capital	0.207	0.186	0.115	0.0927
	(0.168)	(0.148)	(0.210)	(0.197)
Nonattainment CAA old standards	-0.0757	-0.127	-0.186	-0.184
	(0.176)	(0.157)	(0.194)	(0.187)
Nonattainment CAA new standards	0.141	0.160	0.233	0.222
	(0.153)	(0.131)	(0.207)	(0.169)
State fixed effects	Yes	Yes	No	No
US Census Division fixed effecs	No	No	Yes	Yes
Vigintiles of non-green ARRA per capita	No	Yes	No	Yes
R squared	0.336	0.402	0.381	0.446
N	587	587	587	587

Notes: OLS model weighted by CZ population in 2008. Sample: CZ with at least 25,000 residents in 2008. Standard errors clustered by state in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table B2 – Robustness checks: linear specification and outliers

Dep var: Change in employment per capita compared to 2008 Results for the log-log models reported in terms of jobs created per $1 million green ARRA	(1) Lin-lin model State fixed effects	(2) Lin-lin model Census division fixed effects	(3) Lin-lin model State fixed effects 7 outliers excluded	(4) Log-log model State fixed effects	(5) Log-log model Census division fixed effects	(6) Log-log model State fixed effects 7 outliers excluded
Total employment						
Pre-ARRA (2000-2003)	2.7000*	2.9120	1.2393	27.15***	27.65**	23.06**
	(1.5946)	(1.9535)	(3.3593)	(8.88)	(10.47)	(9.61)
Pre-ARRA (2004-2007)	1.3333**	1.1309	2.8974	18.88***	13.52**	18.72***
	(0.5928)	(0.9223)	(1.9497)	(3.95)	(5.21)	(4.40)
Short-run (2009-2012)	1.9700	2.1236	3.5619	15.3***	12.32**	14.18***
	(1.4235)	(1.3954)	(2.6528)	(4.31)	(4.62)	(4.66)
Long-run (2013-2016)	2.4449	2.3518	11.1746*	25.52***	22.26*	25.04**
	(1.9076)	(1.9556)	(6.4234)	(9.41)	(11.49)	(10.53)
R squared	0.7927	0.7233	0.7950	0.7688	0.7032	0.7713
Observations	9979	9979	9860	9979	9979	9860
Manual Labor Employment						
Pre-ARRA (2005-2007)	0.2095	0.0291	2.0982	3.97	1.56	3.71
	(0.7738)	(0.7261)	(1.8807)	(3.26)	(3.46)	(3.32)
Short-run (2009-2012)	0.9557*	1.2477**	1.9001	6.17**	6.97**	6.37**
	(0.5564)	(0.5881)	(2.0206)	(2.75)	(3.02)	(3.00)
Long-run (2013-2017)	1.8889	2.2953	10.0095**	13.4***	17.3***	14.21**
	(1.5535)	(1.5788)	(4.0180)	(4.75)	(6.27)	(5.36)
R squared	0.5353	0.4488	0.5428	0.5849	0.5035	0.5884
Observations	7044	7044	6960	7044	7044	6960
Green Employment						
Pre-ARRA (2005-2007)	0.3432	0.2748	0.2703	0.71	0.26	0.48
	(0.2640)	(0.2296)	(0.5679)	(1.08)	(1.05)	(1.05)
Short-run (2009-2012)	-0.2079*	-0.2439*	0.2348	0.65	-0.15	1.14
	(0.1195)	(0.1227)	(0.4331)	(0.98)	(1.14)	(1.09)
Long-run (2013-2017)	-0.1873	-0.2169	0.9081	2.33*	1.36	3.19**
	(0.1452)	(0.1686)	(0.6321)	(1.37)	(1.75)	(1.45)
R squared	0.4626	0.3713	0.4651	0.3864	0.2998	0.3894
Observations	7044	7044	6960	7044	7044	6960
Construction Employment						
Pre-ARRA (2005-2007)	0.0646	0.0036	-0.2462	0.71	0.22	0.94
	(0.1285)	(0.2286)	(0.4316)	(1.03)	(1.00)	(1.05)
Short-run (2009-2012)	0.1952	0.0703	-0.0849	-0.1	-0.83	-0.16
	(0.1665)	(0.1476)	(0.5460)	(1.00)	(0.82)	(1.03)
Long-run (2013-2017)	0.3506*	0.0845	0.2044	2.54**	1.07	2.21*
	(0.1832)	(0.2008)	(0.7718)	(1.15)	(1.30)	(1.17)
R squared	0.8018	0.7502	0.8025	0.7177	0.6741	0.7186
Observations	7044	7044	6960	7044	7044	6960
Renewable Energy Employment						
Pre-ARRA (2005-2007)	0.0469	0.0618	0.3195	0.03	0.12	-0.07
	(0.0655)	(0.0741)	(0.3690)	(0.69)	(0.59)	(0.77)
Short-run (2009-2012)	-0.0505	-0.0875*	-0.1825	-0.09	-0.35	-0.01
	(0.0483)	(0.0501)	(0.2837)	(0.42)	(0.43)	(0.49)
Long-run (2013-2017)	0.0333	0.0130	0.2673	1.19**	1.21**	1.25**
	(0.0831)	(0.0940)	(0.4379)	(0.56)	(0.56)	(0.59)
R squared	0.3177	0.2448	0.3189	0.2786	0.2230	0.2797
Observations	7044	7044	6960	7044	7044	6960

Notes: OLS model weighted by CZ population in 2008. Sample: CZ with at least 25,000 residents in 2008. Year fixed effects and region (state or census division) fixed effects x period fixed effects included. Additional control variables same as Table 2. Standard errors clustered by state in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Outliers of green ARRA per capita (>2000$) excluded in columns 3 and 6..

Table B3 – Interaction with initial green skills

Dep var: Change in log emp.t per capita compared to 2008	State fixed effects	Census division fixed effects
Share of empl with GGS>p75 (year 2006) x D2000_2003	0.4711	0.2634
	(0.5769)	(0.6151)
Share of empl with GGS>p75 (year 2006) x D2004_2007	0.4067**	0.5039*
	(0.1942)	(0.2627)
Share of empl with GGS>p75 (year 2006) x D2009_2012	0.7252**	1.2306***
	(0.3008)	(0.2947)
Share of empl with GGS>p75 (year 2006) x D2013_2016	0.8358	1.5266**
	(0.4994)	(0.5928)
Green ARRA per capita (log) x D2000_2003	-0.0087	-0.0084
	(0.0142)	(0.0154)
Green ARRA per capita (log) x D2004_2007	-0.0055	-0.0104
	(0.0047)	(0.0064)
Green ARRA per capita (log) x D2009_2012	-0.0143*	-0.0266***
	(0.0075)	(0.0076)
Green ARRA per capita (log) x D2013_2016	-0.0183	-0.0356**
	(0.0133)	(0.0157)
Green ARRA per capita (log) x Share of empl with GGS>p75	0.0555	0.0545
(year 2006) x D2000_2003	(0.0541)	(0.0582)
Green ARRA per capita (log) x Share of empl with GGS>p75	0.0356*	0.0516**
(year 2006) x D2004_2007	(0.0180)	(0.0249)
Green ARRA per capita (log) x Share of empl with GGS>p75	0.0689**	0.1160***
(year 2006) x D2009_2012	(0.0297)	(0.0297)
Green ARRA per capita (log) x Share of empl with GGS>p75	0.0917*	0.1588***
(year 2006) x D2013_2016	(0.0499)	(0.0587)
Jobs created, $1 million green ARRA:		
- First quartile of Share of empl with GGS>p75 in 2006 (0.240)		
Pre-ARRA (2000-2003)	22.9**	23.58*
	(10.86)	(12.71)
Pre-ARRA (2004-2007)	16.06***	9.55
	(4.28)	(5.85)
Short-run (2009-2012)	10.02**	3.63
	(4.33)	(5.23)
Long-run (2013-2016)	18.17	9.92
	(11.40)	(14.09)
- Median of Share of empl with GGS>p75 in 2006 (0.258)		
Pre-ARRA (2000-2003)	28.28***	28.87***
	(8.21)	(9.87)
Pre-ARRA (2004-2007)	19.63***	14.71***
	(3.65)	(5.22)
Short-run (2009-2012)	16.72***	14.91***
	(3.65)	(4.34)
Long-run (2013-2016)	27.61***	26.27**
	(8.12)	(10.64)
- Third quartile of Share of empl with GGS>p75 in 2006 (0.275)		
Pre-ARRA (2000-2003)	33.16***	33.66***
	(8.30)	(9.71)
Pre-ARRA (2004-2007)	22.86***	19.38***
	(3.79)	(5.62)
Short-run (2009-2012)	22.78***	25.12***
	(4.77)	(5.04)
Long-run (2013-2016)	36.16***	41.07***
	(7.33)	(9.94)
R squared	0.7697	0.7056
Observations	9979	9979

Notes: OLS model weighted by CZ population in 2008. Sample: 587 CZ with at least 25,000 residents in 2008. Year fixed effects and state (or Census region) x period fixed effects included. Additional control variables same as Table 2. Standard errors clustered by state in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table B4: interaction with income per capita

Dep var: Change in log emp.t per capita compared to 2008	State fixed effects	Census division fixed effects
Income per capita (2005) (year 2005) x D2000_2003	-0.0054	-0.0038
	(0.0037)	(0.0037)
Income per capita (2005) (year 2005) x D2004_2007	0.0004	0.0007
	(0.0018)	(0.0020)
Income per capita (2005) (year 2005) x D2009_2012	-0.0009	-0.0000
	(0.0012)	(0.0012)
Income per capita (2005) (year 2005) x D2013_2016	-0.0007	0.0010
	(0.0028)	(0.0030)
Green ARRA per capita (log) x D2000_2003	0.0161	0.0138
	(0.0153)	(0.0143)
Green ARRA per capita (log) x D2004_2007	-0.0002	-0.0008
	(0.0077)	(0.0078)
Green ARRA per capita (log) x D2009_2012	0.0047	0.0017
	(0.0043)	(0.0043)
Green ARRA per capita (log) x D2013_2016	0.0092	0.0027
	(0.0104)	(0.0109)
Green ARRA per capita (log) x Income per capita (2005) (year 2005) x D2000_2003	-0.0004	-0.0003
	(0.0005)	(0.0004)
Green ARRA per capita (log) x Income per capita (2005) (year 2005) x D2004_2007	0.0001	0.0001
	(0.0002)	(0.0002)
Green ARRA per capita (log) x Income per capita (2005) (year 2005) x D2009_2012	-0.0001	0.0000
	(0.0001)	(0.0001)
Green ARRA per capita (log) x Income per capita (2005) (year 2005) x D2013_2016	-0.0002	0.0000
	(0.0003)	(0.0003)
Jobs created, $1 million green ARRA:		
- First quartile of Income per capita (2005) in 2006		
Pre-ARRA (2000-2003)	24.89***	26.24***
	(8.14)	(9.51)
Pre-ARRA (2004-2007)	19.64***	14.07**
	(4.10)	(5.30)
Short-run (2009-2012)	14.94***	12.41***
	(4.27)	(4.44)
Long-run (2013-2016)	24.47***	22.49**
	(8.93)	(11.04)
- Median of Income per capita (2005) in 2006		
Pre-ARRA (2000-2003)	13.97	17.76
	(14.91)	(12.90)
Pre-ARRA (2004-2007)	23.33**	17.37*
	(9.92)	(9.83)
Short-run (2009-2012)	13.16**	12.97**
	(5.61)	(5.28)
Long-run (2013-2016)	19.55	23.81*
	(11.82)	(14.19)
- Third quartile of Income per capita (2005) in 2006)		
Pre-ARRA (2000-2003)	13.97	17.76
	(14.91)	(12.90)
Pre-ARRA (2004-2007)	23.33**	17.37*
	(9.92)	(9.83)
Short-run (2009-2012)	13.16**	12.97**
	(5.61)	(5.28)
Long-run (2013-2016)	19.55	23.81*
	(11.82)	(14.19)
R squared	0.7692	0.7034
Observations	9979	9979

Notes: OLS model weighted by CZ population in 2008. Sample: 587 CZ with at least 25,000 residents in 2008. Year fixed effects and state (or Census region) x period fixed effects included. Additional control variables same as Table 2. Standard errors clustered by state in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table B5: Excluding or including observations, state FE

Dep var: Change in log employment per capita compared to 2008. Results reported in terms of jobs created per $1 million green ARRA	(1) Main Model	(2) Drop 2009	(3) Excluding 1st and 20th vigintiles	(4) Excluding CZs w/ R&D Labs	(5) Including CZs with pop< 25ks
Total Employment					
Pre-ARRA (2000-2003)	27.15***	27.15***	18.75**	21.13	26***
	(8.88)	(8.89)	(9.23)	(12.62)	(9.00)
Pre-ARRA (2004-2007)	18.88***	18.88***	14.17***	15.52**	16.18***
	(3.95)	(3.96)	(4.29)	(6.34)	(4.26)
Short-run (2009-2012)	15.3***	16.62***	14.83**	12.72**	12.59***
	(4.31)	(4.94)	(5.65)	(4.75)	(4.40)
Long-run (2013-2017)	25.52***	25.52***	23.12*	23.43**	21.45**
	(9.41)	(9.43)	(11.57)	(10.85)	(9.28)
Observations	0.7688	0.7681	0.7878	0.7590	0.7577
R squared	9979	9392	8976	9571	11679
Manual Labor Employment					
Pre-ARRA (2005-2007)	3.97	3.97	0.54	-1.56	1.58
	(3.26)	(3.27)	(3.73)	(4.37)	(3.08)
Short-run (2009-2012)	6.17**	7.79**	6.28	6.42**	4.55*
	(2.75)	(2.98)	(3.78)	(2.95)	(2.70)
Long-run (2013-2017)	13.4***	13.4***	12.48*	10.63*	11.28**
	(4.75)	(4.76)	(6.81)	(5.73)	(4.85)
Observations	0.5849	0.5901	0.6003	0.5599	0.5717
R squared	7044	6457	6336	6756	8244
Green Employment					
Pre-ARRA (2005-2007)	0.71	0.71	1.23	-0.84	0.41
	(1.08)	(1.08)	(1.47)	(1.09)	(1.03)
Short-run (2009-2012)	0.65	1.15	0.44	1.56	0.69
	(0.98)	(1.07)	(1.34)	(1.02)	(0.93)
Long-run (2013-2017)	2.33*	2.33*	1.33	3.65**	2.52*
	(1.37)	(1.38)	(1.85)	(1.49)	(1.26)
Observations	0.3864	0.3869	0.3914	0.3316	0.3855
R squared	7044	6457	6336	6756	8244
Construction Employment					
Pre-ARRA (2005-2007)	0.71	0.71	0.71	-0.21	-0.29
	(1.03)	(1.03)	(1.01)	(1.02)	(1.03)
Short-run (2009-2012)	-0.1	0.04	0.67	-0.15	-0.15
	(1.00)	(1.08)	(1.02)	(0.91)	(0.83)
Long-run (2013-2017)	2.54**	2.54**	2.76*	2.55**	2.05*
	(1.15)	(1.15)	(1.45)	(1.08)	(1.12)
Observations	0.7177	0.7265	0.7258	0.6878	0.7030
R squared	7044	6457	6336	6756	8244
Renewable Energy Employment					
Pre-ARRA (2005-2007)	0.03	0.03	0.84	-0.43	-0.21
	(0.69)	(0.69)	(0.67)	(0.62)	(0.64)
Short-run (2009-2012)	-0.09	-0.19	-0.07	0.09	-0.12
	(0.42)	(0.40)	(0.53)	(0.40)	(0.42)
Long-run (2013-2017)	1.19**	1.19**	0.97	1.42**	0.98
	(0.56)	(0.56)	(0.73)	(0.61)	(0.59)
Observations	0.2786	0.2964	0.2821	0.2647	0.2709
R squared	7044	6457	6336	6756	8244

Notes: OLS model weighted by CZ population in 2008. Sample: CZ with at least 25,000 residents in 2008 (except column 5). Year fixed effects and state x period fixed effects included. Additional control variables same as Table 2, except that vigintiles of non-green ARRA spending are re-calculated in columns (4) and (5) to reflect the new set of observations. Standard errors clustered by state in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table B6: Excluding or including observations, census division FE

Dep var: Change in log employment per capita compared to 2008. Results reported in terms of jobs created per $1 million green ARRA	(1) Main Model	(2) Drop 2009	(3) Excluding 1st and 20th vigintiles	(4) Excluding CZs w/ R&D Labs	(5) Including CZs with pop< 25ks
Total Employment					
Pre-ARRA (2000-2003)	27.65**	27.65**	18.07*	25.7*	26.78**
	(10.47)	(10.47)	(10.06)	(12.89)	(10.50)
Pre-ARRA (2004-2007)	13.52**	13.52**	7.31	11.99	11.88**
	(5.21)	(5.21)	(5.18)	(7.41)	(5.64)
Short-run (2009-2012)	12.32**	13.9**	10.95**	9.71*	10.37**
	(4.62)	(5.36)	(5.43)	(5.60)	(4.97)
Long-run (2013-2017)	22.26*	22.26*	19.49	21.03	19.24
	(11.49)	(11.50)	(12.93)	(13.69)	(11.56)
Observations	0.7032	0.7005	0.7182	0.6869	0.6898
R squared	9979	9392	8976	9571	11679
Manual Labor Employment					
Pre-ARRA (2005-2007)	1.56	1.56	-1.98	-3.21	-0.45
	(3.46)	(3.47)	(4.07)	(4.71)	(3.24)
Short-run (2009-2012)	6.97**	9.06***	7.1*	6.05*	4.71
	(3.02)	(3.35)	(4.07)	(3.48)	(3.26)
Long-run (2013-2017)	17.3***	17.3***	17.25**	11.88	14.57**
	(6.27)	(6.27)	(8.27)	(7.29)	(6.74)
Observations	0.5035	0.5016	0.5119	0.4736	0.4902
R squared	7044	6457	6336	6756	8244
Green Employment					
Pre-ARRA (2005-2007)	0.26	0.26	0.58	-1.27	-0.15
	(1.05)	(1.05)	(1.36)	(1.17)	(0.99)
Short-run (2009-2012)	-0.15	0.3	-0.57	0.82	0.11
	(1.14)	(1.28)	(1.42)	(1.08)	(1.09)
Long-run (2013-2017)	1.36	1.36	0.48	2.76	1.79
	(1.75)	(1.75)	(2.23)	(1.70)	(1.65)
Observations	0.2998	0.2954	0.3061	0.2543	0.2988
R squared	7044	6457	6336	6756	8244
Construction Employment					
Pre-ARRA (2005-2007)	0.22	0.22	0.23	-0.65	-0.73
	(1.00)	(1.01)	(1.12)	(0.97)	(1.06)
Short-run (2009-2012)	-0.83	-0.73	-0.8	-1.26*	-0.55
	(0.82)	(0.97)	(1.12)	(0.70)	(0.67)
Long-run (2013-2017)	1.07	1.07	0.78	0.58	0.97
	(1.30)	(1.31)	(1.75)	(1.43)	(1.19)
Observations	0.6741	0.6816	0.6783	0.6419	0.6606
R squared	7044	6457	6336	6756	8244
Renewable Energy Employment					
Pre-ARRA (2005-2007)	0.12	0.12	1.06*	-0.31	-0.09
	(0.59)	(0.59)	(0.62)	(0.61)	(0.56)
Short-run (2009-2012)	-0.35	-0.42	-0.65	-0.26	-0.32
	(0.43)	(0.46)	(0.56)	(0.48)	(0.45)
Long-run (2013-2017)	1.21**	1.21**	0.89	1.36*	1.02
	(0.56)	(0.56)	(0.72)	(0.72)	(0.65)
Observations	0.2230	0.2370	0.2266	0.2076	0.2137
R squared	7044	6457	6336	6756	8244

Notes: OLS model weighted by CZ population in 2008. Sample: CZ with at least 25,000 residents in 2008 (except column 5). Year fixed effects and Census division x period fixed effects included. Additional control variables same as Table 2, except that vigintiles of non-green ARRA spending are re-calculated in columns (4) and (5) to reflect the new set of observations. Standard errors clustered by state in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table B7 - Alternate non-green ARRA groupings, state FE

Dep var: Change in log employment per capita compared to 2008. Results reported in terms of jobs created per $1 million green ARRA	(1) 5 non-green ARRA groups	(2) 10 non-green ARRA groups	(3) 15 non-green ARRA groups	(4) 20 non-green ARRA groups
Total Employment				
Pre-ARRA (2000-2003)	25.04***	26.13***	25.73***	27.34***
	(8.91)	(8.86)	(8.57)	(8.94)
Pre-ARRA (2004-2007)	15.95***	18.64***	17.37***	19.04***
	(3.87)	(4.13)	(4.06)	(3.94)
Short-run (2009-2012)	13.03**	14.36***	13.25***	15.23***
	(5.01)	(4.77)	(4.54)	(4.30)
Long-run (2013-2017)	24.88**	24.08**	23.32**	25.47***
	(10.90)	(10.14)	(10.32)	(9.45)
Observations	0.7580	0.7629	0.7650	0.7689
R squared	9979	9979	9979	9979
Manual Labor Employment				
Pre-ARRA (2005-2007)	1.8	4.06	2.25	3.94
	(3.12)	(3.24)	(3.47)	(3.25)
Short-run (2009-2012)	4.81	5.31*	4.75*	6.24**
	(2.91)	(2.72)	(2.69)	(2.76)
Long-run (2013-2017)	12.86**	13.16**	12.17**	13.48***
	(5.42)	(5.11)	(4.73)	(4.71)
Observations	0.5718	0.5765	0.5783	0.5848
R squared	7044	7044	7044	7044
Green Employment				
Pre-ARRA (2005-2007)	0.43	0.7	0.55	0.7
	(1.13)	(1.06)	(1.07)	(1.09)
Short-run (2009-2012)	0.73	0.63	0.59	0.65
	(0.99)	(1.00)	(0.96)	(0.99)
Long-run (2013-2017)	2.98**	2.38*	2.56*	2.36*
	(1.32)	(1.33)	(1.33)	(1.39)
Observations	0.3720	0.3773	0.3813	0.3864
R squared	7044	7044	7044	7044
Construction Employment				
Pre-ARRA (2005-2007)	0.02	0.78	0.67	0.68
	(1.14)	(1.11)	(1.09)	(1.02)
Short-run (2009-2012)	-0.57	-0.33	-0.54	-0.11
	(1.02)	(1.04)	(1.01)	(1.00)
Long-run (2013-2017)	1.68	2.21*	2.18*	2.53**
	(1.30)	(1.24)	(1.09)	(1.15)
Observations	0.7095	0.7130	0.7155	0.7176
R squared	7044	7044	7044	7044
Renewable Energy Employment				
Pre-ARRA (2005-2007)	-0.28	-0.04	-0.09	0.02
	(0.67)	(0.68)	(0.68)	(0.69)
Short-run (2009-2012)	-0.2	-0.14	-0.16	-0.09
	(0.45)	(0.42)	(0.40)	(0.42)
Long-run (2013-2017)	1.13*	1.18*	1.11*	1.2**
	(0.59)	(0.60)	(0.57)	(0.55)
Observations	0.2602	0.2632	0.2739	0.2786
R squared	7044	7044	7044	7044

Notes: OLS model weighted by CZ population in 2008. Sample: CZ with at least 25,000 residents in 2008. Year fixed effects and state x period fixed effects included Additional control variables same as Table 2. Standard errors clustered by state in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table B8 - Alternate non-green ARRA groupings, census division FE

Dep var: Change in log employment per capita compared to 2008. Results reported in terms of jobs created per $1 million green ARRA	(1) 5 non-green ARRA groups	(2) 10 non-green ARRA groups	(3) 15 non-green ARRA groups	(4) 20 non-green ARRA groups
Total Employment				
Pre-ARRA (2000-2003)	27.97**	27.48**	28.42***	27.71**
	(10.60)	(11.01)	(10.02)	(10.53)
Pre-ARRA (2004-2007)	12.56**	12.87**	13**	13.63**
	(5.55)	(5.48)	(5.26)	(5.20)
Short-run (2009-2012)	11.59**	10.84**	11.38**	12.14**
	(5.10)	(5.27)	(5.13)	(4.61)
Long-run (2013-2017)	23.17*	20.92	22.8*	22*
	(12.16)	(12.56)	(12.59)	(11.51)
Observations	0.6896	0.6961	0.6986	0.7031
R squared	9979	9979	9979	9979
Manual Labor Employment				
Pre-ARRA (2005-2007)	0.02	0.89	0.19	1.5
	(3.43)	(3.45)	(3.51)	(3.46)
Short-run (2009-2012)	5.1	5.54*	5.02	7.03**
	(3.34)	(3.11)	(3.20)	(3.02)
Long-run (2013-2017)	16.49**	17.25**	16.04**	17.33***
	(6.85)	(6.51)	(6.68)	(6.26)
Observations	0.4881	0.4926	0.4975	0.5034
R squared	7044	7044	7044	7044
Green Employment				
Pre-ARRA (2005-2007)	-0.09	-0.1	-0.08	0.25
	(1.08)	(1.03)	(0.97)	(1.06)
Short-run (2009-2012)	0.1	0.01	-0.06	-0.16
	(1.10)	(1.14)	(1.07)	(1.15)
Long-run (2013-2017)	2.2	1.83	1.78	1.35
	(1.55)	(1.63)	(1.63)	(1.75)
Observations	0.2861	0.2917	0.2981	0.2997
R squared	7044	7044	7044	7044
Construction Employment				
Pre-ARRA (2005-2007)	0.26	0.14	0.12	0.2
	(1.05)	(0.99)	(1.06)	(1.00)
Short-run (2009-2012)	-0.72	-0.95	-1.02	-0.85
	(0.86)	(0.88)	(0.85)	(0.82)
Long-run (2013-2017)	0.76	0.74	1.06	1.05
	(1.48)	(1.47)	(1.33)	(1.31)
Observations	0.6617	0.6683	0.6717	0.6740
R squared	7044	7044	7044	7044
Renewable Energy Employment				
Pre-ARRA (2005-2007)	-0.14	0.14	-0.03	0.11
	(0.59)	(0.58)	(0.57)	(0.58)
Short-run (2009-2012)	-0.45	-0.45	-0.39	-0.35
	(0.48)	(0.48)	(0.46)	(0.43)
Long-run (2013-2017)	1.02	1.07	1.16*	1.22**
	(0.61)	(0.64)	(0.62)	(0.56)
Observations	0.2066	0.2101	0.2154	0.2232
R squared	7044	7044	7044	7044

Notes: OLS model weighted by CZ population in 2008. Sample: CZ with at least 25,000 residents in 2008. Year fixed effects and Census division x period fixed effects included. Additional control variables same as Table 2. Standard errors clustered by state in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table B9 – Alternate ARRA definitions, state FE

Dep var: Change in log employment per capita compared to 2008. Results reported in terms of jobs created per $1 million green ARRA	(1) Main Model	(2) Include DOL training	(3) Exclude energy R&D	(4) Drop DOE Loans	(5) Drop All Loans	(6) Drop Contracts	(7) Grants Only
Total Employment							
Pre-ARRA (2000-2003)	27.15***	27.09***	29.19***	29.17**	30.19**	26.04**	34.93**
	(8.88)	(9.01)	(10.00)	(10.92)	(12.09)	(12.65)	(13.35)
Pre-ARRA (2004-2007)	18.88***	18.19***	21.67***	22.03***	21.87***	20.43***	26.17***
	(3.95)	(4.10)	(4.65)	(4.97)	(5.15)	(5.71)	(7.02)
Short-run (2009-2012)	15.3***	15.64***	16.17***	17.42***	14.83**	13.7**	16.91**
	(4.31)	(4.30)	(4.85)	(5.24)	(5.62)	(5.85)	(6.88)
Long-run (2013-2017)	25.52***	26.24***	27.03**	24.45**	22.92*	25.8**	24.37
	(9.41)	(9.74)	(10.15)	(11.72)	(12.77)	(12.77)	(14.95)
Observations	0.7688	0.7682	0.7688	0.7682	0.7733	0.7673	0.7689
R squared	9979	9979	9979	9979	9979	9979	9979
Manual Labor Employment							
Pre-ARRA (2005-2007)	3.97	3.53	5.54	2.64	2.53	4.25	1.8
	(3.26)	(3.45)	(3.60)	(4.01)	(3.88)	(4.25)	(5.50)
Short-run (2009-2012)	6.17**	6.21**	5.93*	8.28***	5.71*	5.65	7.8*
	(2.75)	(2.82)	(2.98)	(3.08)	(2.98)	(3.47)	(4.05)
Long-run (2013-2017)	13.4***	13.45***	14***	15.44**	14.02**	13.8**	13.1*
	(4.75)	(4.91)	(4.98)	(6.07)	(6.56)	(5.67)	(6.59)
Observations	0.5849	0.5845	0.5847	0.5848	0.5879	0.5864	0.5839
R squared	7044	7044	7044	7044	7044	7044	7044
Green Employment							
Pre-ARRA (2005-2007)	0.71	0.68	1.01	0.78	0.22	0.55	0.63
	(1.08)	(1.10)	(1.17)	(1.28)	(1.27)	(1.31)	(1.52)
Short-run (2009-2012)	0.65	0.63	0.6	1.02	1.37	1	1.27
	(0.98)	(1.00)	(1.07)	(1.22)	(1.27)	(1.36)	(1.66)
Long-run (2013-2017)	2.33*	2.37	2.75*	2.61	3.05*	3.59**	3.81*
	(1.37)	(1.42)	(1.48)	(1.70)	(1.59)	(1.58)	(1.94)
Observations	0.3864	0.3880	0.3866	0.3864	0.3900	0.3829	0.3832
R squared	7044	7044	7044	7044	7044	7044	7044
Construction Employment							
Pre-ARRA (2005-2007)	0.71	0.56	1.03	1.01	0.34	0.72	0.7
	(1.03)	(0.99)	(1.03)	(1.08)	(1.01)	(1.46)	(1.68)
Short-run (2009-2012)	-0.1	0.01	-0.4	0.11	0.02	-1.16	-0.86
	(1.00)	(1.04)	(1.05)	(1.18)	(0.99)	(1.24)	(1.26)
Long-run (2013-2017)	2.54**	2.71**	2.41**	2.59**	2.17*	1.15	1.89
	(1.15)	(1.19)	(1.18)	(1.24)	(1.23)	(1.37)	(1.47)
Observations	0.7177	0.7180	0.7176	0.7176	0.7213	0.7223	0.7182
R squared	7044	7044	7044	7044	7044	7044	7044
Renewable Energy Employment							
Pre-ARRA (2005-2007)	0.03	-0.01	-0.07	-0.13	-0.74	-0.7	-1.04
	(0.69)	(0.68)	(0.74)	(0.82)	(0.76)	(0.78)	(0.85)
Short-run (2009-2012)	-0.09	-0.08	-0.05	-0.03	0.37	0.21	0.44
	(0.42)	(0.43)	(0.43)	(0.51)	(0.45)	(0.50)	(0.55)
Long-run (2013-2017)	1.19**	1.19**	1.36**	1.46**	1.57**	1.79**	2.16***
	(0.56)	(0.58)	(0.59)	(0.63)	(0.67)	(0.81)	(0.73)
Observations	0.2786	0.2746	0.2787	0.2787	0.2741	0.2724	0.2783
R squared	7044	7044	7044	7044	7044	7044	7044

Notes: OLS model weighted by CZ population in 2008. Sample: CZ with at least 25,000 residents in 2008. Year fixed effects and state x period fixed effects included. Additional control variables same as Table 2. Standard errors clustered by state in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table B10 - Alternate ARRA definitions, census division FE

Dep var: Change in log employment per capita compared to 2008. Results reported in terms of jobs created per $1 million green ARRA	(1) Main Model	(2) Include DOL training	(3) Exclude energy R&D	(4) Drop DOE Loans	(5) Drop All Loans	(6) Drop Contracts	(7) Grants Only
Total Employment							
Pre-ARRA (2000-2003)	27.65**	27.81**	28.76**	34.15**	33.02**	27.46*	40.61**
	(10.47)	(10.99)	(11.67)	(12.76)	(14.49)	(15.98)	(17.43)
Pre-ARRA (2004-2007)	13.52**	12.8**	13.02**	22.41***	22.19***	9.88	21.98**
	(5.21)	(5.57)	(6.29)	(5.34)	(6.06)	(9.09)	(9.50)
Short-run (2009-2012)	12.32**	12.46***	12.89**	16.7***	16.53**	9.48	15.55**
	(4.62)	(4.65)	(5.11)	(5.92)	(6.48)	(6.84)	(7.42)
Long-run (2013-2017)	22.26*	23.66*	22.3*	32.34**	31.97**	20.35	31.47*
	(11.49)	(12.01)	(12.64)	(13.79)	(15.40)	(16.26)	(16.39)
Observations	0.7032	0.7033	0.7029	0.7040	0.7144	0.7072	0.7114
R squared	9979	9979	9979	9979	9979	9979	9979
Manual Labor Employment							
Pre-ARRA (2005-2007)	1.56	0.68	2.39	0.94	-0.23	-0.29	-1.66
	(3.46)	(3.60)	(3.64)	(4.44)	(4.52)	(4.70)	(6.56)
Short-run (2009-2012)	6.97**	6.78**	6.42*	10.59***	9.96***	3.53	9.42**
	(3.02)	(3.15)	(3.22)	(3.24)	(3.11)	(3.97)	(3.84)
Long-run (2013-2017)	17.3***	17.51**	17.66**	23.38***	24.08***	14.7*	21.92***
	(6.27)	(6.70)	(6.71)	(7.02)	(7.80)	(8.12)	(8.03)
Observations	0.5035	0.5025	0.5030	0.5047	0.5035	0.5012	0.5032
R squared	7044	7044	7044	7044	7044	7044	7044
Green Employment							
Pre-ARRA (2005-2007)	0.26	0.2	0.35	0.75	-0.03	-0.4	0.42
	(1.05)	(1.07)	(1.15)	(1.30)	(1.34)	(1.21)	(1.55)
Short-run (2009-2012)	-0.15	-0.19	-0.17	0.54	1.38	-0.08	0.38
	(1.14)	(1.20)	(1.23)	(1.35)	(1.43)	(1.31)	(1.70)
Long-run (2013-2017)	1.36	1.47	1.46	2.87	3.75*	1.54	3.02
	(1.75)	(1.79)	(1.95)	(1.96)	(1.88)	(1.79)	(2.13)
Observations	0.2998	0.3012	0.2998	0.3006	0.3016	0.3002	0.3075
R squared	7044	7044	7044	7044	7044	7044	7044
Construction Employment							
Pre-ARRA (2005-2007)	0.22	0.05	0.13	1.58	0.96	-0.87	0.15
	(1.00)	(0.98)	(0.99)	(1.00)	(1.01)	(1.40)	(1.64)
Short-run (2009-2012)	-0.83	-0.64	-1.16	-0.19	0.17	-1.94*	-1.47
	(0.82)	(0.84)	(0.89)	(0.96)	(0.82)	(1.01)	(0.99)
Long-run (2013-2017)	1.07	1.34	0.83	2.49*	2.27	-0.49	1.53
	(1.30)	(1.33)	(1.45)	(1.28)	(1.36)	(1.74)	(1.60)
Observations	0.6741	0.6749	0.6741	0.6744	0.6832	0.6770	0.6742
R squared	7044	7044	7044	7044	7044	7044	7044
Renewable Energy Employment							
Pre-ARRA (2005-2007)	0.12	0.07	0.08	0.06	-0.63	-0.6	-0.83
	(0.59)	(0.58)	(0.63)	(0.71)	(0.66)	(0.66)	(0.66)
Short-run (2009-2012)	-0.35	-0.37	-0.37	-0.18	0.4	-0.02	0.11
	(0.43)	(0.46)	(0.47)	(0.50)	(0.46)	(0.49)	(0.55)
Long-run (2013-2017)	1.21**	1.25**	1.29**	1.67**	2.02***	1.42	2.1***
	(0.56)	(0.61)	(0.63)	(0.64)	(0.73)	(0.90)	(0.70)
Observations	0.2230	0.2212	0.2230	0.2233	0.2244	0.2201	0.2273
R squared	7044	7044	7044	7044	7044	7044	7044

Notes: OLS model weighted by CZ population in 2008. Sample: CZ with at least 25,000 residents in 2008. Year fixed effects and Census division x period fixed effects included. Additional control variables same as Table 2. Standard errors clustered by state in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table B11: Table with different sectors

Dep var: Change in log employment (by type) per capita compared to 2008	Manufacturing State FE	Manufacturing Census division FE	Waste management State FE	Waste management Census division FE	Public sector State FE	Public sector Census division FE
Green ARRA per capita (log) x D2005_2007	0.0062***	0.0049**	-0.0057	-0.0091	0.0029	0.0022
	(0.0017)	(0.0021)	(0.0116)	(0.0114)	(0.0033)	(0.0033)
Green ARRA per capita (log) x D2009_2012	0.0053**	0.0028	0.0113	0.0137*	-0.0117*	-0.0110
	(0.0023)	(0.0024)	(0.0089)	(0.0077)	(0.0070)	(0.0067)
Green ARRA per capita (log) x D2013_2016	0.0085**	0.0072*	0.0092	0.0131	-0.0066	-0.0070
	(0.0038)	(0.0036)	(0.0100)	(0.0093)	(0.0090)	(0.0089)
Jobs per year created, $1 million green ARRA:						
Pre-ARRA (2005-2007)	4.09***	3.23**	-1.82	-2.89	0.78	0.6
	(1.10)	(1.40)	(3.70)	(3.64)	(0.90)	(0.90)
Short-run (2009-2012)	2.88**	1.53	3.26	3.94*	-3.27*	-3.07
	(1.22)	(1.28)	(2.57)	(2.20)	(1.94)	(1.87)
Long-run (2013-2016)	4.78**	4.01*	2.99	4.3	-1.78	-1.89
	(2.13)	(2.00)	(3.26)	(3.06)	(2.44)	(2.43)
R squared	0.5813	0.5422	0.2327	0.1825	0.3322	0.2760
Observations	7044	7044	7044	7044	7044	7044

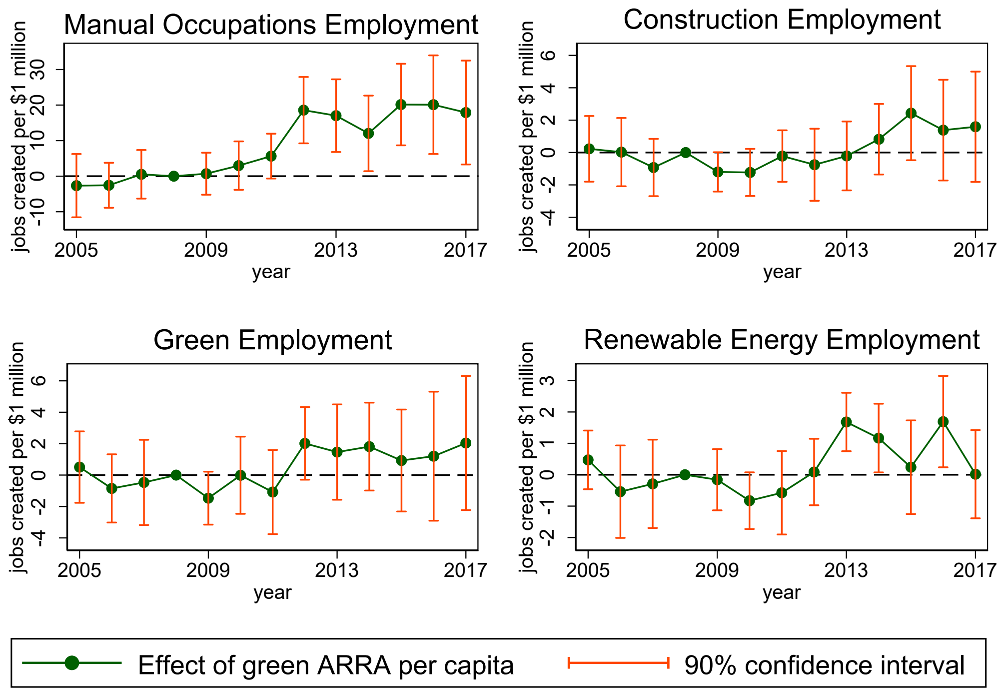
Notes: Regressions weighted by CZ population in 2008. Sample: 587 CZ with at least 25,000 residents in 2008. Year fixed effects and state (or census division) x period fixed effects included. Additional control variables same as Table 2. Standard errors clustered by state in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table B12: Table with different occupations

Dep var: Change in log employment (by type) per capita compared to 2008	Manual occ. State FE	Manual occ. Census division FE	Abstract occ. State FE	Abstract occ. Census division FE	Services occ. State FE	Services occ. Census division FE	Clerical occ. State FE	Clerical occ. Census division FE
Green ARRA per capita	0.0028	0.0011	0.0030*	0.0022	0.0024	0.0014	0.0054**	0.0045**
(log) x D2005_2007	(0.0023)	(0.0025)	(0.0017)	(0.0016)	(0.0024)	(0.0020)	(0.0023)	(0.0021)
Green ARRA per capita	0.0051**	0.0057**	0.0024	0.0009	-0.0005	-0.0013	-0.0009	-0.0004
(log) x D2009_2012	(0.0023)	(0.0025)	(0.0022)	(0.0022)	(0.0031)	(0.0031)	(0.0025)	(0.0025)
Green ARRA per capita	0.0102***	0.0132***	0.0006	-0.0029	0.0008	0.0011	0.0012	0.0025
(log) x D2013_2016	(0.0036)	(0.0048)	(0.0044)	(0.0048)	(0.0041)	(0.0043)	(0.0027)	(0.0026)
Jobs per year created, $1 million green ARRA:								
Pre-ARRA (2005-2007)	3.97	1.56	5.39*	3.95	2.16	1.25	7.47**	6.28**
	(3.26)	(3.46)	(3.17)	(2.97)	(2.16)	(1.78)	(3.17)	(2.94)
Short-run (2009-2012)	6.17**	6.97**	4.37	1.69	-0.51	-1.22	-1.19	-0.45
	(2.75)	(3.02)	(4.18)	(4.12)	(2.88)	(2.90)	(3.26)	(3.16)
Long-run (2013-2016)	13.4***	17.3***	1.25	-5.85	0.77	1.07	1.61	3.2
	(4.75)	(6.27)	(8.83)	(9.65)	(4.11)	(4.32)	(3.45)	(3.33)
R squared	0.5849	0.5035	0.5371	0.4713	0.4548	0.3992	0.4085	0.3478
Observations	7044	7044	7044	7044	7044	7044	7044	7044

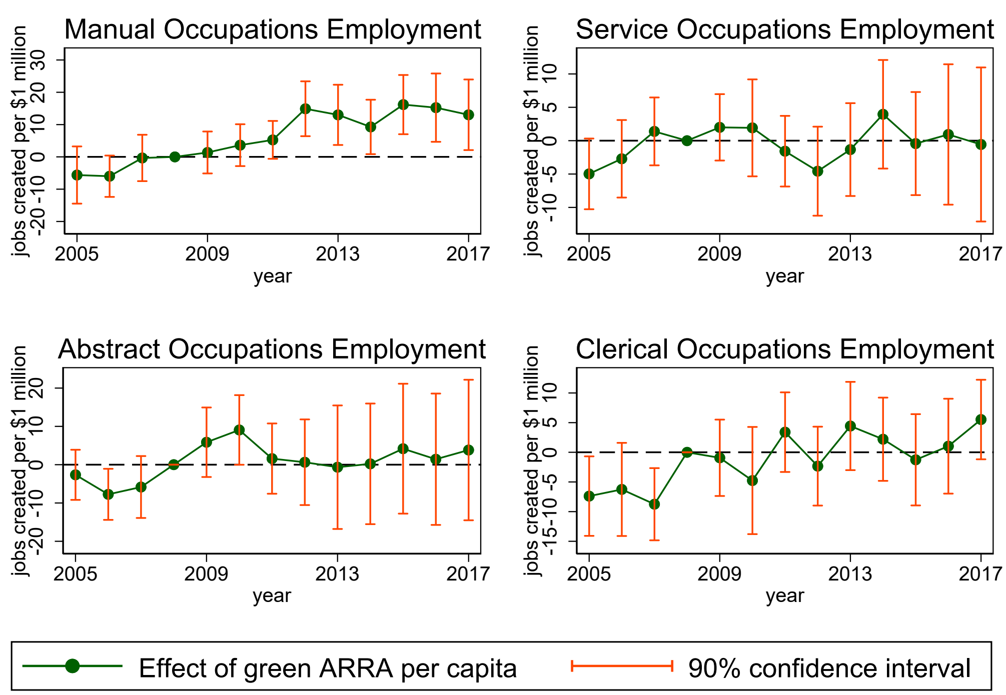
Notes: Regressions weighted by CZ population in 2008. Sample: 587 CZ with at least 25,000 residents in 2008. Year fixed effects and state (or census division) x period fixed effects included. Additional control variables same as Table 2. Standard errors clustered by state in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Figure B1: Jobs per year created by $1 million green ARRA: region fixed effects



NOTE: All models estimated using Census region fixed effects

Figure B2: different occupation types by year



NOTE: All models estimated using state fixed effects

Table B13 - Drivers of upper GGS

Dep var: Share of empl with GGS>p75 (year 2006)	(1) No F.E.	(2 Census F.E.)	(3) State F.E)	(4) No F.E.	(5) Census F.E.	(6) State F.E.
Population 2008 (log)	-0.00738***	-0.00779***	-0.00836***	-0.00750***	-0.00787***	-0.00743***
	(0.00189)	(0.00204)	(0.00262)	(0.00179)	(0.00193)	(0.00269)
Income per capita (2005)	0.00164***	0.00188***	0.00143***	0.00140***	0.00159***	0.00113***
	(0.000361)	(0.000357)	(0.000321)	(0.000315)	(0.000323)	(0.000305)
Import penetration (year 2005)	-0.504	-0.339	-0.232	-0.301	-0.206	-0.113
	(0.388)	(0.389)	(0.394)	(0.351)	(0.374)	(0.367)
Empl total 2008 / pop	0.00445	0.0213	0.0773**	-0.0133	0.0143	0.0725**
	(0.0342)	(0.0318)	(0.0362)	(0.0323)	(0.0301)	(0.0312)
Empl manuf 2008 / pop	0.0894	0.0255	-0.0475	0.00612	-0.0356	-0.0838
	(0.108)	(0.0866)	(0.0866)	(0.0798)	(0.0780)	(0.0748)
Empl constr 2008 / pop	0.260	-0.276	-0.0812	0.389	-0.150	-0.0567
	(0.278)	(0.276)	(0.303)	(0.250)	(0.273)	(0.334)
Empl extractive 2008 / pop	0.532***	0.541***	0.470***	0.960***	0.938***	0.741***
	(0.173)	(0.191)	(0.155)	(0.248)	(0.219)	(0.213)
Empl public sect 2008 / pop	0.432**	0.455***	0.0986	0.558***	0.497***	0.104
	(0.176)	(0.152)	(0.162)	(0.171)	(0.148)	(0.144)
Unempl 2008 / pop	-0.648*	-0.656	-1.099*	-1.153***	-1.172**	-1.277**
	(0.385)	(0.404)	(0.635)	(0.336)	(0.450)	(0.621)
Empl edu health 2008 / pop	-0.102	0.0217	0.0272	-0.0116	0.0942	0.0454
	(0.102)	(0.0859)	(0.0823)	(0.0789)	(0.0715)	(0.0697)
Shale gas extraction in CZ	-0.000198	0.000804	-0.00587	-0.00146	-0.00130	-0.00606*
	(0.00292)	(0.00379)	(0.00384)	(0.00232)	(0.00305)	(0.00337)
Potential for wind energy	-0.00206	-0.00129	-0.00162	-0.00211	-0.00183	-0.00245
	(0.00199)	(0.00161)	(0.00189)	(0.00195)	(0.00164)	(0.00214)
Potential for photovoltaic energy	-0.00716***	-0.00895***	-0.00660	-0.00578***	-0.00940***	-0.00465
	(0.00234)	(0.00231)	(0.00445)	(0.00207)	(0.00244)	(0.00440)
Federal R&D lab	0.0116***	0.0104**	0.00647*	0.0143***	0.0130***	0.00788**
	(0.00412)	(0.00403)	(0.00374)	(0.00374)	(0.00361)	(0.00343)
CZ hosts the state capital	0.00845*	0.00470	0.00884*	0.00398	0.00325	0.00820*
	(0.00464)	(0.00424)	(0.00488)	(0.00447)	(0.00435)	(0.00442)
Nonattainment CAA old standards	0.00537	0.00716**	0.00653	0.00455	0.00571*	0.00558
	(0.00383)	(0.00317)	(0.00400)	(0.00384)	(0.00331)	(0.00386)
Nonattainment CAA new standards	-0.00139	0.00159	-0.000106	0.000238	0.00313	-0.000985
	(0.00409)	(0.00392)	(0.00455)	(0.00401)	(0.00406)	(0.00433)
Pre trend (2000-2007) employment tot / pop				-0.140	-0.00687	-0.0258
				(0.0856)	(0.0824)	(0.0861)
Pre trend (2000-2007) empl manufacturing / pop				0.00889	-0.0142	0.136
				(0.224)	(0.206)	(0.256)
Pre trend (2000-2007) empl constr / pop				-0.105	-0.0770	0.186
				(0.444)	(0.449)	(0.609)
Pre trend (2000-2007) empl extractive / pop				-0.603	-0.727	-0.400
				(0.503)	(0.471)	(0.463)
Pre trend (2000-2007) empl public sect / pop				0.288	0.279	0.274
				(0.340)	(0.301)	(0.269)
Pre trend (2000-2007) unempl / pop				0.994**	1.259**	1.687***
				(0.459)	(0.534)	(0.417)
Pre trend (2000-2007) empl edu health / pop				-0.0557	-0.0834	0.00828
				(0.141)	(0.114)	(0.125)
State fixed effects	No	No	Yes	No	No	Yes
US Census Division fixed effecs	No	Yes	No	No	Yes	No
R squared	0.448	0.507	0.617	0.481	0.529	0.633
N	587	587	587	587	587	587

Notes: OLS model weighted by CZ population in 2008. Sample: CZ with at least 25,000 residents in 2008. Standard errors clustered by state in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Appendix C – Quantification of the green ARRA effects

Because we use a log-log model with per capita variables, interpreting the magnitude of our coefficients is challenging. However, converting our elasticities to jobs created per million dollars of ARRA spending produces estimates that are comparable to other papers.

For this conversion, define the predicted value from our model as:

$$\hat{y}_{i,t} = log\left(\frac{Y_{i,t}}{pop_{i,2008}}\right) - log\left(\frac{Y_{i,2008}}{pop_{i,2008}}\right)$$

$$= \alpha + \sum_t \widehat{\beta_t} log\left(\frac{GreenARRA_i}{pop_{i,2008}}\right) + \sum_t \mathbf{X}'_{it_0}\widehat{\boldsymbol{\varphi}}_t + \sum_t \mathbf{G}'_{it_0}\widehat{\boldsymbol{\vartheta}}_t \text{, (1)}$$

where we skip $\mu_{i\in v,t}$ (vigintiles of non-green ARRA spending) and $\eta_{i\in c,t}$ (period-specific region fixed effects) for simplicity, and t=pre, short and long as usual. We can add \$1 million of green or non-green ARRA and re-calculate:

$$\hat{y}^{+1}_{i,t} = log\left(\frac{Y^{+1}_{i,t}}{pop_{i,2008}}\right) - log\left(\frac{Y_{i,2008}}{pop_{i,2008}}\right)$$

$$= \alpha + \sum_t \widehat{\beta_t} log\left(\frac{GreenARRA_i + 1}{pop_{i,2008}}\right) + \sum_t \mathbf{X}'_{it_0}\widehat{\boldsymbol{\varphi}}_t + \sum_t \mathbf{G}'_{it_0}\widehat{\boldsymbol{\vartheta}}_t \text{. (2)}$$

Subtracting one from the other gives us:

$$\hat{y}^{+1}_{i,t} - \hat{y}_{i,t} = log\left(\frac{Y^{+1}_{i,t}}{pop_{i,2008}}\right) - log\left(\frac{Y_{i,2008}}{pop_{i,2008}}\right) - log\left(\frac{Y_{i,t}}{pop_{i,2008}}\right) + log\left(\frac{Y_{i,2008}}{pop_{i,2008}}\right)$$

$$= log\left(\frac{Y^{+1}_{i,t}}{pop_{i,2008}}\right) - log\left(\frac{Y_{i,t}}{pop_{i,2008}}\right)$$

$$= \sum_t \widehat{\ } \; log\left(\frac{GreenARRA_i + 1}{pop_{i,2008}}\right) - \sum_t \widehat{\beta_t} \; log\left(\frac{GreenARRA_i}{pop_{i,2008}}\right) \text{. (3)}$$

We can re-write the log quotients to simplify further:

$$\hat{y}_{i,t}^{+1} - \hat{y}_{i,t} = log\left(\frac{Y_{i,t}^{+1}}{pop_{i,2008}}\right) - log\left(\frac{Y_{i,t}}{pop_{i,2008}}\right)$$

$$= log\left(Y_{i,t}^{+1}\right) - log\left(pop_{i,2008}\right) - log\left(Y_{i,t}\right) + log\left(pop_{i,2008}\right)$$

$$= log\left(Y_{i,t}^{+1}\right) - log\left(Y_{i,t}\right) = log\left(\frac{Y_{i,t}^{+1}}{Y_{i,t}}\right). (4)$$

Converting to levels, we get:

$$exp^{\log\left(\frac{Y_{i,t}^{+1}}{Y_{i,t}}\right)} = \left(\frac{Y_{i,t}^{+1}}{Y_{i,t}}\right). (5)$$

We want

$$Y_{i,t}^{+1} - Y_{i,t} = \left(\frac{Y_{i,t}^{+1}}{Y_{i,t}}\right) Y_{i,t} - Y_{i,t} = Y_{i,t}\left\{exp^{\log\left(\frac{Y_{i,t}^{+1}}{Y_{i,t}}\right)} - 1\right\}.$$

Using (3), (4) and (5) we can replace (Y^{+1}/Y) above with the difference of our predicted values from (3), giving us:

$$Y_{i,t}^{+1} - Y_{i,t} = Y_{i,t}\left\{exp^{\sum_t \widehat{\beta_t}\ log\left(\frac{GreenARRA_i+1}{pop_{i,2008}}\right) - \sum_t \widehat{\beta_t} log\left(\frac{GreenARRA_i}{pop_{i,2008}}\right)} - 1\right\}.$$

For a given time period (e.g. short-run or long-run), this simplifies to:

$$Y_{i,t}^{+1} - Y_{i,t} = Y_{i,t}\left\{exp^{\widehat{\beta_t}\left(log\left(\frac{GreenARRA_i+1}{pop_{i,2008}}\right) - log\left(\frac{GreenARRA_i}{pop_{i,2008}}\right)\right)} - 1\right\}.$$

Appendix D – Instrumental variable results

As noted in the main text, our instrumental variable results use a shift-share instrument that combines the initial "share" of EPA plus DOE spending in the CZ (over total DOE and EPA spending) with the green ARRA "shift". Such instrument adds an exogenous shock in green expenditures to areas that were already receiving larger amount of green spending before ARRA. The instrument is formally defined as:

$$IV_i = \frac{DoE\ Pre{-}ARRA_{i,2003-04}}{DoE\ Pre{-}ARRA_{2003-04}} \times \frac{Green\ ARRA\ DoE}{Pop_{2008}} + \frac{EPA\ Pre{-}ARRA_{i,2003-04}}{EPA\ Pre{-}ARRA_{2003-04}} \times \frac{Green\ ARRA\ EPA}{Pop_{2008}},$$

where total green ARRA EPA and DOE per capita is reallocated to CZs depending on their respective pre-ARRA shares of spending (federal assistance) over the national total, i.e. $\frac{DoE\ Pre{-}ARRA_{i,2003-04}}{DoE\ Pre{-}ARRA_{2003-04}}$ and $\frac{EPA\ Pre{-}ARRA_{i,2003-04}}{EPA\ Pre{-}ARRA_{2003-04}}$.

Because such an instrument adds an exogenous shock in green expenditures to areas that were already receiving larger green investments before ARRA, we face a problem similar to that put forward by Jaeger et al. (2018), who note that a shift-share instrument conflates short- and long-term effects. We follow their suggestion and take a "share" far in the past (i.e. an average share of DOE plus EPA spending between 2003 and 2004), under the assumption that the effect of past spending gradually fades away and thus it is excludable from the second stage.

Unfortunately, developing a reliable measure of pre-ARRA green government spending to distinguish the additional contribution of green ARRA from that of past trends associated with pre-ARRA green spending is difficult with available data. Quality data on green spending before ARRA would enable us to clearly disentangle the effect of ARRA from that of past government spending. Data on federal spending at the local level are publicly available at USASPENDING.GOV. However, for two reasons these data are not good proxies of green spending before ARRA. First, while EPA spending could be considered as 'green' both during

ARRA and prior of ARRA, the same is not true for DOE. While a very large part of DOE local spending in ARRA goes to fund renewable energy investments, energy efficiency and other green programmes (Aldy, 2013), much DOE spending in earlier years was aimed at the exploitation and use of fossil fuels and nuclear energy (Department of Energy Budget Highlights, various years). More importantly, local spending for assistance available at USASPENDING.gov (e.g. CFDA Catalogue of Federal Domestic Assistance) is attributed to the prime recipient while sub-awards are consistently recorded only starting from 2010-2012 onwards. As a result, assistance given to local state governments to be distributed to countries is recorded as fully attributed to the CZ where the state capital is. Despite these important limitations, we do observe a relatively strong correlation (0.419) between DOE+EPA local spending per capita in 2003-2004 and DOE+EPA (i.e. green) ARRA spending per capita. Overall, we can use these data to build our instrument but not as a direct proxy of pre-ARRA spending.

For our shift-share instrument, we use all federal assistance from the DOE and EPA in 2003 and 2004. While our ARRA data include contracts, we do not include contracts in our instrument. Contracts make up the majority of 2003-2004 spending in USASpending.gov. 82% of DOE & EPA spending is from contracts, and just 18% from assistance. However, many of these contracts are for providing basic services, such as IT services. In contrast, there are fewer contracts in the ARRA data – just 18 percent of green ARRA were from contracts. These are generally contracts that are relevant for green jobs, such as hazardous waste remediation. Thus, while contracts are appropriate to include in our green ARRA data, the contracts in USASpending.gov are not comparable. Our robustness analysis in Appendix B shows that our main results are robust to excluding contracts from the ARRA data.

Table D1 presents the first-stage estimation using our shift-share instrument. The instrument does have a statistically significant positive impact on per-capita green ARRA investments. However, the F-stat of the instrument only exceeds 10 when using Census division fixed effects. The weak instrument problem is consistent with green ARRA redirecting DOE spending towards green programs.

Table D1 – First stage IV

Dep var: Green (EPA+DoE) ARRA per capita (in log)	State fixed effects	Census division fixed effects
Shift-share IV for green ARRA	0.0564***	0.0542***
	(0.0185)	(0.0167)
F-test of excluded IV from first stage	9.263	10.56
R squared	0.466	0.422
N	587	587

Notes: OLS model weighted by CZ population in 2008. Sample: CZ with at least 25,000 residents in 2008. Standard errors clustered by state in parentheses. * p<0.1, ** p<0.05, *** p<0.01. , Control variables: Vigintiles of non-green ARRA per capita Share of empl with GGS>p75 (year 2006), Population 2008 (log), Income per capita (2005), Import penetration (year 2005), Pre trend (2000-2007) empl manufacturing / pop, Pre trend (2000-2007) employment tot / pop, Pre trend (2000-2007) empl constr / pop, Pre trend (2000-2007) empl extractive / pop, Pre trend (2000-2007) empl public sect / pop, Pre trend (2000-2007) unempl / pop, Pre trend (2000-2007) empl edu health / pop, Empl total (average 2006-2008) / pop, Empl manuf (average 2006-2008) / pop, Empl constr (average 2006-2008) / pop, Empl extractive (average 2006-2008) / pop, Empl public sect (average 2006-2008) / pop, Unempl (average 2006-2008) / pop, Empl edu health (average 2006-2008) / pop, Shale gas extraction in CZ interacted with year dummies, Potential for wind energy interacted with year dummies, Potential for photovoltaic energy interacted with year dummies, Federal R&D lab, CZ hosts the state capital, Nonattainment CAA old standards, Nonattainment CAA new standards.

Table D2 shows our instrumental variable results. As noted in the main text, the IV estimation overstates both the pre-trends for total employment ($\hat{\beta}_{pre}$), increasing the pre-trend in each regression by an order of magnitude compared to the OLS results. We also observe larger total and net effects of green ARRA on employment. As expected, these effects are imprecisely estimated due to the weak instrument problem. Although the IV results are still informative, suggesting that the effect of green ARRA is highly heterogeneous and much stronger on compliers, they exacerbate the source of endogeneity associated with the presence of pre-trends. Thus, we focus on the OLS results in the main text of the paper.

Table D2 – Instrumental variable results

Dep var: Change in log employment per capita compared to 2008. Results reported in terms of jobs created per $1 million green ARRA	(1) State fixed effects	(2) Census division fixed effects
Total Employment		
Pre-ARRA (2000-2003)	188.04***	142.73**
	(68.16)	(61.98)
Pre-ARRA (2004-2007)	71.8**	60.05*
	(32.24)	(34.19)
Short-run (2009-2012)	68.05***	49.95*
	(24.02)	(26.45)
Long-run (2013-2017)	160.05***	120.42**
	(45.48)	(45.86)
Observations	0.6857	0.6553
R squared	9979	9979
Manual Labor Employment		
Pre-ARRA (2005-2007)	7.23	2.77
	(25.38)	(26.15)
Short-run (2009-2012)	1.83	9.06
	(19.46)	(18.64)
Long-run (2013-2017)	59.24*	52.32
	(33.36)	(32.42)
Observations	0.5629	0.4898
R squared	7044	7044
Green Employment		
Pre-ARRA (2005-2007)	-4.73	-2.41
	(6.63)	(6.42)
Short-run (2009-2012)	2.95	-1.61
	(6.87)	(7.82)
Long-run (2013-2017)	16.71**	8.27
	(7.93)	(8.59)
Observations	0.3472	0.2897
R squared	7044	7044
Construction Employment		
Pre-ARRA (2005-2007)	0.06	2.49
	(6.38)	(6.93)
Short-run (2009-2012)	2.56	2.18
	(3.96)	(4.09)
Long-run (2013-2017)	5.85	6
	(6.43)	(6.09)
Observations	0.7158	0.6702
R squared	7044	7044
Renewable Energy Employment		
Pre-ARRA (2005-2007)	1.99	3.73
	(3.54)	(3.48)
Short-run (2009-2012)	0.62	0.47
	(2.80)	(2.56)
Long-run (2013-2017)	5.07	3.58
	(3.26)	(3.26)
Observations	0.2662	0.2125
R squared	7044	7044

Notes: IV regressions weighted by CZ population in 2008. Sample: 587 CZ with at least 25,000 residents in 2008. Excluded IV from the first stage: shift-share IV of ARRA spending by Department/Agency; local spending share 2003-2004. Results for the first stage are shown in Table D1. Standard errors clustered by state in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Appendix References

Acemoglu, D. and Autor, D. 2011. Skills, Tasks and Technologies: Implications for Employment and Earnings. Handbook of Labor Economics Volume 4, Orley Ashenfelter and David E. Card (eds.), Amsterdam: Elsevier.

Aldy, J.E. 2013. Policy Monitor—A preliminary assessment of the American Recovery and Reinvestment Act's Clean Energy Package. Review of Environmental Economics and Policy, 7(1): 136-155.

Department of Energy. FY 20XX Congressional Budget Request. Budget Highlights. Office of Management, Budget, and Evaluation, various years.

Dierdorff, Erich C., Norton, Jennifer J., Drewes, Donald W., Kroustalis, Christina M., Rivkin, David, and Lewis, Phil. 2009. Greening of the World of Work: Implications for O*NET-SOC and New and Emerging Occupations. National Center for O*NET Development.

Popp, D. 2016. Economic Analysis of Scientific Publications and Implications for Energy Research and Development. Nature Energy, 1(4), 1-8, DOI: 10.1038/nenergy.2016.20.

Ruggles, S., Flood, S., Goeken, R., Grover, J., Meyer, E., Pacas, J. and Sobek, M., 2020. IPUMS USA: Version 10.0 [dataset]. Minneapolis, MN: IPUMS. https://doi.org/10.18128/D010.V10.0

Schott, P. K., 2008. The relative sophistication of Chinese exports. Economic Policy, 23, 5–49.

Vona, F., Marin, G., Consoli, D., Popp, D., 2018. Environmental Regulation and Green Skills: an empirical exploration, Journal of the Association of Environmental and Resource Economists vol. 5(4): 713–753

Vona, F., Marin, G., Consoli, D., 2019. Measures, Drivers and Effects of Green Employment: evidence from US metropolitan and non-metropolitan areas, 2006-2014, Journal of Economic Geography 19, 1021–1048.