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From Polluting to Green Jobs: A Seamless Transition in the U.S.?

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ABSTRACT: What are the implications of the needed climate transition for the potential reallocation of the U.S. labor force? This paper dissects green and polluting jobs in the United States across local labor markets, industries and at the household-level. We find that geography alone is not a major impediment, but green jobs tend to be systematically different than those that are either neutral or in carbon-emitting industries. Transitioning out of pollution-intensive jobs into green jobs may thus pose some challenges. However, there is a wage premium for green-intensive jobs which should encourage such transitions. To gain further insights into the impending green transition, this paper also studies the impact of the Clean Air Act. We find that the imposition of the Act caused workers to shift from pollution-intensive to greener industries, but overall employment was not affected.

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Keywords:	Green and polluting employment; Green Labor Market Transition; Environmental Regulation

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1 Introduction

The U.S. administration announced ambitious climate goals that require determined policy actions and pitched the "green transition" as an opportunity to create new, unionized, high-paying jobs.

At the same time, a transition of this magnitude has the potential to result in "winners and losers" (Economic Advisors, 2022). A large existing literature shows that technological change, automation, and trade policy have boosted the productivity of many but have also displaced workers whose jobs are either automated or outsourced (Autor et al., 2003, Acemoglu and Autor, 2012). A prominent example is seen in the rising import competition from China which negatively affected U.S. manufacturing employment, particularly among workers with lower skills (Acemoglu et al., 2016, Autor et al., 2013a, Hakobyan and McLaren, 2016).

This paper tries to assess the magnitude of the challenge posed by the transition to a low carbon economy by (i) dissecting green and polluting jobs in the U.S. to offer clues on existing labor market mismatches and (ii) studying the employment implications of past environmental policies as an indicator of the potential costs of a broader "green" transition. Detailed data on occupations, industries, and households are employed for the former. Plant-level environmental regulations under the Clean Air Act (CAA) are used to examine effects of the latter.

Crucial for this work is the definition of green job intensity. Here we follow a recent but rapidly-expanding literature (Consoli et al., 2016, Vona et al., 2018, Bowen et al., 2018, IMF, 2022, and Bluedorn et al., 2022). We rely on a green index constructed by Vona et al., 2018 based on the O*NET dataset, where "green" jobs are those either expected to see increased demand from the green transition, or those with markedly enhanced or changed skill sets required for a low-carbon economy. To do so, O*NET first classifies tasks as either green or non-green. Vona et al., 2018 then create a "green index" capturing the ratio of green tasks to total tasks for each occupation. Vona et al., 2019 estimate that between 2-3 percent of U.S. employment is green as of 2014, similar to the findings in IMF, 2022 and Bluedorn et al., 2022 for a broader group of countries. Pollution-intensive occupations are defined as those predominant in polluting or environmentally-damaging sectors (obtained from Vona et al., 2018).

There is a significant geographical overlap for green and polluting jobs in the U.S. Data on employment-weighted green and polluting job intensity at the commuting zone-industry level reveals that many areas with significant pockets of green jobs are either close to, or overlap with, areas with significant numbers of polluting jobs. At the industry level, while pollution-intensive jobs seem to be concentrated in a few industries, green-intensive jobs seem more widespread and several industries have the potential to improve the green intensity of jobs by simply emulating firms in the same industry in different locations (an option that is much more limited for pollution-intensive jobs).

Household-level data suggest green intensive jobs are systematically different from other jobs. Greener jobs tend to be held by workers that earn higher income, are more skilled, are less subject to automation, and live in urban areas. In terms of age, both green- and pollution-intensive jobs are held by prime working-age workers. On the other hand, "neutral" jobs (those that are non-green and non-polluting) are more prevalent among the youngest and oldest. Moreover, we find that green jobs attract a wage premium that goes beyond observable characteristics.

We find that moving from polluting to green jobs is unlikely. The transition from polluting to neutral jobs seems easier. Of course, this dynamic may well change as more green job opportunities become available. Transitions to greener jobs tend to attract a wage increase but so do transitions from neutral to more pollution-intensive jobs. However, those who held green jobs but subsequently became unemployed, end up returning to the workforce at lower hourly wages. The same is not true for those returning to the workforce who held pollution-intensive jobs and then became unemployed.

Taken together the anatomy of green and polluting jobs suggests green jobs and workers are systematically different and most of the transition out of polluting jobs will likely take place by workers being re-employed in neutral jobs. On average, neutral jobs tend to pay similarly to pollution-intensive jobs although it is not entirely clear if other aspects of the work (e.g. working conditions) are comparable.

We find that the past application of the Clean Air Act does not have a measurable effect on employment within the local area. This finding contributes to a growing literature on whether regulation can increase input costs and reduce the overall demand for labor (as job losses in affected sectors may not be made up by other sectors). One strand of this literature focuses on energy prices or carbon prices and finds mixed results. While Kahn and Mansur (2013) find that energy intensive industries concentrate in low-electricity price areas, Martin et al. (2014) show that a carbon tax on manufacturing in the UK had no significant effect on employment or plant exit. Popp et al. (2020) find that green fiscal measures through the American Recovery and Reinvestment Act did increase total employment but more slowly than other stimulus investment. Most closely related to our project are analyses on the regulation of environmental pollutants. Berman and Bui (2001) and Morgenstern et al. (2002) analyze local regulations at the plant level and fail to find significant effects on employment. Other studies focus on the Clean Air Act where evidence is more negative. Greenstone (2002) shows that stricter regulation affected employment outcomes negatively and Walker (2011) shows that this happens through job destruction rather than lower hiring rates. At the micro level, Walker (2013) shows that workers in newly regulated plants experienced, in aggregate, more than $5.4 billion in forgone earnings for the years after the change in policy, mainly driven by nonemployment and lower earnings in future employment.

We find that while employment and the number of establishments[1] contract in those region-industries affected by the Clean Air Act, the effects on total employment at the local labor market level are not significant. As expected for affected industries, environmental regulations are found to shift employment away from pollution-intensive industries into industries and areas that are relatively greener. We also study the response of average pay within the local area after the application of the Clean Air Act regulations and find no significant change either for the affected region-industries or for the local labor market more broadly.

Taken as a whole, the green transition will necessitate a shift in labor markets and this will be a complex process (not a simple and seamless move from polluting to green jobs). Workers are likely to move to neutral jobs with similar average pay levels on average. Geographic moving costs, however, do not seem to be a major obstacle. Past transitions resulting from environmental regulation have found local U.S. labor markets to responded flexibly with no major disruptions to employment or average pay. However, what is pending is a much larger scale transition and so there is still a policy role to make the reallocation of labor that will be needed as smooth as possible, especially given the different characteristics of pollution-intensive and green jobs.

The remainder of this paper is organized as follows: Section 2 details the data used in this paper, Section 3 presents an anatomy of green and polluting jobs in the U.S., and Section 4 discusses findings on labor market transitions driven by environmental regulation. Finally, Section 5 concludes.

2 Data

This paper matches definitions of green and pollution-intensive jobs with: (i) geographical (county and commuting zone) and industry-level data, (ii) Household-level data, and (iii) environmental regulation data at the plant level. This section describes these different datasets in detail.

[1] The U.S. Census defines establishments as "...a single physical location at which business is conducted or services or industrial operations are performed. An establishment is not necessarily equivalent to a company or enterprise, which may consist of one or more establishments."

2.1 Defining Green- and Pollution-intensive Occupations or Jobs

We follow Vona et al., 2018, and its application in IMF, 2022, in defining green- and pollution-intensive jobs, and the reader should refer to those references for details beyond those summarized below and in Appendix B.

Green-intensive Jobs. The starting point for estimating the green intensity of a given job is the taxonomy of tasks into green and non-green at Standard Occupational Classification (SOC) 8-digit level put together by O*NET's Green Task Development Project (Center, 2010 and Center, 2021). O*NET distinguishes three types of green tasks as those that are: (i) existing occupations that are expected to be in high demand due to the greening of the economy; (ii) are expected to undergo significant changes in task content due to the greening of the economy (green-enhanced); and (iii) new occupations in the green economy.[2]

Using the O*NET green task taxonomy, Vona et al., 2018 compute a ratio of green tasks to total tasks as a measure of the green intensity of a given occupation (see Table A1 in their paper and "the greenness ratio" defined in their equation 1). Finally, Vona et al., 2018 assume employees are uniformly distributed across 8-digit occupations within each 6-digit SOC occupation to get the green intensity of a given 6-digit SOC occupation. This is done because the 6-digit level is the maximum level of disaggregation available in publicly-available employment data provided by the Bureau of Labor Statistics.[3]

Pollution-intensive Jobs. Vona et al., 2018 define polluting occupations as those prevalent in polluting industries. Polluting industries are a set of 62 4-digit NAICS industries that are in the 95th percentile of pollution intensity for at least 3 pollutants among CO2, CO, VOC, NOx, SO2, PM10, PM2.5, and Lead. Pollution-intensive occupations are then defined as those with a 7 times higher probability of working in polluting sectors than in any other job.[4]

A final note on these two definitions. These definitions are inherently different at the occupational level, i.e. green intensity of a job is its share of green tasks and thus it is a continuum between 0 and 1 at the 6-digit occupation level, while pollution intensity is occupation-based and thus only takes the value of 0 or 1 at the 6-digit occupation level.

[2]Vona et al., 2018 cite an example of an occupation— Sheet Metal Workers (47-2211.00)— that performs a mix of green, e.g. construct ducts for high efficiency heating systems or components for wind turbines, and non-green tasks, e.g. develop patterns using computerized metal working equipment.

[3]Appendix B in Vona et al., 2018 has a good discussion of this assumption. Crucially, most variation in green tasks is at the 6-digit level and, moreover, 83.3 percent of workers are in occupations without an 8-digit sub-category.

[4]This choice involves judgement and Vona et al., 2018 discuss why this particular threshold was chosen in footnote 16.

However, most of our paper collapses occupation-level data further, e.g. by aggregating occupations to a coarser 5-digit level, or by mapping different vintages of SOC codes across time which is never perfect even at the 6-digit level or even by collapsing to industry-level, which means we need to weigh occupations based on their employment. Another example is when we convert 6-digit SOC occupation codes to alternative occupation codes (e.g., IPUMS Current Population Survey occupation codes that are consistent across time). All of these collapses entail generating an employment-weighted measure of green and pollution intensity which is a continuum between 0 and 1 for both cases. Still the fundamental difference between definitions means that interpretations of the green intensity and the pollution intensity are not the same, and magnitudes should be compared with caution.

2.2 Green- and Pollution-intensive *Employment* at State/National and Industry Levels

There is no public dataset that breaks down employment at county- or commuting zone-, industry- and occupation-levels.[5]

Hence, we estimate employment-weighted green and pollution job intensity by combining (i) the definitions of green and pollution-intensive occupations discussed in the previous subsection and (ii) state/national-industry-occupation employment from the U.S. Bureau of Labor Statistics Occupational Employment Wage Statistics (OEWS). The OEWS data includes occupations at the SOC 6-digit level and industries at varying degrees of disaggregation ranging from NAICS 4- to 6-digit levels. After 2012, state-industry-occupation data are available from the OEWS Research Estimates. Prior to 2012, national-industry-occupation information is used.

For charts of green or polluting jobs over time presented in Section 3 we make use of state-occupation level data for 2004-2019 also from OEWS. It can thus be easily merged with the occupational level definitions of green- and pollution-intensity discussed in the previous subsection directly. As the BLS notes, the OEWS is not a panel dataset and rather repeated cross-sections. Because of changes over time in the classification of occupations, one should interpret time-series variation in employment-weighted green and polluting intensities with care as elaborated for employment here.[6]

[5]The closest is State or Metropolitan Statistical Area (MSA) level data from Occupational Employment Wage Statistics. We chose to use commuting zones for some analyses and thus estimate county-level data to aggregate up to commuting zones rather than imperfectly mapping MSA data into commuting zones. Both carry potential measurement errors.

[6]We purposefully excluded 2002-2003 from the charts over time, because occupational codes for those years are not as detailed, which seems to shift state-level employment-weighted green intensities, although not visibly for pollution-intensities. See Appendix B.1 for details on how occupational classifications were merged across time.

2.3 Estimating Employment-weighted Green and Pollution Intensities at County/Commuting Zone and Industry Levels

With measures of employment at the State/National-industry-occupation-year level, we estimate the employment-weighted green and polluting job intensity at the county level using county employment from Eckert et al., 2020, who harmonize data and fill censored observations from the U.S. Census County Business Patterns (CPS). Industries are disaggregated at NAICS 6-digit level.

The assumption behind our county estimates is that the occupational breakdown of State-industry-year observations (post-2012) and National-industry-year observations (pre-2012) of green and pollution intensities are representative for all counties either in the same State (post-2012) or for the whole country (pre-2012) in the same industry for the same year. For this analysis, industries are aggregated to 5-digit NAICS. While this surely introduces noise, this is mitigated by the fine level of industry disaggregation.

Finally, we also convert all county-level data into 2000 census commuting zones (see B.3 for details).

2.4 County Business Patterns (CBP) Establishments and Payroll Data

We also complement employment data with CBP data for number of establishments, annual payrolls, and number of establishments divided by twelve employment size buckets. This data does not depend on the definitions of green- and pollution-intensive jobs. For more details on how CBP data was processed see Appendix B.2.

2.5 Current Population Survey (CPS)

We use IPUMS U.S. Current Population Survey (CPS) March Supplements between 1998 and 2019. The U.S. CPS March Supplements survey around 190,000 individuals on average each year and contain information on demographic characteristics (gender, age, education), labor market status (labor force status, occupation, and industry), and earnings. Using the annual earnings and usual hours worked per week, we can infer hourly wages. Hourly wages are deflated by U.S. Consumer Price Index for All Urban Consumers (CPI-U) to be expressed in 2015 constant U.S. dollars.

We merge the definitions of green and pollution-intensive jobs (see 2.1) with our IPUMS CPS data. IPUMS CPS contains harmonized occupation codes (variable named occ2010) across years. We first merge 6-digit SOC 2010 occupation code to CPS unharmonized occupation code using the concordance table of the Bureau of Labor Statistics, and then merge unharmonized 2010 CPS occupation codes to harmonized 2010 occupation IPUMS occupation codes using the sample in the IPUMS CPS Data.

The CPS March Supplements data allow us to study demographic characteristics of those who hold green- and pollution-intensive jobs. We can also study how prevalent green- and pollution-intensive jobs are across different income groups and age groups as well as the wage premium associated with holding green- vis-a-vis pollution-intensive jobs. Since the CPS re-samples workers after eight months, we can investigate transitions from pollution-intensive to green-intensive jobs and any associated wage changes.

2.6 Data on the Clean Air Act

The Clean Air Act (CAA) was first established in 1963 and is still the most important federal environmental law in the United States. It requires the Environmental Protection Agency (EPA) to develop and enforce regulations to protect the general public from exposure to hazardous airborne contaminants. This is done by enforcing national ambient air quality standards (NAAQS) which specify the minimum level of air quality acceptable for six criteria of air pollutants, namely sulphur dioxide (SO_2), particulates (total suspended particulate (TSP), particulate matter 2.5 and 10 — PM2.5, and PM10 respectively), nitrogen dioxide (NO_2), carbon monoxide (CO), ozone (O_3), and lead (Pb). The EPA deems a county as "out of attainment" if the presence of one or more of these pollutants is beyond certain thresholds. In this case, the EPA requires states to adopt regulatory plans, known as state implementation plans (SIPs), to bring the particular non-attaining county into compliance. In addition, the EPA can impose sanctions at the federal level in areas that fail to comply with these requirements, such as through the withholding of federal grants to state and local governments.

We combine two main data sets in order to measure which industry in which county is not meeting NAAQS at each point in time. The Integrated Compliance Information System (ICIS) database provides plant level information detailing the regulatory programs for which a plant is regulated as well as the specific pollutants for which the regulatory permit is issued.[7] However, this data does not provide the timeline as to when the regulatory status was active. For this reason, we use panel data from the EPA which records non-attainment designation over time at the county level. Combining this with the sector information of the affected plant, we obtain a panel data set at the county industry level.

[7]We follow Walker (2013) and label a plant as regulated if it records one of the following permits within the "Air Program Code" field of the ICIS database: Title V Permit, State Implementation Plant (SIP) Source, SIP Source under federal jurisdiction, Prevention of Significant Deterioration (PSD) permit, New Source Review (NSR) permit, or New Source Performance Standards (NSPS) permit.

3 An Anatomy of Green- and Pollution-intensive Jobs

This section dissects green- and pollution-intensive jobs in the U.S. It finds that the two types of jobs overlap significantly geographically, even at the local labor market level. However, household data suggests that green-intensive jobs may be systematically different than both pollution-intensive and "neutral" (non-green and non-polluting) jobs.

As noted in Section 2.1, green intensity of a job is its share of green tasks and thus it is a continuum between 0 and 1 at the 6-digit occupation level. Pollution intensity is occupation-based and thus only takes the value of 0 or 1 at the 6-digit occupation level. This section uses employment weighted average of green and pollution intensities across occupations at a geographic location (e.g., county level, commuting zone level, state level) in Section 3.1 and for specific demographic groups (e.g., high-skilled workers, workers in routine occupations, workers living urban occupations in Section 3.2.

3.1 Geographic and Industry Composition

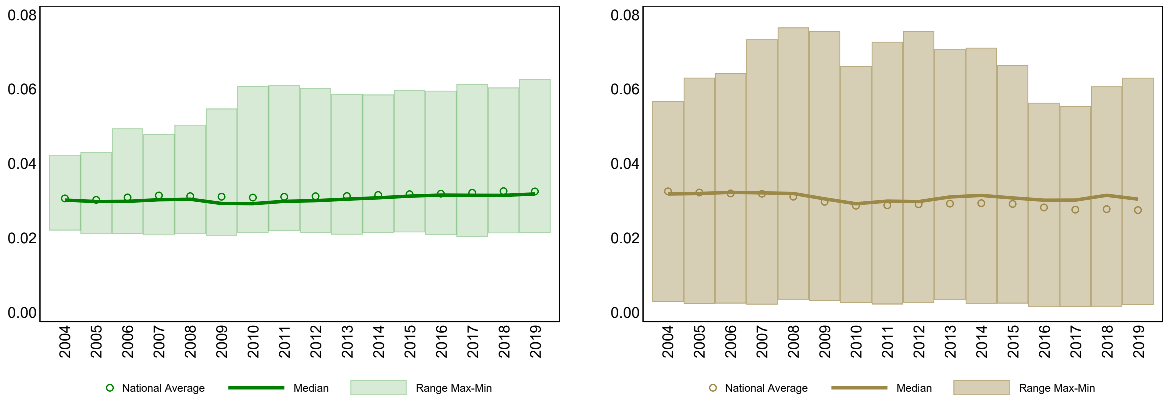
The share of green jobs has not materially grown over time at the national level, although the aggregate share hides rising cross-state dispersion. Figure 1.a shows a summary of the distribution of the share of green jobs across states and the District of Columbia in 2004-2019. While both the national share of green jobs (hollow circles) and the median across states (solid line) is remarkably stable and not clearly rising, the range (bars) across states rose following the global financial crisis and has remained fairly steady thereafter.

Pollution-intensive jobs do appear to be declining slightly as a share of total national employment. Figure 1.b shows a summary of the distribution of the share of polluting jobs across states in 2004-2019. The national share of polluting jobs is on a slight downward trend (hollow circles), while the median across states (solid line) seems more stable. The range across states (bars) is similarly stable, having risen in the late 2000s but declining after 2015.

Moving to the industrial make up of green and polluting jobs across states, we find that polluting jobs seem to vary most importantly *between* industries. However, the distribution of green jobs varies significantly *within* industries. Figure 2 decomposes the variance of green and polluting job intensities for each year into its between (solid lines, across industries for each given state) and within (dashed lines, within the same industry across all states) dimensions. Because of the differences in average intensity of green and polluting jobs, it is not appropriate to compare the levels of the brown lines with the green lines in Figure 2 and we rather focus on the comparison across solid and dash lines for each color. The fact that polluting jobs vary more between industries is not surprising by the very nature of the way they are constructed, i.e. these are jobs prevalent in especially

Figure 1: Employment-weighted Green and Polluting Jobs Across States Over Time

(a) Green Jobs (b) Polluting Jobs



Source: Vona et al., 2018, OEWS, and Authors' calculations.

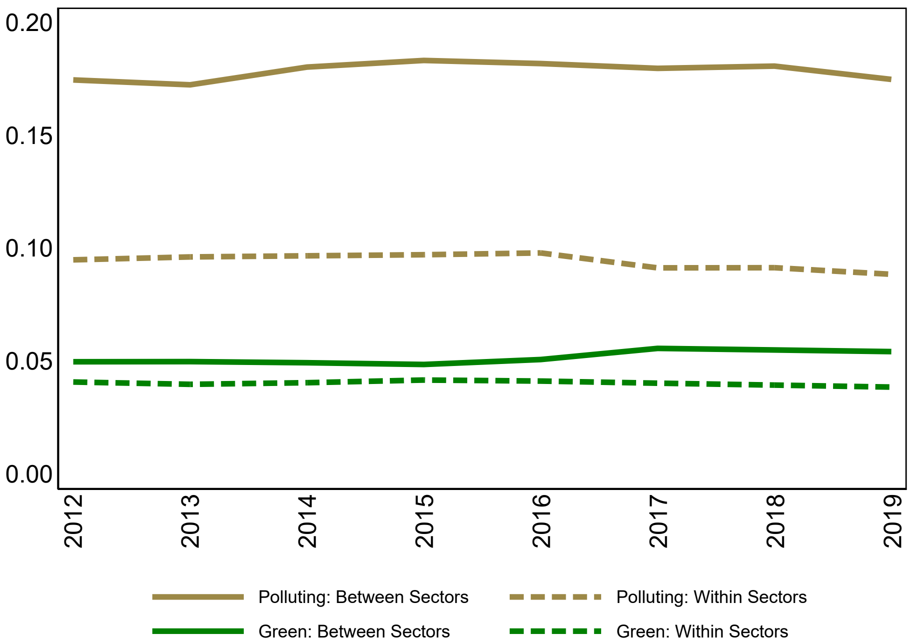
Notes: Underlying these charts is the share of each state's green and polluting jobs in total employment of the State. The solid line is the median for each year of those numbers; the hollow circles is the employment-weighted mean or the national level share; and finally the bars denote the minimum to maximum range of shares across all states. Because of changes over time in the classification of occupations, one should interpret time-series variation in employment-weighted green and polluting intensities with care as elaborated for employment here. See Section 2 for more details.

polluting industries, as explained in 2. Interestingly, the variation across states of green job intensity for the same industry is almost as high as the between industry variation for each state. This suggests that (1) green jobs are relatively more dispersed across industries than polluting jobs; and thus (2) there may be opportunities to increase the share of green jobs without necessarily having large shifts in the sectoral composition of activity within a particular state (in contrast with polluting jobs where certain industries are more dominant).

Turning to the geographic dimension, green- and pollution-intensive jobs seem concentrated in certain parts of the United States. The West, Southwest, and parts of the Midwest seem to have important concentrations of green-intensive jobs (Figure 3.a). Some notable industries in these regions with green-intensive jobs are research and development, engineering services, and aerospace manufacturing. At the same time, the Southeast and Southwest appear to have a particular prevalence of higher pollution-intensive jobs which include extractive industries, electric power generation, transmission and distribution, wood, and textile industries (Figure 3.b).

At the commuting zone level, green and pollution-intensive jobs tend to be located close together (Figure 3.c). Commuting zones are commonly used as measures of local labor markets in the literature (e.g., Autor et al., 2013b, Chetty et al., 2014, and Amior and Manning, 2018). The map shows that commuting zones that have a significant share

Figure 2: Variance Between and Within Sectors At Sector-State Level



Source: Vona et al., 2018, OEWS, and Authors' calculations.

Notes: This chart shows the within-between variance decomposition of green- and polluting job intensities across states for each year. The dashed lines show variation within the same industry across all states for green (colored green) and polluting (colored brown) jobs. The solid lines show variation across industries for each given state. Because of changes over time in the classification of occupations, one should interpret time-series variation in employment-weighted green and polluting intensities with care as elaborated for employment here. See Section 2 for more details.

of green-intensive employment[8] (represented by dark green or light green colors on the map) either also have a significant share of pollution-intensive jobs (light green)[9] or are adjacent to areas with a high number of pollution-intensive jobs (dark brown). Concretely, 72 percent of commuting zones that are in the top 25th percentile for pollution-intensive jobs are either also in the top 25th percentile for green jobs or border a commuting zone that is.

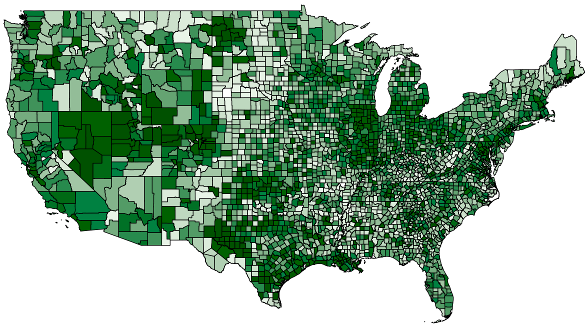
As such, Figure 3 suggests that geographic mobility may not be a meaningful friction in preventing workers in pollution-intensive industries from reallocating to more environmentally friendly jobs. The next subsection uses household data to go beyond the geography of green- and pollution-intensive jobs to ascertain whether there could be mismatches in the characteristics of the workers in these different types of jobs.

[8]For this chart alone, we define "green" rich regions as those at the top 25th percentile in terms of green job intensity.

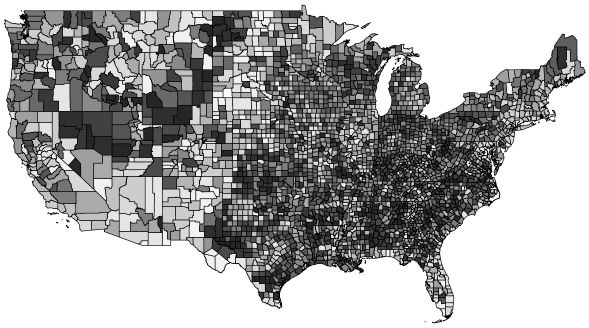
[9]For this chart alone, we define "polluting" rich regions as those at the top 25th percentile in terms of polluting job intensity.

Figure 3: Employment-weighted Green and Polluting Jobs in 2016

(a) Green Jobs Across Counties

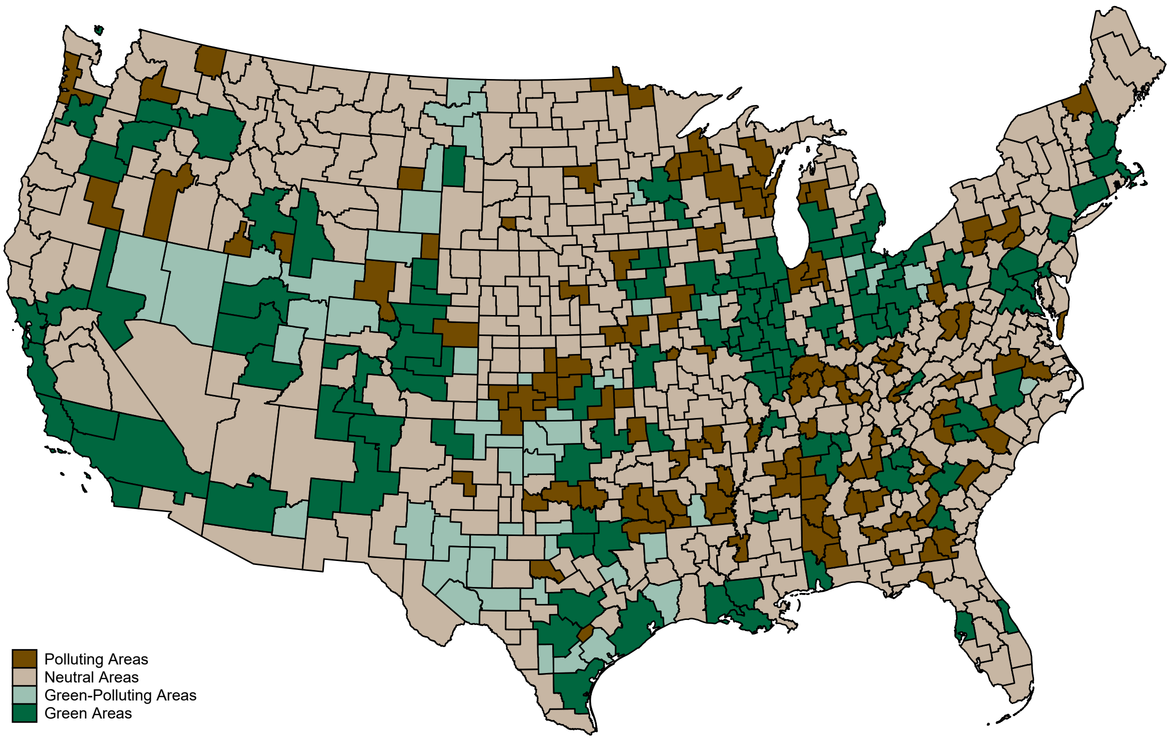


(b) Polluting Jobs Across Counties



Notes: Maps use a relative coloring scheme, i.e. greener (darker) coloring means that employment is very green(pollution)-intensive in a relative rather than an absolute sense. Estimates of green(pollution)-intensive jobs combine three datasets (see Section 2) (i) definitions of green/polluting occupations; (ii) industry-state occupational breakdowns; and (iii) county-industry employment. See Section 2 for more details.

(c) Overlaps at the Commuting Zone-level



Source: Vona et al., 2018, OEWS, Eckert et al., 2020, and Authors' calculations.

Notes: "Green Areas" denotes commuting zones for which the share of employment-weighted green jobs exceeds the 75th percentile across commuting zones and the share of employment-weighted polluting jobs is below the 75th percentile across commuting zones; "Green-Polluting Areas" denotes commuting zones for both the share of employment-weighted green and the share of employment-weighted polluting jobs exceed their respective 75th percentile across commuting zones; "Neutral Areas" denotes commuting zones for which both the share of employment-weighted green jobs and the share of employment-weighted polluting jobs is below their respective 75th percentile across commuting zones; "Polluting Areas" denotes commuting zones for which the share of employment-weighted green jobs is below the 75th percentile across commuting zones and the share of employment-weighted polluting jobs exceeds the 75th percentile across commuting zones. See Section 2 for more details.

3.2 Household-level Evidence

In this section, we study (i) the demographic characteristics of workers who hold green-intensive, pollution-intensive, and neutral jobs, where neutral jobs are those that have zero green tasks and are not polluting occupations, (ii) the prevalence of different environmental properties of jobs by income decile and age groups, (iii) the wage premium of workers who hold average green-intensive score vis-a-vis those who hold average pollution-intensity score, and (iv) hourly wage implications for those who experience transitions across different types of jobs depending on the environmental properties of jobs. We find that green jobs appear to be systematically different than both polluting and neutral jobs along a number of dimensions.

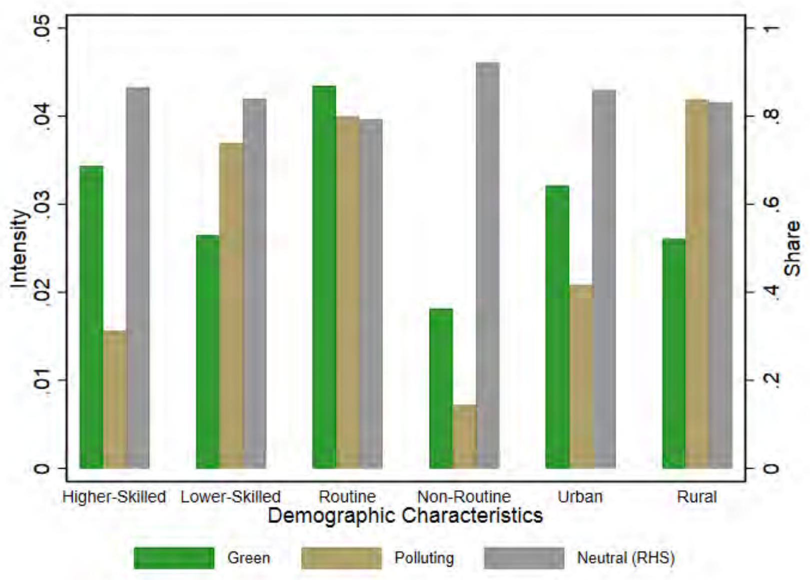
Polluting jobs tend to be held by workers that are less skilled and more vulnerable to automation. Figure 4 plots the average green intensity and the share of workers holding neutral and polluting jobs by skill, routine/non-routine, and urban/rural over the entire sample period. We find that high-skilled workers, on average, have more green intensive jobs than low-skilled workers.[10] Routine jobs tend to have both higher green- and higher pollution-intensity than non-routine jobs. However, workers with non-routine occupations tend to work proportionally more in greener jobs. Finally, urban workers also tend to have higher green (lower pollution) intensity than rural workers. When we regress green intensity and pollution dummy on all demographic characteristics simultaneously, we find that indeed workers that are high-skilled, living in urban, and hold jobs that are less vulnerable to automation tend to have greener jobs, after controlling for the rest of the variables,. Neutral jobs seem well distributed across skill and urban/rural.

When we compare the environmental properties of jobs by age groups, we find that the share of workers holding neutral jobs has a slight U-shape over the life cycle with the highest concentration of neutral jobs among the youngest age group, 16-19 years old, while green and pollution intensities have an inverted U-shape over the life cycle (Figure 5). This contradicts our prior that green jobs are predominantly held by young workers and older workers tend to be in polluting jobs. This finding also goes against the belief that the green transition can naturally be accomplished over time by older workers retiring from pollution intensive jobs while younger workers disproportionately begin their careers in green jobs.

Green intensive jobs tend to be held by higher income groups. Figure 6 plots the environmental properties of jobs by income deciles. The green intensity of jobs increases across income deciles. In other words, higher income groups tend to hold greener jobs.

[10]High-skilled workers are defined to be those with educational attainment level with some college or above. We follow Carrillo-Tudela et al., 2016 to define routine/non-routine jobs. For the definitions of urban or rural areas where individuals live, we use "METRO" variable in IPUMS to see whether a household lives in a metropolitan area.

Figure 4: Environmental Properties by Demographic Characteristics



Source: Current Population Survey and Authors' calculations.

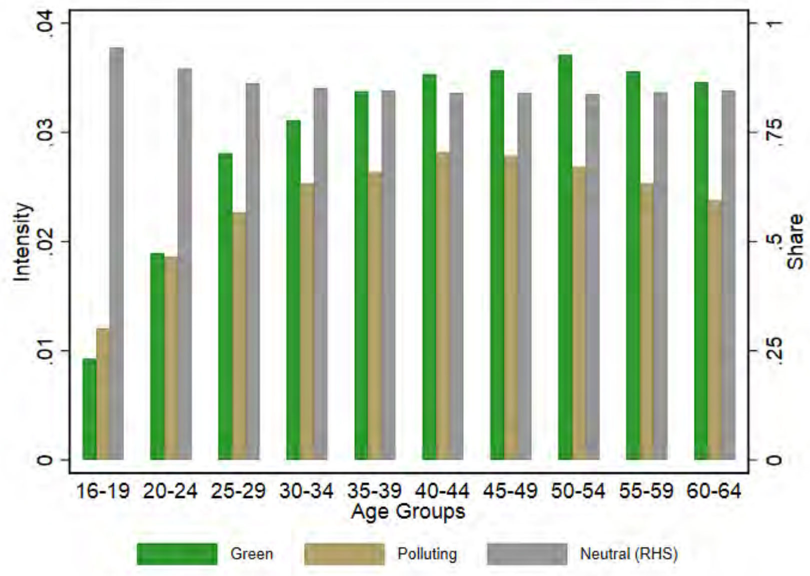
Notes: This chart shows the employment weighted average of green and pollution intensities and the employment share of neutral jobs within each demographic group, where green intensity is the employment weighted average share of "green" tasks and pollution intensity is the employment share of polluting occupations. Higher-skilled is defined as someone with some college or more, while lower-skilled are those with high school degree and below. For routine/non-routine, we follow (Carrillo-Tudela et al., 2016). For urban/rural, we use "METRO" variable in IPUMS to see whether a household lived in a metropolitan area.

On the other hand, pollution intensity has an inverted-U shaped relationship with income so, in contrast to green jobs, the average pollution intensity score declines at the top few deciles of the income distribution.

We also examine whether workers with green jobs earn more than those with pollution intensive jobs and, if so, how this wage differential has evolved over time. To this end, we run a Mincer-type regression for each year between 1998 and 2019 in which the dependent variable is log of real hourly wage and the key explanatory variables are green intensity and pollution intensity. A high-skilled dummy (whether the worker attended some college or above), age, age squared, and an urban dummy (whether the worker lives in an urban area) are included in the regression as additional controls.

The wage premium of green vs. polluting jobs is estimated to be around 2 percent and has trended modestly upward over time. Figure 7 plots the evolution of real hourly wage premium of average green intensive jobs vis-a-vis average pollution intensive job. We find that there is a small but statistically significant wage premium for a green job holder vis-a-vis a pollution intensive job holder. Such a premium could incentivize the transition

Figure 5: Environmental Properties by Age Groups



Source: Current Population Survey and Authors' calculations.

Notes: This chart shows the employment weighted average of green and pollution intensities and the employment share of neutral jobs within each age group where green intensity is the employment weighted average share of "green" tasks and pollution intensity is the employment share of polluting occupations.

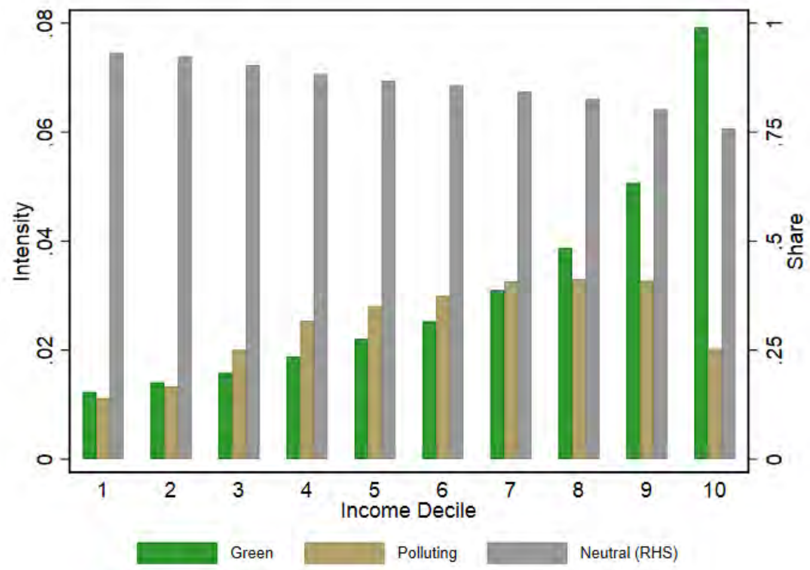
toward a greener economy. However, this apparent premium could be reflective of other important characteristics of green jobs (e.g. of specific skills) that are not appropriately controlled for in our Mincer regressions.

However, transitions into green jobs are relatively infrequent for workers who held jobs that are pollution intensive. Figure 8 shows the transition probabilities by original occupation type. Workers who previously held a green-intensive job, and decide to change jobs, have a more than 40 percent chance of moving to a new green-intensive job. This is a much higher likelihood than those who initially held either pollution-intensive (around 15 percent) or neutral jobs (around 10 percent only) and choose to move jobs. However, given there is a large share of neutral jobs in the total, workers who held pollution-intensive jobs can transition much more easily to neutral jobs (at a probability of around 60 percent).[11]

Those that change occupation and used to hold a green job experience a fall in their

[11] Note that the probability of transitioning from a pollution-intensive job to a neutral jobs is much higher in this paper (around 60 percent) than those estimated in IMF, 2022 (around 14 percent) based on cross-country data from European Union Statistics on Income and Living Conditions (EU-SILC). This is mainly due to the fact that the US CPS data contains much more granular occupation categories than EU-SILC data does, which results in the US data having a much higher employment share of neutral jobs.

Figure 6: Environmental Properties by Income Decile



Source: Current Population Survey and Authors' calculations.

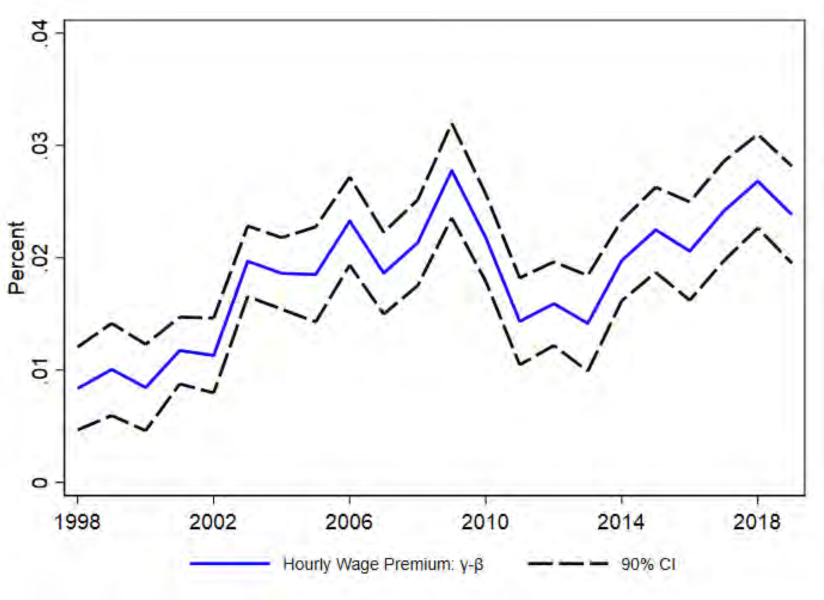
Notes: This chart shows the employment weighted average of green and pollution intensities and the employment share of neutral jobs within each income decile group, where green intensity is the employment weighted average share of "green" tasks and pollution intensity is the employment share of polluting occupations.

wage, unlike those with polluting jobs. Table 1 shows estimates from regressing the change in real hourly wage among workers who are continuously employed for two consecutive years (EE) conditional on workers switching occupation for those: (i) who previously held a job with positive green intensity ("$OccSwitch \times Green_{t-1}$"); (ii) a job with positive polluting intensity ("$OccSwitch \times Polluting_{t-1}$"); or finally (iii) any other occupational switches ("$OccSwitch$"). There is wage penalty for those who previously held green jobs ("$OccSwitch \times Green_{t-1}$") when switching occupations, but not for those who previously held polluting jobs ("$OccSwitch \times Polluting_{t-1}$"). For those who held neutral jobs in the previous year, an occupational switch is associated with a real hourly wage increase ("$OccSwitch$").[12] These conclusions are robust to the inclusion of individual characteristics such as age, age-squared, dummy for male, high-skill dummy, and urban dummy (column 2), instead controlling for year fixed effects (column 3), and controlling for both individual characteristics and year fixed effects (column 4).

The wage loss of green job holders when switching is driven by those who switched to less green jobs, which is not the case for those who switched to less polluting jobs. Table

[12]Those who continue to be employed for two consecutive years and do not change occupation, as captured by the constant term, on average, experience real wage increases.

Figure 7: Hourly Wage Premium of Green Jobs



Source: Current Population Survey and Authors' calculations.

Notes: This chart shows hourly wage premium of an occupation with the average green intensive job vis-a-vis the average polluting job after controlling for skill, age, age-squared, gender, and an urban dummy.

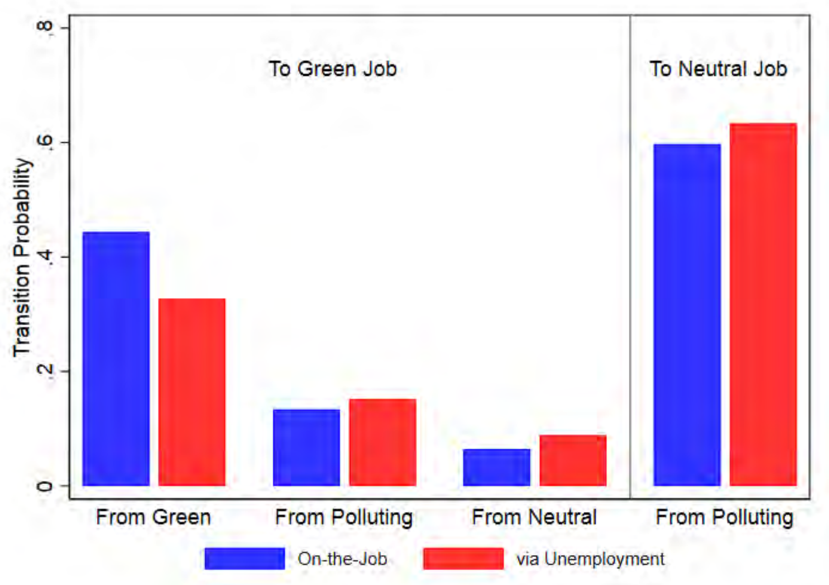
2 shows the real hourly wage change for workers who have been employed for two consecutive years and have switched to a greener job ("*Greener*"), a less green ("*LessGreen*"), a more polluting job ("*MorePolluting*") or a less polluting ("*LessPolluting*") job. Those who moved to less green jobs experience a real wage loss relative to those who did not switch occupations or switched but their jobs did not change in terms of green or pollution intensity, which is captured by the constant term. However, those switching to less polluting jobs do not experience such a wage loss[13].

We turn to studying workers that moved to a job after an unemployment spell. Unfortunately, the CPS does not collect the last wage of those that reported being unemployed in the previous year and it does not track workers beyond two consecutive years. Luckily, the CPS does ask about the previous occupation held by unemployed persons. To understand the wage implications of occupational switches for those who were unemployed last year but found a job this year (UE), we take the following approach. First, for each occupation[14], we run a Mincer-type wage regression among the sample of employed workers. Using the estimated coefficients, we impute the predicted wages of those unemployed

[13]We find that those who move to either a greener or a more polluting job experience additional wage gains.

[14]We use IPUMS CPS harmonized occupation code ("*occ*2010") for this analysis, which includes 4-digit codes corresponding to more than 450 occupations

Figure 8: Probability of Job Transitions by Original Job Type Held



Source: Current Population Survey and Authors' calculations.

Notes: This chart shows the transition probabilities from moving from a green/polluting/neutral occupation to another green occupation for those who switch jobs without/with an unemployment spell ("on-the-job"/"via Unemployment").

given their past occupation as well as their demographic characteristics (age, age-squared, skill, and whether they live in urban or rural area). We then calculate the difference in actual real wage when they become employed and the predicted wage based on their past occupation and demographic characteristics.

Similar to workers employed for two consecutive years, those unemployed who previously held green jobs and switch occupations to a non-green job upon reemployment earn less, while the unemployed who previously held polluting jobs do not suffer from wage loss regardless of whether their new job is green or not. Table 3 shows the regression results of those who were unemployed and found a job (UE). First, those who experience an unemployment spell and return to work experience a wage loss, as shown in the constant, and an occupational switch via unemployment is generally associated with additional wage losses, consistent with the existing literature. Similar to those who were continuously employed, workers who previously held a green job and found a job after an unemployment spell earn a lower wage when switching to an occupation ($OccSwitch \times Green_{t-1}$), while those who previously held a polluting or a neutral job do not experience wage losses. These conclusions are robust to the inclusion of controls, namely controlling for individual characteristics such as age, age-squared, dummy for male, high-skill dummy, and urban dummy (column 2), instead controlling for year fixed effects (column 3), and controlling

Table 1: Changes in Real Hourly Wages of Workers Employed in Two Consecutive Years (EE) based on the Environmental Properties of Jobs Held in the first Year

	(1) ΔlnW_t	(2) ΔlnW_t	(3) ΔlnW_t	(4) ΔlnW_t
$OccSwitch \times Green_{t-1}$	-0.0528***	-0.0429***	-0.0524***	-0.0427***
	(0.00637)	(0.00679)	(0.00653)	(0.00693)
$OccSwitch \times Polluting_{t-1}$	-0.00637	0.00464	-0.00749	0.00395
	(0.0108)	(0.0114)	(0.0109)	(0.0115)
$OccSwitch$	0.0100***	0.000446	0.0102***	0.000602
	(0.00288)	(0.00305)	(0.00289)	(0.00299)
$Constant$	0.0580***	0.453***	0.101***	0.490***
	(0.00345)	(0.0208)	(0.00130)	(0.0184)
Indiv. Chara	No	Yes	No	Yes
Year FE	No	No	Yes	Yes
Observations	349,128	346,865	349,128	346,865
R-squared	0.000274	0.00416	0.000719	0.00456
Adjusted R-squared	0.000265	0.00414	0.000653	0.00448

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: U.S. CPS and Authors' calculations.

Notes: The table shows changes in log real hourly wage between two consecutive years for workers who have reported to be employed for two consecutive years (EE). Controls for individual characteristics include age, age-squared, dummy for male, high-skill dummy, and urban dummy.

for both individual characteristics and year fixed effects (column 4).

In sum, our results suggest that on average a worker who previously held a green job experiences a wage loss when changing occupations, driven mainly by those moving into a less green job. On the other hand, a worker who previously held a polluting job does not experience a wage loss upon switching occupations. This is true for both those who are employed in two consecutive years (EE) and those who found a job after an unemployment spell (UE).

4 The Effects of Exogenous Green Transitions

Along with carbon pricing and subsidies, environmental regulation is a common policy tool to curb emissions. Regulation can be seen as an increase in production costs, and thus may reduce the demand for labor in the affected industry. at the same time, regulations may generate new "green" jobs in other industries or even some residual "green" jobs in

Table 2: Changes in Real Hourly Wages of Workers Employed in Two Consecutive Years (EE) based on Changes in the Environmental Properties of Jobs Held

	(1) ΔlnW_t	(2) ΔlnW_t	(3) ΔlnW_t	(4) ΔlnW_t
$Greener$	0.0256***	0.0299***	0.0262***	0.0305***
	(0.00727)	(0.00678)	(0.00725)	(0.00674)
$LessGreen$	-0.0542***	-0.0496***	-0.0538***	-0.0493***
	(0.00694)	(0.00695)	(0.00715)	(0.00714)
$MorePolluting$	0.0507***	0.0561***	0.0497***	0.0555***
	(0.0110)	(0.0111)	(0.0110)	(0.0111)
$LessPolluting$	-0.00888	-0.00296	-0.0100	-0.00367
	(0.0116)	(0.0122)	(0.0118)	(0.0123)
$Constant$	0.0604***	0.454***	0.103***	0.491***
	(0.00352)	(0.0206)	(0.000658)	(0.0183)
Indiv. Chara	No	Yes	No	Yes
Year FE	No	No	Yes	Yes
Observations	349,128	346,865	349,128	346,865
R-squared	0.000393	0.00436	0.000840	0.00475
Adjusted R-squared	0.000382	0.00433	0.000771	0.00467

Standard errors are clustered by year and are in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: U.S. CPS and Authors' calculations.

Notes: The table shows changes in log real hourly wage between two consecutive years for the workers who have reported to be employed for two consecutive years. Dependent variable dlnrhrwage is the difference in log real hourly wages between two consecutive years. Individual characteristics controls include age, age-squared, dummy for male, high-skill dummy, and urban dummy. Source: U.S. CPS.

affected industries driven by efforts to comply with the regulation. We use the Clean Air Act (CAA) in the U.S. (as described in Section 2.6) as policy shocks to estimate potential effects on employment in the regulated industry. In a second step, we look at local labor markets overall to test whether additional employment in non-affected industries can compensate reallocative costs of environmental regulation in affected industries. We find that affected industries shed jobs, particularly if their employment is pollution-intensive, but that overall employment is unaffected at the local labor market level.

Table 3: Changes in Real Hourly Wages of Workers Currently Employed that Were Unemployed in the Previous Year (UE) based on the Environmental Properties of Jobs Held Prior to Getting Unemployed

	(1) $ln(\frac{Wt}{\hat{W_{t-1}}})$	(2) $ln(\frac{Wt}{\hat{W_{t-1}}})$	(3) $ln(\frac{Wt}{\hat{W_{t-1}}})$	(4) $ln(\frac{Wt}{\hat{W_{t-1}}})$
$OccSwitch \times Green_{t-1}$	-0.0850***	-0.0831***	-0.0816***	-0.0808***
	(0.0274)	(0.0261)	(0.0272)	(0.0255)
$OccSwitch \times Polluting_{t-1}$	-0.0361	-0.0630	-0.0323	-0.0576
	(0.0717)	(0.0716)	(0.0716)	(0.0716)
$OccSwitch$	-0.175***	-0.191***	-0.179***	-0.195***
	(0.0246)	(0.0246)	(0.0235)	(0.0235)
$Constant$	-0.375***	0.0213	-0.362***	-0.0168
	(0.0262)	(0.120)	(0.0186)	(0.120)
Indiv. Chara	No	Yes	No	No
Year FE	No	No	Yes	Yes
Observations	9418	9418	9418	9418
R-squared	0.00690	0.0206	0.0125	0.0263
Adjusted R-squared	0.00658	0.0198	0.0101	0.0234

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: U.S. CPS and Authors' calculations.

Notes: The table shows changes in log real hourly wage between two consecutive years for the workers who have reported to be employed for two consecutive years (EE). Individual characteristics controls include age, age-squared, dummy for male, high-skill dummy, and urban dummy. Source: U.S. CPS.

4.1 Defining Clean Air Act Shocks

We define our regulatory shock, $shock_{l,i,t}$, as follows

$$shock_{l,i,t} = \sum_{c \in l} NA_{c,i,t} * \frac{emp_{c,i,t-2}}{emp_{l,i,t-2}} \tag{1}$$

where $NA_{c,i,t}$ is a dummy for "non-attainment" in county c, the 5-digit NAICS industry i, and time t. It combines "non-attainment" status from EPA with plant-level information on the pollutant, the type of CAA program, and the industry at the NAICS 5-digit level (see Section 2.6). An industry is deemed as affected if not attaining for at least one pollutant. $emp_{c,i,t-2}$ and $emp_{l,i,t-2}$ is employment in industry i, at time $t-2$, and in county c and in commuting zone l, respectively.[15] The shock is aggregated to commuting

[15]Because we want to relate a shock in t to employment changes between $t-1$ and $t+h$, we use employment in $t-2$ for weighting the shock to avoid a mechanical relationship.

zone l which is a typical measure of U.S. local labor markets (see Appendix B.3). The term on the very right uses the employment in the county-industry to account for the fact that at the commuting zone-industry level, county-industries that employ more workers should carry a greater weight.

The shocks defined in equation (1) are well distributed across industries, states, and time. Out of the 624 NAICS 5-digit industries in our dataset, 426 (close to 70%) were affected in at least one commuting zone at least at one point in time. Similarly for geography, out of the 50 states plus District of Columbia, 46 (over 90%), were affected in at least one industry at least at one point in time. Although only a few commuting zone-industry observations are affected at a given point in time, Figure 9 shows that the degree to which local industries are affected is also well distributed over time.

Figure 9: Share of Commuting Zone-Industry That Are Affected

Source: Authors' calculations.

Notes: This graph shows the share in percentage points of commuting zone - industry observations affected by the regulation in the years 2000-2016.

4.2 Employment Effects of Environmental Regulation: Baseline Results

In our baseline specification, we study the effect of the regulatory shock on employment. For this, we estimate the following local projection regression a la Jordà (2005):

$$Y_{l,i,t+h} = \alpha^h + \beta^h * shock_{l,i,t} + \delta^h_{l,t} + \gamma^h_{i,t} + \epsilon_{l,i,t+h} \tag{2}$$

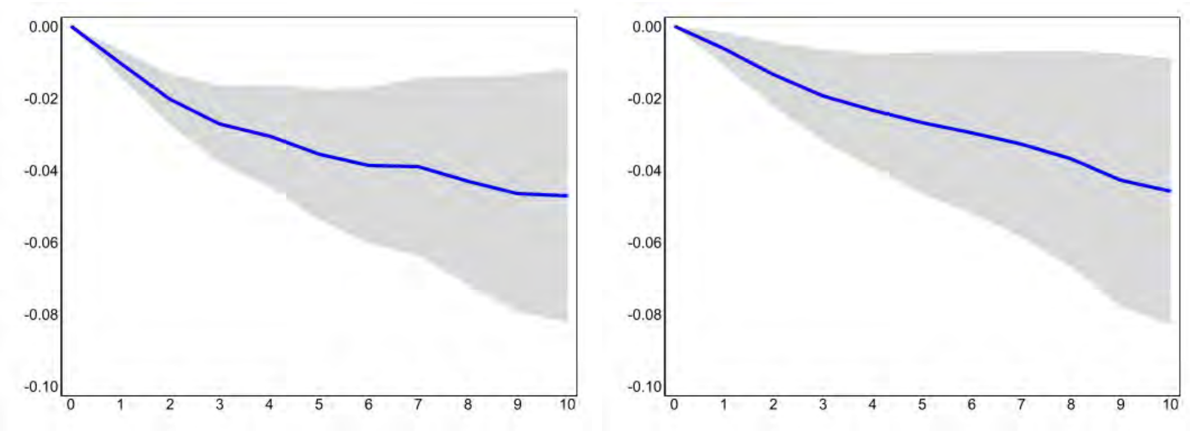
where $Y_{l,i,t+h}$ represents the the change in (i) log employment or (ii) log number of establishments between $t-1$ and $t+h$. We explore horizons (h) up to 10 years ahead. As described in equation (1), $shock_{l,i,t}$ is the regulatory affectedness of industry i in commuting zone l at time t. We also add commuting zone x time fixed effects to control for unobserved local economic dynamics specific to commuting zone l at a particular time t and industry x time fixed effects to control for unobserved industry-specific dynamics, such as other regulations or industry specific changes in technology and demand. We run these regressions unweighted as well as weighted by average employment in the commuting zone and industry in order to gauge whether the effects are significant on overall employment. Finally, we cluster standard errors at the industry (NAICS 5-digit) level.

Employment in the affected industry decreases significantly in response to the environmental regulation. Figure 10 shows the results of (a) weighted and (b) unweighted regressions. The effect is the most significant in the first years while confidence bands widen in later years due to declining observations. This suggests that, after an initial employment loss, locally affected industries see their level of employment stabilize. In terms of magnitude, we interpret the results as follows: we can see that after two years, the coefficient is at approximately -0.02%. This means that if today, 100% of employment in a particular industry in a particular commuting zone were affected, we would expect a decline in employment of 2% after two years in that particular industry and commuting zone. Effects are of similar magnitude for the weighted regressions albeit with wider confidence bands. The latter could suggest that our significant effect is driven by relatively smaller industry and commuting zone combinations. One possible explanation could be that industries and commuting zone observations with a large number of employees might likely be in larger commuting zones with more opportunities in other sectors and are therefore better able to adjust to the shock or re-shuffle employment in response to regulation.

We also find that the number of establishments in the affected industry decreases significantly in response to the environmental regulation. We test this by running the regression described in equation 2 with the log change of the number of employers on the left-hand side. Figure 11 presents the results of the unweighted and weighted regressions and shows that the effect is only significant for the weighted regressions. This suggests that the significantly negative effect of environmental regulation on the number of establishments in a given industry and sector is driven by industry-regions with a large number of employees. The intuition could be that larger industry-regions may include several establishments of the same firm, making it easier for them to adjust employment by reducing the number of establishments compared to smaller industry-regions that may only have a single establishment.

Figure 10: Response of Employment to Environmental Regulation

(a) Non-weighted (b) Weighted by average employment

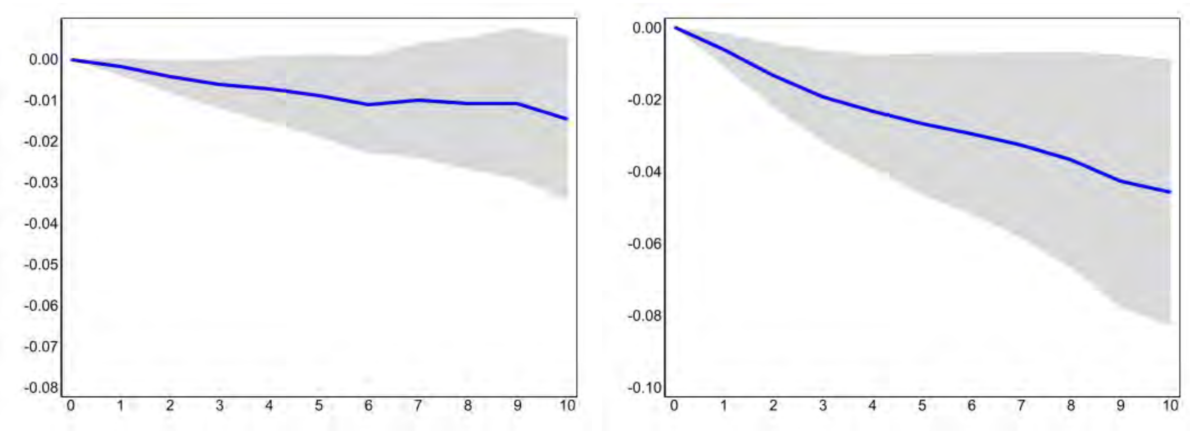


Source: Authors' calculations.

Notes: This graph shows coefficient β from regression 2 over horizon $h = 1, ..., 10$.

Figure 11: Response of Number of Establishments to Environmental Regulation

(a) Non-weighted (b) Weighted by average employment



Source: Authors' calculations.

Notes: This graph shows coefficient β from regression 2 over horizon $h = 1, ..., 10$.

4.3 Employment Effects of Environmental Regulation: Interaction with Green and Polluting Job Intensity

We use the data on the Green- and Pollution intensity of jobs described in Sections 2.1-2.3 in order to test which type of jobs are particularly affected by environmental regulation. For this, we use our baseline regression equation (2) and interact the shock with the green- and pollution intensity of the affected industry and commuting zone:

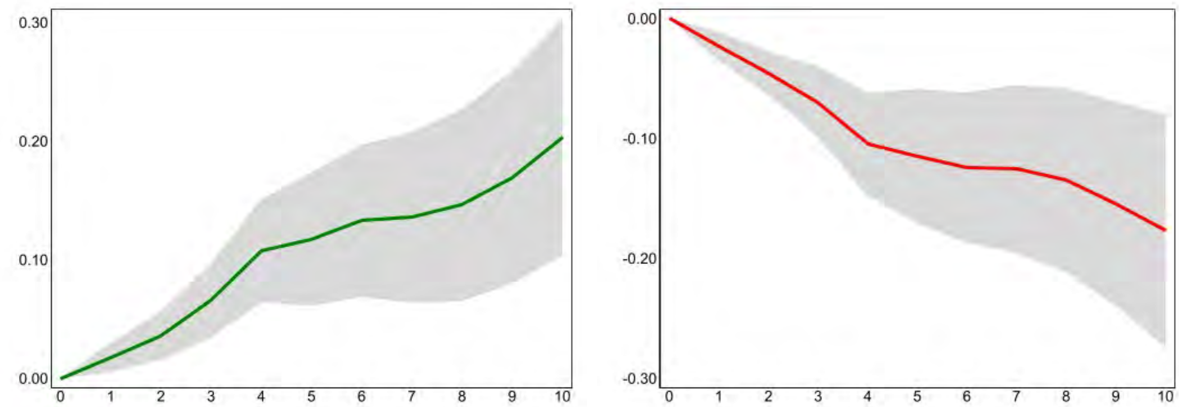
$$\begin{aligned} Y_{l,i,t+h} = & \alpha^h + \beta_1^h * shock_{l,i,t} + \beta_2^h * shock_{l,i,t} * green_{l,i,t-1} + \\ & \beta_3^h * shock_{l,i,t} * poll_{l,i,t-1} + \delta_{l,t}^h + \gamma_{i,t}^h + \chi_{l,i,t+h} \end{aligned} \tag{3}$$

where $green_{l,i,t-1}$ and $poll_{l,i,t-1}$ are dummies that indicate whether an industry in a commuting zone was above the median of green or pollution intensity, respectively, in $t-1$.

We can see that the effect on industries with green jobs is positive while the contrary is found for polluting jobs. At the ten-year horizon, total employment increased in commuting zones and industries that already had a large share of green jobs before the regulatory shock. It decreased in areas with a large share of polluting jobs. The results are presented in Figure 12. In order to show the total effect of environmental regulation on industries with particularly green or polluting jobs, we estimate equation (3) and plot $\hat{\beta}_1 + \hat{\beta}_2$ on the left-hand side and $\hat{\beta}_1 + \hat{\beta}_3$ on the right-hand side. These results would be expected and give some credence to the definition of green and polluting job intensity we follow.

Figure 12: Response of Employment to Environmental Regulation

(a) Green Jobs (b) Polluting Jobs



Source: Authors' calculations.

Notes: This graph is based on equation 3 and shows coefficient $\beta_1 + \beta_2$ on the LHS $\beta_1 + \beta_3$ on the RHS over horizon $h = 1, ..., 10$.

4.4 Spillovers

Until now, we have found that employment in a particular industry falls after environmental regulation becomes binding for that industry in a given commuting zone. This does not necessarily translate to lower employment in the entire commuting zone. It could be that new opportunities emerge in other industries within the same commuting zone in which case overall employment in that area will remain unchanged.

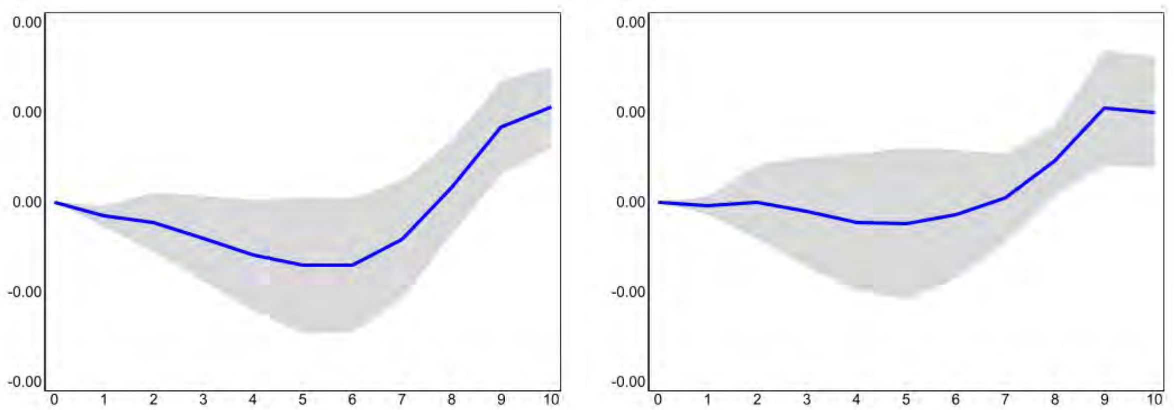
We test this by running equation 2 at the commuting zone level, controlling for commuting zone and time fixed effects and clustering standards at the commuting zone level:

$$Y_{l,t+h} = \alpha^h + \beta^h * shock_{l,t} + \delta_t^h + \gamma h_l + \epsilon_{l,t+h} \tag{4}$$

The effect on employment at the commuting zone level is found to be insignificant which suggests that employees who lost their job due to the impact of the CAA on their industry were able to find work in another industry within their commuting zone. Figure 13 shows the results again for the unweighted and for the weighted regressions. Both show a mostly insignificant effect of the environmental regulation on employment and an even positive effect in the last 2 years of the horizon. The comparably small magnitude of the coefficient also hints at economically negligible effects.

Figure 13: Response of Employment to Environmental Regulation

(a) Unweighted (b) Weighted by average employment



Source: Authors' calculations.

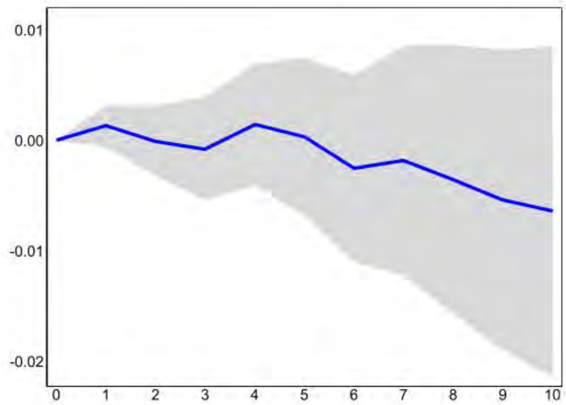
Notes: This graph shows coefficient β from regression 4 over horizon $h = 1, ..., 10$..

4.5 Effects on pay

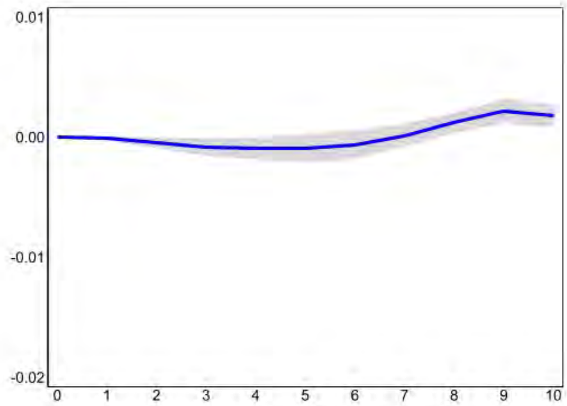
In the previous subsections, we showed that the enforcement of the Clean Air Act significantly reduced employment in affected industries but employees who lost their jobs were able to transition to other industries. Following the imposition of the provisions of the Act, the overall effect on the local labor market was insignificant. The question remains whether and how the pay of employees in affected industries and in the overall commuting zone was impacted. To test this, we use our baseline equation (equation 2 for the industry-commuting zone level and equation 4 for the commuting zone level) and use the log of the average payroll per employee as the dependent variable.In order to also capture non-wage benefits, we use total payroll over number of employees as our measure of interest. This includes all forms of compensation, such as salaries, wages, commissions, dismissal pay, bonuses, vacation allowances, sick-leave pay, and employee contributions to qualified pension plans paid during the year to all employees. It also includes deductions for social security, income tax, insurance, and union dues.

Figure 14: Response of Average Pay to Environmental Regulation

(a) Industry-Commuting Zone Level



(b) Commuting Zone Level



Source: Authors' calculations.

Notes: This graph shows coefficient β from regression 2 (lhs) and regression 4 (rhs), respectively, over horizon $h = 1, ..., 10$.

We find that average payroll does not fall in response to environmental regulation. Figure 14 shows that this is true for affected industries but also for the commuting zone level which is in line with the finding that employees are able to switch to other industries after their industry is affected by the policy shock. Because of this labor market flexibility, affected industries are not able to take advantage of any potential increased slack due to their own employment loss and thus cannot significantly decrease wages if they want to retain the remaining workers.[16]

Taken together, this suggests that because of flexible labor markets, labor supply rebalances across industries when environmental regulation binds, so that average payroll remains unaffected. One may argue that this does not consider benefits which are often higher for hard jobs, such as shift-work on oil rigs or in coal mines. Our payroll measure does consider all benefits that are paid out with wages. We argue that other potential non-payroll benefits (e.g. co-payments for health care insurance premia) exist to compensate for expected costs and hazards inherent with some jobs, e.g. health problems. Provided they are at least fairly valued, they would not constitute additional remuneration for the work in expectation and on average over time.

[16]In the Appendix (Figure 15), we show that total payroll, however, does decrease in affected industries, at least in the first three years. This is expected: since employment decreases and average payroll is unchanged, the total payroll would be expected to decline in affected industries.

5 Conclusion

Tackling climate change is the most pressing challenge facing humanity today. It will require a transformation of the global economy that will involve shifting workers away from carbon-intensive production processes into jobs that help emit far less greenhouse gases.

Whether or not such a "green" transition can be accomplished smoothly force is a first order welfare question. Even when such transitions entail aggregate benefits, they often also have distributional implications, generating winners and losers. The political economy of past, systemic labor market transitions has taught us that any losses, even if just perceived, can significantly impact the speed and scope of the transition itself (as well as the societal support or opposition to the change). Therefore, supporting affected workers and mitigating the transition costs for them remains a priority for governments.

This paper makes two contributions: (i) it assesses the current "state of play" by using micro-data to dissect the characteristics and current location of green- and pollution-intensive jobs, and (ii) it studies how the Clean Air Act, the most important environmental regulation in the U.S., has affected local labor markets.

We find that many areas with abundant green jobs are either close to or overlap with areas with abundant polluting jobs. Despite some regional differences in the concentration of the two types of jobs, the data points to geographical reallocation being less of an issue in the green transition.

Looking at household-level data, however, we find that green jobs appear systematically different from non-green employment. Except for workers who already hold a green job, transitioning into a green jobs is not easy, even though such transitions are associated with a wage premium. This suggests a role for public policy to help workers become more competitive for the green jobs that are likely to be available during the transition to a low-carbone economy.

For those who come from a pollution-intensive job and experience a period of unemployment in the transition, there is typically not a reduction in hourly wages from the transition (beyond the reduction in wages due to having spent a period where the worker was not employed). We also find that workers with higher income, more skills, and/or living in an urban areas are more likely to hold green jobs. Finally, it appears that more pollution-intensive occupations are also more vulnerable to automation. As such, green jobs may prove to be more resilient over time.

Looking at the Clean Air Act in the U.S., our findings suggest that environmental regulation might have an asymmetric impact on the local labor market. We find that affected industries do shed workers and contract the number of establishments in the face of binding environmental regulations. However, the overall effects on employment and wages within the local labor market level are not significant. As expected, environmental regulations shift employment away from pollution-intensive industries and into industries and areas that are relatively greener. Environmental regulations can prove an effective tool to help incentivize the transition from polluting to green jobs and can do so without negatively affecting overall employment or average pay. This should also mean that, on average, local governments will not see a meaningful impact on their fiscal position (e.g. due to reduced income taxes or higher costs of social support). However, this does not imply there will not be potentially significant effects in some local areas which will require federal or state-level support.

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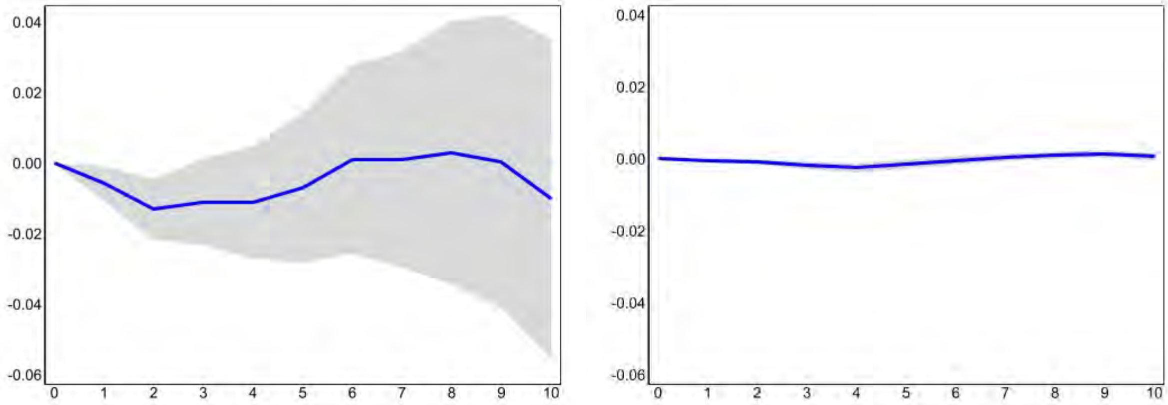
A Extra Tables and Figures

Figure 15: Response of Total Payroll to Environmental Regulation

(a) Industry-Commuting Zone Level (b) Commuting Zone Level



Source: Authors' calculations.

Notes: This graph shows coefficient β from regression 2 (lhs) and regression 4 (rhs), respectively, over horizon $h = 1, ..., 10$..

B Further Details on Data Construction

B.1 Merging Occupational Employment Wage Statistics (OEWS) and Green/Polluting Intensities

OEWS data for 2002 to 2016 is downloaded directly from here. OEWS is really a repeated cross-section and occupation and industry codes are not consistent across vintages, see link for a detailed discussion. Industry vintages are harmonized using NAICS 2002 to 2007 and 2007 to 2012 to convert all data into NAICS 2012.

Harmonizing occupation vintages requires more care given the OEWS use of hybrid vintages.[17] Green and polluting intensities as defined in Section 2 are defined at SOC 2010 level. To merge with OEWS data, we follow a two step approach, first we get national employment at SOC 2010 level and then concord with the relevant occupational vintage in OEWS from SOC 2010 using 2011 employment weights.

Table B1 presents the mapping between OEWS vintages and occupation vintages. For the Hybrid classification used in OEWS 2010 and 2011, we follow section F, question 8 here and use the excel provided. Concordance codes for SOC 2000 and 2010 are sourced from here. For the 2017-18 vintages, the BLS consolidated a few 6-digit codes and we

[17] We thank Amy Hopson for a very helpful exchange of emails on this issue.

use this link to merge with SOC 2010. When the exact 6-digit code is not available in OEWS, the closest 6-digit or the 5-digit level is used for green/pollution intensity.

Table B1: Concordance Across OEWS Vintages

OEWS Vintage	Occupation Vintage Code
2002-2003	SOC 2000 5-digit
2004-2009	SOC 2000
2010-2011	Hybrid SOC 2000/10
2012-2016	SOC 2010
2017-2018	SOC 2010 with changes
2019	SOC 2018

B.2 County Business Patterns (CBP)

CBP data for 1998 to 2016 at 6-digit industrial level is downloaded directly from here. Data is then merged with the native panel of Eckert et al., 2020 available from here and then harmonized across NAICS vintages using concordances for NAICS 1997 to 2002, 2002 to 2007, 2007 to 2012 from the same link to create a panel from 1998 to 2016 at NAICS 2012 level for total number of establishments, buckets of number of establishments by employment size, employment, and payroll.[18] Note that because of the CBP's suppression of data to protect confidentiality (the reason Eckert et al., 2020 create an algorithm to impute employment), data for establishments, buckets of number of establishments by employment size, employment, and payroll from CBP are sparser than the employment data provided by Eckert et al., 2020.

The above 6-digit industry level dataset is collapsed to 5-digit level for use in Section 4. Moreover, since 5-digit industrial level data is at least marginally less likely to be censored, we complement that collapsed dataset with a 5-digit industrial level dataset that we construct by first isolating 5-digit NAICS industries that can be matched exactly across NAICS vintages and then using those data points to fill missing observations from the collapsed dataset.

B.3 2000 Census Commuting Zones

2000 census commuting zones data is downloaded from USDA.

[18] The latter includes all forms of compensation, such as salaries, wages, commissions, dismissal pay, bonuses, vacation allowances, sick-leave pay, and employee contributions to qualified pension plans paid during the year to all employees.

Several minor adjustments are made to this data. The first is taken from David Dorn's webpage. Secondly, some adjustments to counties in Alaska are made following this document.