Doing the Dirty Work: Employment vulnerability to the energy transition and its implications for climate policy and politics

by

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Submitted to the Institute for Data, Systems, and Society and the
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ABSTRACT

As the world moves away from fossil fuels, there is growing recognition of the need for policy to support a just transition of those working in carbon-intensive industries. However, little work has thoroughly investigated which communities are most vulnerable to economic disruption in the energy transition and therefore require policy support. This thesis analyzes the distribution of employment vulnerability in the United States by calculating the average "employment carbon footprint" of close-to every job in the U.S. economy at high geographic and sectoral granularity. I find that existing efforts to identify at-risk communities both in the literature and the Inflation Reduction Act exclude regions of high employment vulnerability, and thereby risk leaving these communities behind in the energy transition. I also identify significant within-sector heterogeneity in employment carbon footprints that are unexplained by fuel mix or power grid carbon intensity, and find that carbon-intensive regions tend to be more rural, less racially and ethnically diverse, less educated, and more likely to vote Republican, and that these regions often lack institutional capacity to retrain laid-off workers. This thesis also uses these new data to empirically test the salience of employment impacts for political representatives. I find that legislators from districts with carbon-intensive employment are less likely to vote in favor of climate policy, while household carbon footprints have no effect despite being correlated with public opinion on climate action; I also note the significance of the partisan divide on climate voting. Altogether, this thesis argues that just transition policy is crucial to progress action on climate change by addressing politically salient employment impact concerns; underscores the importance of proactive and continuous measures of employment vulnerability in targeting such policy; provides policymakers with the much-needed data to do so; and makes the case that such policies should be place-based and tailored to the communities they strive to serve.

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Introduction

As U.S. and international economies reduce their reliance on fossil fuels, there will be winners and losers. While an extensive literature has shown that the energy transition will bring aggregate improvements in macroeconomic indicators such as unemployment and GDP (Metcalf 2023; Brown, Li, and Soni 2020; Barker et al. 2016), these benefits and associated costs are not evenly distributed, with some communities potentially facing net losses from the transition. Communities reliant on fossil fuels will be vulnerable to economic disruption; indeed, many are already suffering from the decline of industries such as coal mining (Ansolabehere et al. 2022; Bergant, Mano, and Shibata 2022). Central to this disruption are the employment impacts and job losses that will occur as the economy shifts away from fossil fuel consumption. The highly localized nature of these effects presents serious distributive justice concerns and a policy imperative to ensure no community is "left behind."

There is therefore increasing interest in ensuring a "just transition" of vulnerable workers as the economy decarbonizes, both in academic and policy spheres. Originally developed by U.S. trade unions in 1970s and 80s in response to perceived threats of environmental regulation on employment in the energy and chemicals industries (McCauley and Heffron 2018; Newell and Mulvaney 2013), the contemporary just transition advocates for the protection of those employed in industries vulnerable to the energy transition through compensation, retraining, and the creation of new, "clean" jobs with good wages and working conditions (Newell and Mulvaney 2013). Not only are such policy efforts important from a distributive justice perspective, but evidence suggests they are also essential for winning the support of coalitions that have previously blocked climate and energy policy due to employment concerns (Gazmararian 2022a; Tvinnereim and Ivarsflaten 2016; Bergquist, Mildenberger, and Stokes 2020).

Despite growing recognition of these facts, there is limited work that has thoroughly investigated the extent to which communities might be vulnerable to disruption and therefore require transition policy support. Considerations of employment have largely focused on fossil fuel extraction industries such as coal mining, and to a lesser extent fossil fuel power plants (Snyder 2018; Raimi, Carley, and Konisky 2022). However, workforce impacts of the energy transition will be felt beyond these production sectors and also affect industries heavily reliant on fossil fuel consumption such as heavy manufacturing (Carley and Konisky 2020; Vona 2019). Similarly, previous efforts have tended not to consider relative differences in employment vulnerability between facilities in a given industry that might arise due to differences in fossil fuel consumption or production rates. Furthermore, aside from acknowledging skill barriers to re-employment for those displaced from polluting jobs (Vona et al. 2018; Bergant, Mano, and Shibata 2022), there has been little work evaluating the distribution of employment impacts of the energy transition across demographics.

In the first part of this thesis, I address these gaps by calculating the carbon intensity of U.S. jobs at high geographic and sectoral granularity, and using these "employment carbon footprints" (ECFs) to identify communities vulnerable to employment impacts of the energy transition. My analysis covers eight major sectors: agriculture, manufacturing, commercial sectors, construction, coal mining, oil & gas extraction, other mining, and fossil-fuel power generation; I also consider both direct and indirect emissions. These sectors account for 86% of total U.S. employment and 94% of U.S. carbon emissions outside of the transportation sector. I then analyze what drives differences in these employment carbon footprints (ECFs) across counties, and analyze their distribution across demographics to shed light on the equity implications of employment impacts.

For each sector, I calculate every county's average exposure to fossil fuels per employee, and aggregate across sectors to obtain an overall ECF for each county in metric tonnes CO_2e per employee. The resulting metric is holistic and continuous, and reflects the relative vulnerability of the average job in a county to economic shocks from the energy transition.

Importantly, this measure not only captures fossil fuel extraction, but also how these fuels' downstream carbon emissions (and therefore the costs of abating them) permeate throughout the economy. By considering both direct emissions from on-site fossil fuel consumption and indirect and downstream emissions from electricity consumption and fossil fuel extraction/refining, respectively, I measure how shifts in fossil fuel demand will affect each point of the energy supply chain and allocate carbon emissions accordingly without double-counting. This approach provides a more complete picture of which communities are likely to be vulnerable to the energy transition as its impacts ripple through the economy.

The overall ECF serves as a holistic single summary measure of a community's employment vulnerability to the energy transition; however, this approach has its drawbacks. While impacts of the energy transition will be felt across the economy, policies to mitigate these impacts and support communities will need to vary significantly by industry. Industries such as manufacturing may be able to decarbonize their operations, but fossil fuel extraction sectors will not be able to continue unabated in a low-carbon world—as such, communities that appear similarly vulnerable through their overall ECFs may require very different policy interventions depending on the industrial makeup of the local economy (Moniz and Kearney 2022; Carley and Konisky 2020; Ansolabehere et al. 2022). For this reason, I supplement the overall ECF results with separate ECFs for fossil fuel extraction sectors and all other sectors (as well as ECFs by sector), enabling policymakers to distinguish between the different types of impacts communities may face in the energy transition and thereby design targeted policy approaches that account for these specific circumstances.

This work is especially pertinent given the recent passing of the United States' Inflation Reduction Act (IRA). The IRA, passed in 2022, is the first major piece of U.S. climate legislation to attempt to integrate just transition measures through its definition of "energy communities," and has underlined the importance of understanding the distribution of community employment vulnerability for future policymaking.

I find that existing efforts to identify vulnerable communities, both in the Inflation Reduction Act and the literature, exclude several regions of high employment carbon intensity. These exclusions are significant—they represent the communities at risk of being left behind if current measures of vulnerability are used to inform transition policy. Some of the regions left out of the IRA's definition are the most carbon-intensive in the country, including counties with large fossil fuel power generation industries whose ECFs are orders of magnitude greater than the national average. Other regions that are missed do not have large fossil fuel industries, but are nonetheless vulnerable to transition shocks due to their high fossil fuel consumption in industries such as manufacturing, particularly in the western Midwest.

These findings highlight the need for more continuous, economy-wide, and proactive measures of employment vulnerability to inform just transition policy. While I find that fossil fuel communities tend to be those with the greatest risk of employment impacts, focusing exclusively on these industries neglects impacts on other sectors that will still face economic pressure as the economy decarbonizes. Furthermore, using reactive metrics such as the unemployment rate limits the delivery of assistance until *after* jobs have been lost, instead of proactively supporting communities to transition before employment impacts are felt. The results also highlight that, despite clear sectoral trends in carbon intensity, there is significant heterogeneity in employment carbon footprints between firms in the same industry even when controlling for fuel mix and power grid carbon intensity, and data-driven measures such as the ECF are needed to capture these differences during policy decision-making.

Just transition policy should consider the cultural, social, and demographic context of vulnerable communities (Carley, Evans, and Konisky 2018; Ansolabehere et al. 2022), and I shed light on several intersectional trends to inform place-based approaches to just transition planning. Rural counties tend to have higher employment vulnerability and rely on carbon-intensive industries for high-income employment, while urban areas have lower vulnerability that decreases as average income increases. Carbon-intensive communities tend to be less educated, particularly in rural counties, and I find that many such regions have little to no capacity to bridge the skills gaps between "polluting" and "clean" employment in two-year associate degree-granting institutions such as community colleges.

The derivation of the ECF dataset also allows me to interrogate questions of political economy in Part II of this thesis relating to the political salience of employment in climate politics. The issue of jobs is omnipresent in the political discourse around climate and energy policy, however opposition to such policies also often stems in part from the perception that they will increase energy prices. To what extent do politicians take account of their constituents' employment vulnerability when deciding how to vote on climate policy, compared to other potential economic costs to households? To investigate which factor is more salient in climate politics, I use a dataset on household carbon footprints (HCFs) produced by Green and Knittel (2020) as a measure a household's carbon consumption; in a carbon-penalized economy, high-HCF households will bear higher costs of the energy transition than low-HCF households. By analyzing the effects a congressional district's ECF and HCF have on the climate voting record of its political representative, I test whether potential jobs impacts are more of a driver for politicians to vote against climate policy than increased energy and goods costs at the household level.

I find that the greater the average employment carbon footprint (ECF) of a district, the lower the likelihood of its representative voting in favor of climate policy, while the household carbon footprint (HCF) of the district does not have an effect. The correlation of anti-climate voting with constituency ECF is robust even when controlling for the district's support for further congressional action on climate change and political donations from fossil fuel industries, indicating that legislators are willing to vote down climate policy to avoid potential employment impacts in carbon-intensive industries even when their constituents would rather they vote in favor. Interestingly, this public support for congressional climate action is correlated with both employment and household carbon footprints, suggesting that while household consumption decisions are salient for the public, this salience is not transferred to political representatives.

Despite these correlations, by far the greatest determining factor of legislators' voting behavior is their political party. Representing identical districts and receiving the same campaign contributions from fossil fuel industries, Republican legislators are significantly more likely to oppose climate policy than Democratic legislators. This brings further empirical evidence to an increasingly observable theory in U.S. political economy—that political polarization over climate policy is increasingly a function of fights between partisan elites rather than constituency preferences.

This work makes several contributions to the literature. While previous studies have analyzed the carbon footprint of household consumption patterns (Green and Knittel 2020), no study to the author's knowledge has derived the carbon exposure of U.S. jobs as an indicator for energy transition employment vulnerability. Similarly, this analysis is the first to present a (close-to) economy-wide estimation of the distribution of employment risks that covers sectors far beyond the fossil fuel extraction sectors targeted by the literature to date. This approach captures geographic, between-sector and within-sector differences in employment vulnerability in a way which considers both fossil fuel consumption and production effects. Importantly, I identify vulnerable regions missed by the literature to date, and demonstrate that the definition of energy communities under the IRA is inadequate in exclusively identifying at-risk regions. This work also adds to the nascent literature that seeks to understand employment vulnerability to the energy transition in the context of a community's sociodemographic characteristics.

This thesis also contributes to the political economy literature by bringing empirical results to the topic of the political salience of employment in the context of climate policy. The employment and household carbon footprint datasets allow me to interrogate the relative effects of different forms of economic vulnerability to the energy transition on both public climate opinion and congressional voting behavior with holistic, continuous measures that have not been used by the literature to date.

The remainder of this thesis is structured as follows. Part I presents my calculation and analysis of the distribution of employment carbon footprints as well as my assessment of the energy communities in the Inflation Reduction Act. Part II presents my analysis of the political salience of employment vulnerability. Each part contains a chapter on the relevant literature for that analysis, the methodology used, and the relevant results. Finally, Part III discusses the policy implications of this work and concludes.

Part I

Employment carbon footprints: Calculation, distribution & policy implications

Chapter 1

Literature Review

1.1 Employment impacts of the energy transition

Communities reliant on polluting industries are particularly vulnerable to economic shifts arising from the energy transition, similar to those that have previously been disrupted by automation, technology change, and trade policy (Bergant, Mano, and Shibata 2022). The closure of polluting facilities has been shown to result in significant job losses and increased unemployment in local communities, and these employment impacts are often sustained long after the closure (Burke, Best, and Jotzo 2019). Such disruptions can extend beyond directly impacted sectors, affecting local tax revenue and causing spillover effects in adjacent industries (Jolley et al. 2019).

Environmental regulation has been found to contribute to these distributed employment impacts. Using the U.S. Clean Air Act as a natural experiment, Walker (2011) shows that stricter environmental regulation results in job destruction by firms, and Walker (2013) finds that affected employees experience significant wage decreases either through nonemployment or lower wages following re-employment. Bergant, Mano, and Shibata (2022) found that while overall employment in an area was not affected following the introduction of the Clean Air Act, polluting industries in the area tended to shed jobs. Using industry-specific employment data following the introduction of British Columbia's carbon tax, Yamazaki (2017) estimates that, while overall employment and employment in clean industries increased, employment declined in carbon-intensive industries such as manufacturing. Yip (2018) corroborates this finding, adding that this particularly affects less-educated parts of the workforce who tend to work in such industries.

Predictions of the future employment impacts of the energy transition consistently show positive aggregate effects, largely through the emergence of "green" jobs offsetting losses in "dirty" jobs—however, these often mask the distribution of employment costs, which tend to be highly concentrated. Computable general equilibrium (CGE) modelling has proven helpful for predicting intersectoral and regional trends in employment following the introduction of climate policy, generally finding that climate policy increases overall employment despite job losses in polluting sectors such as coal mining, manufacturing, and oil and gas extraction (Nystrom and Lucklow 2014; Brown, Li, and Soni 2020; Scrimgeour, Oxley, and Fatai 2005). But the inherent limitations of CGE modelling mean that few are able to speak to highly localized impacts.

It is also not clear whether predicted growth in green jobs will translate into meaningful transition pathways for workers displaced from polluting industries. Green jobs tend to be high-paying, held by workers with more skills and more alternate employment options, less subject to automation, and be located in urban areas; by contrast, while jobs in polluting industries are often similarly high-paying, they tend to be low-skilled, located in rural areas, and held by those with fewer employment alternatives (Carley and Konisky 2020; Bergant, Mano, and Shibata 2022; Vona et al. 2018). For example, many workers in coal communities began their careers before completing high school, limiting their adaptability in the face of economic disruption (Carley, Evans, and Konisky 2018). Furthermore, Carley and Konisky (2020) note that both green and polluting jobs tend not to be held by women or people of color, and Ash and Boyce (2018) finds that while minority populations disproportionately bear the environmental and health burdens of polluting industries, they do not see equivalent employment benefits. These distributional justice concerns have given rise to increased interest in the topic of a "just transition" in order to secure the futures of displaced workers.

1.2 Political economy of the just transition

Highly concentrated employment costs of the energy transition present a collective action problem in which those bearing the costs (in this case, workers in carbon-intensive industries) are able to effectively organize and block or hinder progress towards the "public good" the energy transition provides both environmentally and economically (Vona 2019). Coal communities may remain politically opposed to energy and just transition policies even after industry closures threaten their livelihoods (Cha 2020). Such strong opposition has been shown to override partisan politics, with communities switching political allegiances after perceiving their previously preferred party to be hostile to polluting industries and the jobs they represent (Gazmararian 2022b).

Support or opposition to decarbonization is often perceived to be immovably based on a community's ideology of being climate change "believers" or "skeptics," however a growing literature indicates that this is not the case. Rather, political support is highly sensitive to the specific economic circumstances of a community, and perceived harms can vary significantly in their nature between different carbon-intensive communities (Graff, Carley, and Konisky 2018). Tvinnereim and Ivarsflaten (2016) find that while fossil fuel employees oppose climate policies that are costly to their industries, they are equally likely to support policies that provide compensation and/or alternate employment pathways. When assessing how just transition policy design might affect individuals' support for climate policy in coal country, Gazmararian (2022a) finds that "a majority ... would move away from fossil fuels in exchange for resources that smooth the cost of transition." Including social and economic programs in climate policy also expands their support amongst the broader public, particularly amongst people of color (Bergquist, Mildenberger, and Stokes 2020), and Diamond and Zhou (2022) find that a "job creation" framing increases public support for clean energy policies. Kono (2020) finds that these effects are salient with legislators, showing that congressional representatives from districts with carbon-intensive employment were less likely to vote against climate policy if their state offered generous unemployment benefits.

In addition to economic disruption, just transition policies must also address the disruption by the energy transition to a community's sense of place and identity. Polluting industries are often intertwined into the social fabric of communities in a way that makes them central to their culture and identity (Della Bosca and Gillespie 2018). Carley, Evans, and Konisky (2018) note that many U.S. coal communities are in fact aware and accepting of the energy transition but regard its disruption to their cultural fabric as a fundamental challenge. This presents a difficult problem for policymakers during the energy transition—as put by Carley, Evans, and Konisky (2018), "arguably it is easier to implement a job training program through investment of financial resources than it is to change long-standing mindsets of individuals with deep ties to a place and economic past."

Evidence suggests that many existing just transition policy measures have failed to adequately integrate both local economic and sociocultural factors into their design. Krawchenko and Gordon's (2021) international review on just transition policies found that those focused on economic development were poorly integrated with workforce development and tended to display an urban bias, while job-focused initiatives tended not to address societal concerns such as identity and place. Carley, Engle, and Konisky (2021) find that the majority of U.S. transition programs focus on infrastructure investment (particularly in renewable energy) rather than investing in workforce development, and also highlight that there is little existing literature evaluating the success of these programs, or indeed how one even measures this success. The United States' Inflation Reduction Act is one such policy that targets transition assistance via infrastructure investment; its mechanisms are discussed in the following section.

1.3 The Inflation Reduction Act, "energy communities" & previous estimates of transition vulnerability

The Inflation Reduction Act (IRA) is the most significant piece of U.S. climate legislation in history and is unique in its provisions to tie many of its incentives to labor, project location and supply chain requirements. One such requirement is that projects receiving one of the policy's tax credits can see their credit increased by 10% if the project is located within an "energy community," broadly conceived as those that will be (or have been) impacted by a shift away from fossil fuels.[1] The IRA's definition of an energy community comprises brownfield sites, metropolitan statistical areas (MSAs) or non-MSAs with high employment or tax revenue from fossil fuel industries along with unemployment higher than the national average, and census tracts in which a coal mine has closed and/or a coal-fired power plant has recently been downsized or closed, as well as the tracts directly adjacent to these tracts[2] (In-

1. It should be noted that, as suggested in the previous section, tax credits for infrastructure and project investments do not necessarily translate into improved outcomes for the communities in which they are located. As such, it is yet unclear whether the energy community provisions in the IRA will be effective at supporting a just transition for the communities it identifies.

2. Brownfield sites are properties with abandoned, often polluted land, as determined by the U.S. Environmental Protection Agency. The U.S. Department of Treasury considers "fossil fuel employment" to be any employment in the following NAICS codes: 211 (Oil & Gas Extraction), 2121 (Coal Mining), 213111 (Drilling Oil and Gas Wells), 213112 (Support Activities for Oil & Gas Operations), 213113 (Support Ac-

teragency Working Group on Coal & Power Plant Communities & Economic Revitalization 2023). Academia, policy research organizations and the private sector alike have attempted to identify areas that would classify as energy communities under the IRA (Raimi and Pesek 2022; Lococo et al. 2022; Isaac 2022), and as of mid-2023 the U.S. Treasury Department and Internal Revenue Service have released formal guidance on the language in the IRA defining energy communities as well as an early stage online mapping tool of qualifying energy communities through the Interagency Working Group on Coal & Power Plant Communities & Economic Revitalization (hereafter, "the IWG").[3]

While the integration of just transition strategies into major climate policy should be applauded, the specific definitions and binary classification of energy communities in the IRA have raised questions over the act's ability to target truly vulnerable parts of the country. Raimi and Pesek (2022) map qualifying sites under various interpretations of the language, finding that the provisions could cover between 42 and 50% of U.S. land area and are "unlikely to specifically support the communities that are or will be most heavily affected by a decline or cessation of fossil fuel activities." They produce an alternate definition based on modified thresholds on the percent of fossil fuel employment and local tax revenue and an expanded definition of coal communities. Raimi and Pesek (2022) particularly critique the use of metropolitan statistical areas as the unit of analysis for the fossil fuel employment and tax revenue, finding this granularity to be too coarse and proposing county-level estimates instead.

In a similar vein to Raimi and Pesek's (2022) analysis, a small but emerging literature has focused on estimating and mapping the vulnerability of communities to the energy transition for the purpose of informing the design of targeted policy. Within this literature, "vulnerability" has broadly been conceived as some combination of exposure to economic shocks or policy changes and socioeconomic factors that may exacerbate or mitigate this exposure. Carley et al. (2018) present a conceptual framework that defines a community's transition vulnerability as a function of its exposure, sensitivity, and adaptive capacity to negative impacts of energy policies, and derive a "vulnerability score" combining measures of each of these dimensions. In line with their analysis on IRA energy communities, Raimi (2021) focuses on employment vulnerability by identifying vulnerable counties based on their fossil fuel employment share. Similarly, Snyder (2018) derives a vulnerability index based on the percent of fossil fuel employment in a county, along with its child poverty rate, rate of educational attainment and degree of geographic isolation.

In an extension of Carley et al.'s (2018) work on vulnerability frameworks, Raimi, Carley, and Konisky (2022) apply the framework to identify vulnerable U.S. fossil fuel communities. They measure exposure as the level of fossil fuel extraction, refining, and power generation in a county, neglecting levels of employment due to concerns over data suppression for rural areas. In line with previous studies, they find that counties in Appalachia, Texas, the Gulf

tivities for Coal Mining), 32411 (Petroleum Refineries), 4861 (Pipeline Transportation of Crude Oil), and 4862 (Pipeline Transportation for Natural Gas). Treasury and IRS rules consider any census tract in which a "coal-fired generating unit has been retired after December 31, 2009" to qualify as an energy community; as such, it is possible for plants that are still operating to qualify if a part of the plant (e.g. one of four generating units) was closed in that timeframe (U.S. Internal Revenue Service and U.S. Department of Treasury 2023).

3. The tool is available at https://energycommunities.gov/energy-community-tax-credit-bonus/.

Coast, and the Intermountain West are likely to experience the most significant impacts, and also note that the inclusion of socioeconomic indicators adds a layer of insight into the distribution of vulnerability that is missing from analyzing exposure alone.

The present paper focuses on estimating the distribution of employment carbon footprints as a measure of employment vulnerability. It builds on work by Green and Knittel (2020) that used household consumption data to determine granular household carbon footprints and evaluate the distributed effects of climate policy across them. Few studies have attempted a similar analysis with employment. One exception is Wagner et al.'s (2020) analysis of European manufacturing jobs, which calculates the ratio of direct carbon dioxide emissions to the number of employees in European firms, finding a large degree of variability between firms and a long-tailed distribution. However, this paper did not use these footprints to assess the vulnerability of employment to the energy transition, and excluded indirect emissions from electricity consumption as well as other carbon-intensive sectors from its analysis.

While the studies above address similar goals to this paper, my approach is novel in several ways. Firstly and most significantly, while the above papers have for the most part narrowly focused on fossil fuel extraction industries, I present a close-to economy-wide assessment of vulnerable employment in the United States. This is important given that the effects of economic shifts away from fossil fuels will be felt not only by those producing the fuels but those consuming them, such as industrial facilities—my analysis sheds light on these between-sector differences. Secondly, computing a carbon footprint as a measure of employment vulnerability better enables me to capture within-sector differences between firms in both the absolute level of pollution and firm efficiency. Thirdly, by accounting for direct emissions from fossil fuel consumption, indirect emissions from electricity consumption, and future emissions from fossil fuel production, my measure of employment vulnerability anticipates supply chain effects that might extend impacts of the energy transition beyond those directly emitting carbon dioxide. And finally, my cross-sectoral analysis allows me to dissect the socioeconomic distribution of employment vulnerability, an under-explored area in the literature. These advantages make the estimates attractive for policymakers in determining the distribution of employment vulnerability to the energy transition, as well as a measure of exposure that could be complemented by sensitivity and adaptive capacity metrics in future academic work.

Chapter 2

Methodology

My aim is to estimate the carbon exposure of as much of the United States economy and workforce as possible. For a given sector, this requires the availability of both energy consumption and employment data at county level granularity. My analysis therefore considered the following sectors, for which such data were publicly available: agriculture,[1] construction, manufacturing, mining, commercial sectors,[2] and fossil-fuel power generation. These sectors were chosen on the basis of their relative contributions to overall U.S. carbon emissions, their contributions to overall U.S. employment, and the availability of energy consumption/production and employment data at high sectoral and geographic granularity. The sectors covered in the analysis account for 86% of average total U.S. employment between 2016–2020, corresponding to 60% of U.S. carbon emissions from fossil fuel combustion across that timeframe and 94% of such emissions outside of the transportation sector[3] (U.S. Bureau of

1. My analysis of agricultural emissions consisted only of emissions from stationary energy consumption (i.e. fuel combustion in machinery, generators etc.) and did not consider livestock, land-clearing or soil management emissions. It should be noted that these emissions categories not covered in the analysis comprise more than 90% of U.S. agricultural emissions (U.S. Environmental Protection Agency 2023b)—however, I also note that, given the significance of agriculture in U.S. politics, it is less than certain whether such emissions categories would be subject to future U.S. emissions reductions policies or exempted, as is the case in the European Union's Emissions Trading Scheme.

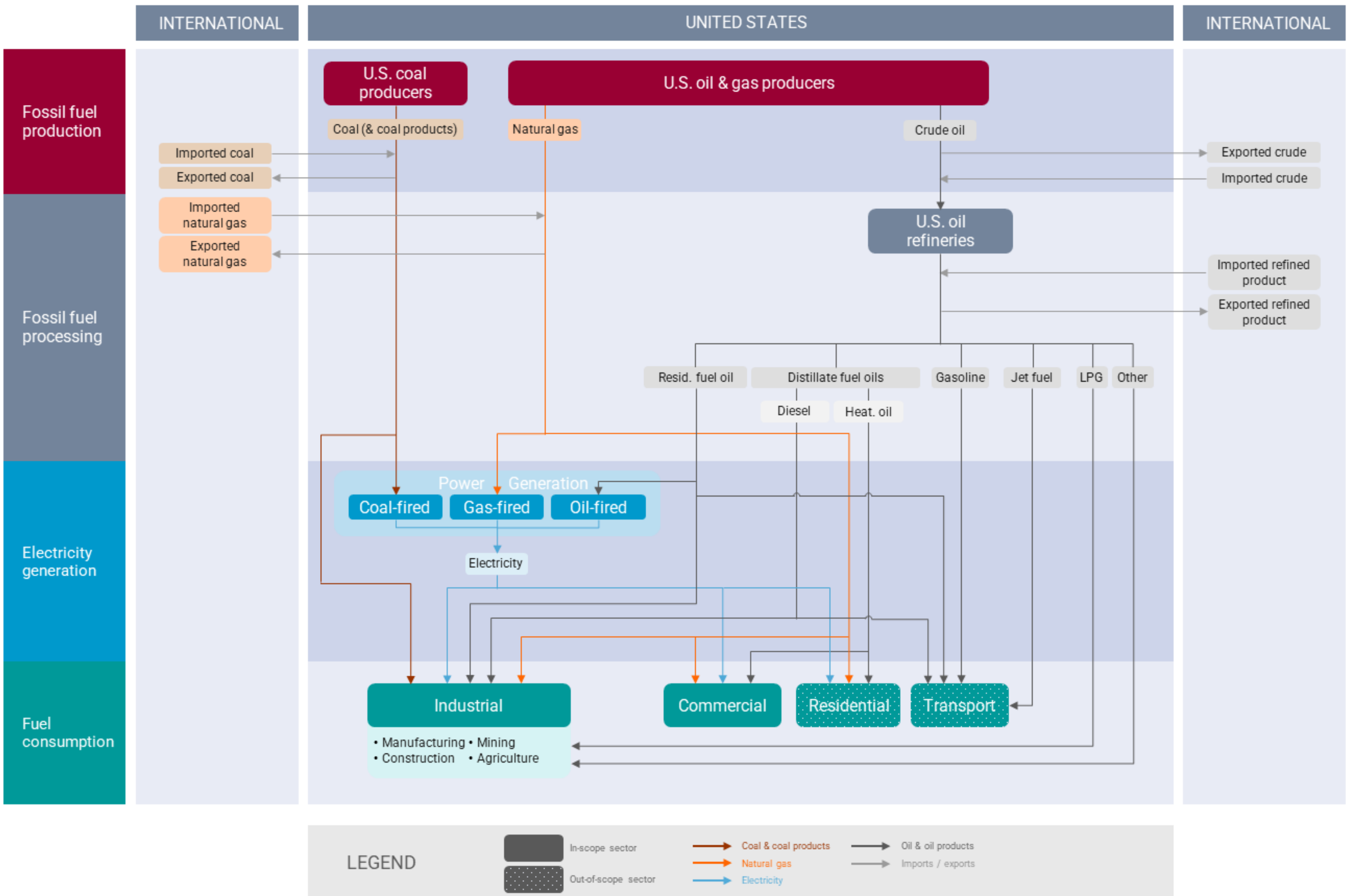
2. Commercial sector emissions were limited to those for which public commercial building energy consumption data were available. The covered building types were: offices, retail, warehousing & storage, restaurants, accommodation, schools, hospitals, and outpatient facilities. These are the building types covered by NREL's ComStock model, and comprise roughly 65% of U.S. commercial building floor area.

3. While on-site transportation emissions are captured within the agriculture, manufacturing, mining and construction sectors (i.e. those calculated using the NREL Industrial Energy data Book dataset), a more holistic analysis may have included transportation for work activities (e.g. flights for business) in jobs' carbon footprints. However, doing so would require a significant expansion of the "Scope 3" emissions I consider in my analysis, not to mention considerable additional data on such emissions, and it is not clear how such transportation emissions could be attributed to specific counties in my analysis, nor how this would translate into an increase in employment vulnerability. Similarly, while auto manufacturing jobs will likely be affected as consumers transition from internal combustion engine vehicles to electric vehicles, incorporating these differences would compel a much broader incorporation of Scope 3 emissions across the entire economy into the ECF than current data allow. Furthermore, it is not clear whether these transition costs will be borne by firms, nor is it clear whether the employment impacts of such a transition will be broadly positive or negative for the auto manufacturing industry (Curtis, O'Kane, and Park 2023). Given these challenges, as well as the fact that emissions from personal transportation (including commuting for work) are more

Labor Statistics 2023a, 2023b; U.S. Environmental Protection Agency 2023b). Figure 2.1 illustrates the scope of my analysis and theoretical framework of the value chain of energy consumption in the U.S. economy used.

At a high level, my methodology consisted of the following steps. First, I assembled datasets on energy consumption/production as well as employment for each of the aforementioned sectors, and used these to determine the direct and indirect carbon emissions from firms in each sector and each county. Next, I computed the "employment carbon footprint" of these firms across direct and indirect emission "scopes." I then used the carbon footprints to calculate the social cost per employee borne by firms, using the latest values for the social cost of carbon (proposed by the Environmental Protection Agency in late 2022) as a shadow price. I then assess the extent to which differences in carbon footprints are explainable by between-sector differences versus within-sector differences. Finally, I analyzed how both employment carbon footprints and their social costs are distributed across geography, demographic, and socioeconomic status using American Community Survey (ACS) data. The following sections describe each of these steps in more detail.

suitable for measures of personal economic vulnerability rather than employment vulnerability, the exclusion of the transportation sector seems reasonable.



Notes: This figure depicts the model of the U.S. economy I use in this paper. Each arrow represents fuel use. Each colored box represents a sector or sectors that I consider in the analysis. The rest of this paper assumes that all energy flows follow the schematic outlined here. Note that the residential and transport sectors are out of scope for this work.

Figure 2.1: Theoretical framework of energy consumption across U.S. industries used in determining ECFs.

2.1 Data sources

Employment data are often suppressed at high geographic and sectoral granularities to avoid publishing individually identifiable information and preserving confidentiality. Therefore, multiple datasets were needed on both the energy consumption/production side and the employment side of my analysis to cover all the targeted sectors. Table 2.1 summarizes the sectors covered in the analysis as well as the data used in calculating their employment carbon footprints.

The primary dataset of employment figures used in my analysis was the Quarterly Workforce Indicators (QWI) dataset (U.S. Census Bureau 2023b) from the Longitudinal Employer-Household Dynamics (LEHD) program, a partnership between the Census Bureau and U.S. states to fill gaps in public economic data with employment data at 2-, 3- and 4-digit NAICS code granularities.[4] This dataset was chosen due to its sectoral and geographic granularity (data are available at the county level), and its national coverage. While the QWI occasionally exhibit data suppression at such high granularities, this suppression is less extensive than in similar datasets such as the Bureau of Labor Statistics' Quarterly Census of Employment and Wages (QCEW). The effects of suppression in the QWI are limited to the calculation of sectoral ECFs—overall ECFs are calculated using total employment figures which are not suppressed for any county (see Equation 2.7). For the fossil-fuel power generation sector (NAICS 221112), data from the U.S. Energy & Employment Report (USEER) were used NASEO, EFI, and BW Research 2020, as neither the QWI nor QCEW provide county-level employment data at the 6-digit NAICS code level without significant data suppression.

The National Renewable Energy Laboratory (NREL) Industrial Energy Data Book (McMillan and Narwade 2018) dataset of county energy estimates was used to determine fuel and electricity consumption in the manufacturing, construction, agriculture and mining sectors. NREL's End-Use Load Profiles for the U.S. Building Stock dataset (Wilson, Parker, and Frick 2021), derived using the ComStock commercial building energy consumption model, was used for the energy consumption of commercial buildings. The Energy Information Administration (EIA) dataset on power plant emissions by plant and region (U.S. Energy Information Administration 2021b), constructed using the annual Form EIA-860 and Form EIA-923 surveys, was used to calculate the direct emissions of the electric power generation sector. A private oil and gas database, WellDatabase, was used to compile annual oil and gas production figures from all U.S. wells and used to calculate the indirect emissions of the oil and gas sector (*WellDatabase* 2021). Finally, the EIA Detailed Data from Form EIA-7A and the U.S. Mining Safety and Health Administration U.S. Energy Information Administration 2021a was used to determine annual coal production and therefore indirect emissions of the coal mining sector, as well as provide employment figures for employment carbon footprint calculations in this sector.

4. The North American Industry Classification System (NAICS) is the hierarchical standard for classifying sectors, and uses codes ranging from 2 to 6 digits in length to do so, with the granularity of classification increasing with the number of digits.

Table 2.1: Summary of sectors and corresponding data sources used in deriving ECFs.

<table>
<tr><th>Sector</th><th>Energy data source</th><th>Year</th><th>Employment data source</th><th>NAICS granularity</th></tr>
<tr><td>Mining</td><td rowspan="4">NREL Industrial Energy Data Book</td><td rowspan="4">2016</td><td>LEHD QWI + EIA-7A</td><td>6-digit within NAICS 21, aggregated to 2- and 3-digit.</td></tr>
<tr><td>Manufacturing</td><td rowspan="5">LEHD QWI</td><td>6-digit within NAICS 31-33, aggregated to 2- and 3-digit.</td></tr>
<tr><td>Construction</td><td>3-digit within NAICS 23, aggregated to 2- and 3-digit.</td></tr>
<tr><td>Agriculture</td><td>4- to 6-digit agricultural[5] within NAICS 11, also aggregated to 2-digit.</td></tr>
<tr><td>Commercial buildings</td><td>ComStock</td><td>2018</td><td>Varied[6]</td></tr>
<tr><td>Oil & gas production[7]</td><td>WellDatabase</td><td>2020</td><td>NAICS 211</td></tr>
<tr><td>Fossil-fuel power generation</td><td>EIA Emissions by Plant and Region</td><td>2019</td><td>USEER</td><td>NAICS 221112</td></tr>
<tr><td>Coal mining</td><td>EIA-7A</td><td>2020</td><td>EIA-7A</td><td>NAICS 2121</td></tr>
</table>

2.2 Deriving Employment Carbon Footprints (ECFs)

The key metric I target is the employment carbon footprint (ECF), which I define generally as the average carbon emissions from a set of firms divided by the total number of employees in those firms. Equation 2.1 shows the general formulation of the ECF:

$$ECF = \frac{\sum_f Q_f \cdot ef_f}{E}, \tag{2.1}$$

where f denotes fuel type, ef_f denote the CO_2 emissions factor of a given fuel, Q_f denotes the total quantity of fuel f consumed by firms, and E denotes total employment.

5. The NREL Industrial Energy Data Book considered only crop and animal production sector, and excluded hunting & fishing as well as forestry & logging.

6. ComStock gives commercial building emissions by building type rather than NAICS code. Each building type was mapped onto a NAICS code to obtain the corresponding employment data. The building types and corresponding allocated NAICS codes considered were: offices (NAICS 51-55, 92, 561, 425), retail (NAICS 44-45), warehousing & storage (NAICS 493, 423, 424), restaurants (NAICS 722), accommodation (NAICS 721), schools (NAICS 6111), hospitals (NAICS 622), and outpatient facilities (NAICS 621).

7. Note that oil & gas production (NAICS 211) and coal mining (NAICS 2121) both fall within the "Mining" sector (NAICS 21) according to the NAICS standard. The separate energy data shown here refer to the data used to calculate the Scope 3 emissions embedded in the produced fossil fuel products—on-site emissions are covered in the analysis of the mining sector.

While the direct production of carbon emissions by a firm will clearly be penalized by climate policies such as a carbon price, actions taken by a firm that result in carbon emissions elsewhere are likely also to be penalized indirectly. In greenhouse gas accounting, direct carbon emissions are referred to as "Scope 1" emissions, while indirect emissions can be categorized as either "Scope 2"—the emissions associated with the consumption of electricity produced using fossil fuels—or "Scope 3"—the emissions that occur somewhere else in the firm's value chain (GHG Protocol 2011). In order to faithfully reflect the impact of climate policy on jobs throughout the energy supply chain, I consider Scope 1, Scope 2 and Scope 3 emissions, with some caveats. I calculate Scope 1 emissions using data on the direct consumption of fossil fuels by firms, and calculate Scope 2 emissions using the consumption of electricity by firms in combination with the average carbon intensity of the power grid region they operate within.[8] Scope 3 emissions are notoriously difficult to measure, and the degree to which climate policies affect firms based on their Scope 3 footprint is varied and not well understood. I assume that the Scope 3 emissions that will have the most significant impact on firms are the downstream emissions associated with the production of fossil fuels, so I only consider the emissions embedded in fossil fuel products produced by the oil and gas and coal mining sectors to be "Scope 3" in my analysis. It is important to note that while for the purposes of this work I will refer to these embedded emissions as Scope 3 emissions, this is actually an incomplete definition according to international greenhouse gas accounting standards, which consider all indirect emissions in the entire value chain.

For completeness, my results include separate ECFs for each scope of emissions. However, it is of interest to produce an aggregate measure (an "overall" ECF) that reflects a county's relative carbon exposure across *all* scopes. Simply aggregating carbon emissions in a firm's value chain to obtain an overall ECF would result in double-counting between scopes. For example, if in a given county there is a facility that produces natural gas (Scope 3 emissions), a power station that burns this natural gas to produce electricity (Scope 1 emissions), and a commercial facility that consumes this electricity (Scope 2 emissions), summing these emissions would be counting the same CO_2 emissions three times. In reality, only the power station's operations are directly emitting carbon dioxide, but any measures to reduce the emissions of the station would impact the entire supply chain.

To simulate how emission abatement costs will be spread across these scopes (and avoid double-counting emissions), I conduct a pass-through analysis that simulates how fossil fuel demand and supply will respond to shifts in fossil fuel prices. I weight the emissions at each scope by an "effective pass-through rate," a function of the price elasticities of the fuels being produced/consumed. Using this, I calculate the "effective" carbon emissions of a firm as the portion of the firm's emissions that would "see" a full price on carbon. I use this measure as a proxy for the exposure of the firm to the impacts of climate policies, using a carbon tax as a representative policy. To calculate the effective emissions, I consider the incidence rate that the firm would bear if a carbon tax was implemented, based on the price elasticities of the energy products it consumes/produces and the sector within which it operates. I then calculate the effective emissions as the firm's absolute emissions (direct

8. The emissions factors used in the Scope 2 emissions calculation are from the Department of Energy's Emissions & Generation Resource Integrated Database (eGRID) (U.S. Environmental Protection Agency 2023a), which estimates the carbon intensity of the electricity grid in 27 eGRID subregions across the U.S.

or indirect) from a given energy product multiplied by the incidence rate for that product. Under this approach, the overall ECF technically becomes a measure of a job's vulnerability to emissions-penalizing policies specifically, as under these policies we would expect supply and demand to shift according to the price elasticities used in my calculation. An employee's overall ECF is therefore wholly representative of the employee's exposure to cap-and-trade policies and carbon taxes as these policies result in direct losses in surplus to consumers and producers of fossil fuels. It is also a good approximation of exposure to other indirect carbon pricing mechanisms, such as emissions/clean energy standards. This method is less representative of the potential impact on dirty jobs posed by subsidies to cleaner industries, as such policies do not directly impact the surplus of carbon-intensive firms but rather squeeze these firms from the market as cleaner firms enter. Acknowledging this limitation, the use of incidence to divide carbon exposure across the supply chain is still an effective proxy for policy exposure while avoiding double counting.

As is illustrated in Figure 2.1, my conception of the energy product value chain includes several vertical supply chains (e.g., the supply chain of electricity, from fossil fuel production to electric power generation to electricity consumption). I model the interactions between firms and consumers at each segment of these supply chains using the standard double marginalization problem framework, in which upstream and downstream firms price non-cooperatively and downstream firms incorporate the margins of upstream firms into their marginal costs (Spengler 1950). As has been done in the literature on vertical supply chain tax incidence (Rozema 2018; Weyl and Fabinger 2013), I do not specify a particular model of firm interactions.

Given the definition outlined above, the rate of incidence is equivalent to the effective pass-through rate[9] ρ_{eff} of a carbon tax onto consumers for a given energy product. I seek to calculate the effective pass-through rate $\rho_{eff,i}$ on firms at each step i of the vertical supply chains I consider, such that the social cost of carbon (SCC) borne by these firms is $\rho_{eff,i} \cdot SCC$, where $\sum \rho_{eff,i} = 1$. The effective pass-through rate onto end-use consumers is calculated using the standard formula for pass-through rate, outlined in Equation 2.2.

$$\rho_{eff,cons} = \frac{\epsilon_{S,cons}}{\epsilon_{S,cons} + \epsilon_{D,cons}}, \tag{2.2}$$

where $\epsilon_{S,cons}$ is the price elasticity of supply to end-use consumers and $\epsilon_{D,cons}$ is the price elasticity of demand for end-use consumers, for a given energy product in a given sector.[10] The effective pass-through rate onto firms is therefore $(1 - \rho_{eff,cons})$, and the effective pass-through rate onto downstream firms is the portion of firm burden borne by the downstream firms multiplied by the effective pass-through rate onto firms, as in Equation 2.3:

$$\rho_{eff,d} = I_d(1 - \rho_{eff,cons}), \tag{2.3}$$

where I_d is the portion of firm burden borne by downstream firms. I estimate I_d as the relative incidence between upstream firms (i.e. wholesale producers) and downstream firms

9. I define these pass-through rates such that they do not necessarily correspond to relative changes in wholesale or retail prices, as is the definition elsewhere in the literature (Rozema 2018), but rather the relative change in a firm's margin. I use the term "effective pass-through rate" to highlight this distinction.

10. The elasticity figures and assumptions used in this analysis are given in Appendix A.1 and Table A.1.

(i.e. wholesale consumers), calculated in Equation 2.4 the same way as the effective pass-through rate for end-use consumers in Equation 2.2:

$$I_d = \frac{\epsilon_{S,u}}{\epsilon_{S,u} + \epsilon_{D,d}}, \tag{2.4}$$

where $\epsilon_{S,u}$ is the price elasticity of supply from upstream producers to downstream firms and $\epsilon_{D,d}$ is the price elasticity of demand for downstream firms. The effective pass-through rate onto upstream firms (i.e. producers) is calculated as in Equation 2.5:

$$\rho_{eff,u} = 1 - \rho_{eff,d} = 1 - I_d(1 - \rho_{eff,cons}). \tag{2.5}$$

I use the logic outlined above to calculate the effective pass-through rate at every stage of the value chains outlined in Figure 2.1, for all covered fuel types and sectors. I then calculate the elasticity-adjusted employment carbon footprint for a given sector s in a given county c according to Equation 2.6:

$$\begin{aligned} ECF_{ovr\,c,s} = \frac{1}{E_{c,s}} \Bigg[& \left(\sum_f \rho_{eff\,f,s} \cdot Q_{c,s,f} \cdot ef_f \right)_{Scope1} + \left(\rho_{eff\,elec,s} \cdot Q_{elec_{c,s}} \cdot ef_{elec} \right)_{Scope2} \\ & + \left(\sum_{fossil} \rho_{eff\,fossil,s} \cdot Q_{fossil,prod_{c,s}} \cdot ef_{fossil} \right)_{Scope3} \Bigg], \end{aligned} \tag{2.6}$$

where f is a fuel burnt to produce direct CO_2 emissions, $elec$ refers to electricity consumed by a firm, $fossil$ refers to the production of either coal, oil or natural gas, and ρ_{eff_s} is the pass-through rate of a carbon tax in sector s for a given energy product. Finally, I conceive the final overall ECF for a county as the sum of the effective emissions across all covered sectors divided by the total employment in the county[11], as in Equation 2.7:

$$ECF_{ovr\,c} = \frac{\sum_s ECF_{ovr\,c,s} \cdot E_{c,s}}{E_c}. \tag{2.7}$$

Given that several measures are described here and presented in the results, it is useful to establish the nomenclature used in the rest of this thesis. "Overall ECF" refers to the aggregate, elasticity-adjusted measure presented in Equation 2.7, $ECF_{ovr\,c}$, representing the

11. Note that the denominator in Equation 2.7 is the overall employment of the county (as given by the QWI), as opposed to the total employment in covered sectors. This decision was taken for two reasons. Firstly, it may be the case (particularly in urban sectors) that a county has a large population working in non-covered sectors with low carbon intensities, and a very small population working in covered sectors with high carbon intensities. In this case, only counting employment in covered sectors would mark this county as highly carbon intensive, while in reality the county's overall carbon intensity would be quite low. Secondly, there are several datapoints for which disaggregated employment data is suppressed for confidentiality; counting covered employment only for these datapoints would result in overly high ECFs, as a sector's emissions would be counted but their corresponding employment figures would be missing. Using total county employment instead of covered county employment had no material impact on the overall distribution of ECFs across counties, and reduced the average county's ECF by roughly 20%. Given that most of the excluded sectors are low carbon intensity, this seems appropriate.

total abatement costs across all sectors accrued in county c per employee in that county. This is the central measure of this analysis. "Sectoral ECF" refers to the elasticity-adjusted measure derived in Equation 2.6, $ECF_{ovr\,c,s}$, representing the aggregate abatement costs per employee for a given sector s, accounting for all emission scopes. Finally, "Scope 1 ECF," "Scope 2 ECF," and "Scope 3 ECF" refer to the non-adjusted ECFs for each scope of emissions, calculated according to Equation 2.1.[12] These Scope ECFs are presented for completeness, to add validity without relying on the results of the pass-through analysis.

2.3 Calculation of social costs

I use the ECFs derived above to assess how the social costs of carbon-intensive jobs are distributed. To do so, I use the EPA's updated social cost of carbon (SCC) figures introduced in its recent proposal rule on regulating methane emissions. The EPA's central estimate is \$190 per metric tonne (or around \$172 per short ton) of carbon dioxide. I apply this SCC in combination with the effective pass-through rates derived earlier to calculate the social cost borne by firms in a given sector and county, as in Equation 2.8:

$$social\ cost_{c,s} = \sum_f \rho_{eff\,f,s} \cdot SCC \cdot Q_{f,s,c}. \tag{2.8}$$

The total social cost borne by each employee in a given county is given by Equation 2.9.

$$social\ cost\ per\ employee_c = \frac{\sum_s \sum_f \rho_{eff\,f,s} \cdot SCC \cdot Q_{f,s,c}}{E_c}. \tag{2.9}$$

2.4 Explained variance analysis

There are several variables that may influence the degree of ECF variation between counties. Clearly, some sectors are more carbon intensive than others, but there are also differences across counties in the carbon intensity of the grid, and identical firms in the same industry may emit at different rates due to operational or productivity differences. I perform an explained variance analysis using regression techniques to understand the extent to which each of these factors explains the observed variance in ECF across counties.

Understanding the extent to which different variables contribute to a county's Overall ECF is important for three reasons. Firstly, it may be helpful in developing policy approaches to reduce employment vulnerability. For example, if the carbon intensity of the grid was found to be highly correlated with counties' Overall ECFs, one might conclude that policy measures to promote electricity decarbonization are a pragmatic way to reduce employment vulnerability. Secondly, it may better enable policymakers to target at-risk communities in circumstances where the requisite data are not available or implementable. Measures like the ECF are difficult to legislate; instead, targeted policy often singles out populations based on their geographic, economic or sociodemographic characteristics. Therefore, if variables

12. Technically, Scope ECFs for county c are calculated as $ECF_{c,scope} = \left(\sum_s \sum_f Q_{c,scope,s,f} \cdot ef_f\right) / E_c$.

are highly correlated with Overall ECFs, one might be able to use them as proxies for employment vulnerability. The analysis here allows me to further evaluate the efficacy of the IRA's energy communities definition, and determine whether the criteria it uses are the right ones or whether others should be used in future policy efforts.

Finally, if a significant share of the variance in Overall ECFs remains unexplained, this may indicate substantial differences in the emissions efficiency of firms. It is helpful to frame this analysis in the context of production economics. Firms have different productivities when they produce different levels of output with the same set of inputs, typically conceived as capital and labor (Syverson 2010). Total-factor productivity (TFP) measures productivity with respect to all inputs, with differences in TFP representing shifts in the production function of a firm, conceptualized generally as:

$$Y_t = A_t \cdot f(K_t, L_t), \tag{2.10}$$

where Y_t, K_t and L_t are output, capital and labor, respectively, and A_t is the TFP. TFP can therefore be estimated using regression analysis by controlling for capital and labor. Assuming a Cobb-Douglas production function and taking the logarithm, we get:

$$\log Y_t = \beta_0 + \beta_k \log K_t + \beta_l \log L_t + \varepsilon, \tag{2.11}$$

in which case $TFP = A_t = \beta_0 + \varepsilon$.

Researchers have extended these concepts to carbon emissions efficiency in attempts to understand performance differences between firms in emissions intensity (Li et al. 2022). This work estimates the "total-factor carbon emissions efficiency" (TFCEE), which measures the extent to which a firm minimizes CO_2 emissions while maximizing output, controlling for capital, labor and energy inputs (Zhou, Ang, and Han 2010; Li et al. 2022).

According to this literature, ECFs could be categorized as a single-factor carbon emissions efficiency measure, but there may also be TFCEE differences between counties and within sectors that are not immediately obvious in the ECFs. While I do not seek (nor possess the adequate data) to rigorously derive TFCEE values in this analysis, it is useful to understand how much of the variance in ECFs is unexplained by the data and may be due to differences in carbon emissions performance between otherwise identical firms.

Broadly, I split ECF differences into *between*-sector differences and *within*-sector differences. Between-sector differences arise from the innate carbon intensity of the industry—coal mining clearly has a higher carbon footprint than retail, and one would expect a county with a large coal mining industry to have a greater ECF than one that relies mostly on retail activity. In the absence of within-sector differences, one would expect any variance in ECF between counties to be wholly explained by between-sector differences.

Within-sector differences, on the other hand, comprise differences in carbon intensity between firms in the same sector. These may be due to the technology and fuel mix used, geographic factors such as the carbon intensity of the electricity grid, or differences in total-factor carbon emissions performance. Note that differences in carbon emissions performance are unobservable; therefore, if I control for both between-sector differences and all observable within-sector differences, the unexplained variance should (in theory) be attributable to carbon emissions performance differences.

To conduct the explained variance analysis, I target six sets of independent variables, each representing a different potential explanatory factor. First, I control for between-sector differences by calculating workforce allocation across each of the eight high-level sectors as the share of total county employment in each sector s ($x_{c,s} = E_{c,s}/E_c$). I also control for demographic differences between counties. While these fall outside of my production economics framing of the variance in Overall ECFs, such characteristics are often used as proxy variables in order to target policies (for example, unemployment rate is used as a criterion in the IRA energy communities definition). The demographic variables I consider are: average annual personal income; minority (i.e. non-white and/or Hispanic) population share; rate of tertiary educational attainment; unemployment and poverty rates; and population density per square mile. I also include an interaction term between population density and annual personal income, as correlations between income and Overall ECF differ between urban and rural counties (see Section 3.3.2). In addition to demographic variables, I separately control for two political variables: percent of county that voted Democratic versus Republican in the 2020 presidential election, and whether Republican was the preferred party of the state. While these are likely highly correlated with demographics, it is useful to separate the two to determine which sets of variables might be better proxies for employment vulnerability.

I break within-sector differences into three sets of variables: power grid carbon intensity (ef_{elec}), 30-year annual average heating and cooling degree days[13] (HDD and CDD, respectively) to control for climatic differences between counties, and fuel mix. I control for fuel mix by defining an aggregate variable EF_{ss}, which I define as the average carbon intensity of fossil fuel consumption for subsector ss in tons CO_2e per MMBtu, or the subsector's total Scope 1 emissions divided by its total energy consumption i.e. $EF_{ss} = \sum_f (ef_f \cdot Q_{ss,f})/Q_{ss}$. This aggregate variable is a summary measure of the fuel mix of the subsector in a given county. I purposefully exclude emissions from electricity consumption from the numerator, as this is captured by ef_{elec}.

I conduct a separate linear regression for each set of variables, with the logarithm of Overall ECF, $\log ECF_{ovr}$, as the outcome variable, to determine the correlation between ECFs and each factor individually. I then combine the sets of variables in a stepwise model, first controlling for workforce allocation, then demographics, power grid carbon intensity, heating and cooling degree days, and fuel mix. In this model, I include interaction terms between ef_{elec} and x_s, ef_{elec} and heating/cooling degree days, and x_s and EF_{ss} values within the same high-level sector (see Table B.1 in Appendix B for subsectors considered). Log transformations were applied to the independent variables where appropriate.

For each regression I record the R^2 values to see how much more of the variance is explained with each additional set of controls. The residuals of each regression represent the differences in carbon footprints that are not explained by sectoral allocation, demographics and politics, grid carbon intensity, climatic differences, or fuel mix.

13. Obtained from the NOAA's U.S. Climate Normals (1981-2010) dataset (Anthony Arguez et al. 2010).

2.5 Analyzing distributive effects

The exposure to economic shocks arising from the energy transition is captured in the Overall ECF measure. However, it is important to understand how this exposure is correlated with socioeconomic and demographic characteristics that might affect a community's sensitivity and adaptive capacity and therefore exacerbate economic impacts (Carley et al. 2018). I assess how Overall ECFs are distributed across urbanity, population density, income, race, educational attainment, workforce development capacity and political affiliation.

Income, population, race, and educational attainment data for each county was obtained from the U.S. Census Bureau's American Community Survey (U.S. Census Bureau 2023a). Measures of urbanity were assigned to each county using the nine Rural-Urban Continuum Codes defined by U.S. Department of Agriculture Economic Research Service (ERS). Counties were assigned a Rural-Urban Continuum Code (RUCC) between one (most urban) and nine (most rural), with counties with an RUCC greater than four considered "rural" as is common practice. Political affiliation was assessed by share of total votes in the 2020 U.S. presidential election using data from the MIT Election Lab (MIT Election Data and Science Lab 2020).

I also explore the extent to which areas of high employment vulnerability might be colocated with areas that have limited capacity for workforce development. It is anticipated that two-year community college institutions will have a significant role to play in helping workers transition from polluting industries to high-skilled employment (Ansolabehere et al. 2022), so I take data from the National Center for Education Statistics' Integrated Postsecondary Education Data System (IPEDS) on the number of and enrollment in two-year postsecondary institutions across counties (U.S. Department of Education 2023). In order to capture the fact that in some regions commuting between adjacent counties may be reasonable and commonplace for both work and education, I aggregated these data by ERS Commuting Zone (CZ), a slightly coarser geographical unit of analysis that aims to more faithfully reflect the boundaries of the local economy which may span several counties.[14]

14. The ERS stopped updating their CZ definitions in 2000. In 2010, researchers at Pennsylvania State University applied the ERS' methodology to provide publicly available updates to the CZs (Fowler and Jensen 2020) These represent the most current definition of CZs available and were used for this analysis.

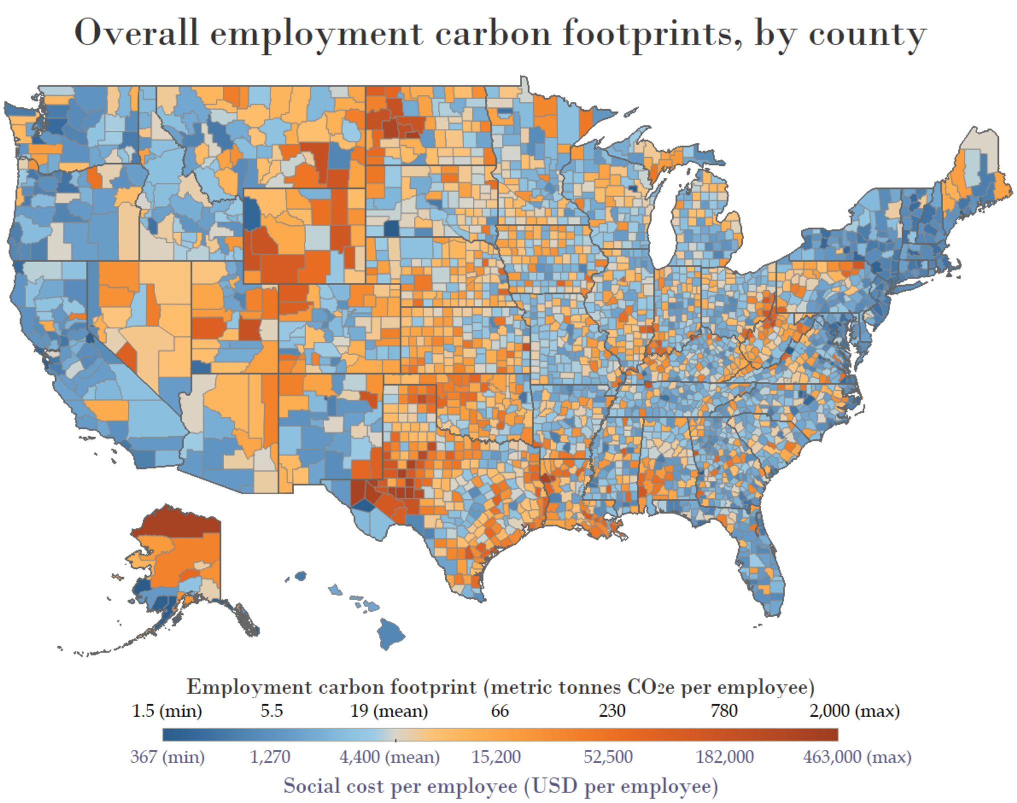
Chapter 3

Results

3.1 Employment vulnerability of communities

3.1.1 Employment carbon footprints & social costs

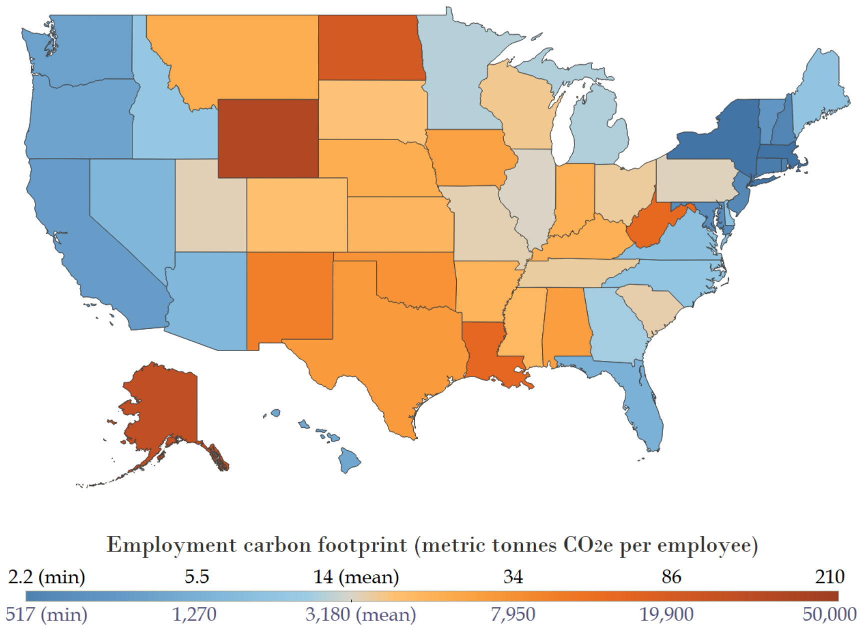
Figure 3.1 displays Overall ECFs for each county. Figure 3.2 aggregates Overall ECFs to the state level, with a clear disparity between coastal and inland states.



Notes: This figure maps Overall ECFs across U.S. counties on a logarithmic scale due to the highly skewed distribution. Counties with higher Overall ECFs are more vulnerable to employment impacts of the energy transition. Counties in orange have Overall ECFs above the national logarithmic average; those in blue have Overall ECFs below the average.

Figure 3.1: Distribution of Overall ECFs across U.S. counties.

Overall employment carbon footprints, by state



Notes: To derive state-level ECFs, county-level employment and effective CO_2e emissions values were aggregating by state. It should be noted that this approach inherently gives more weight to populous counties, which tend to have low ECFs.

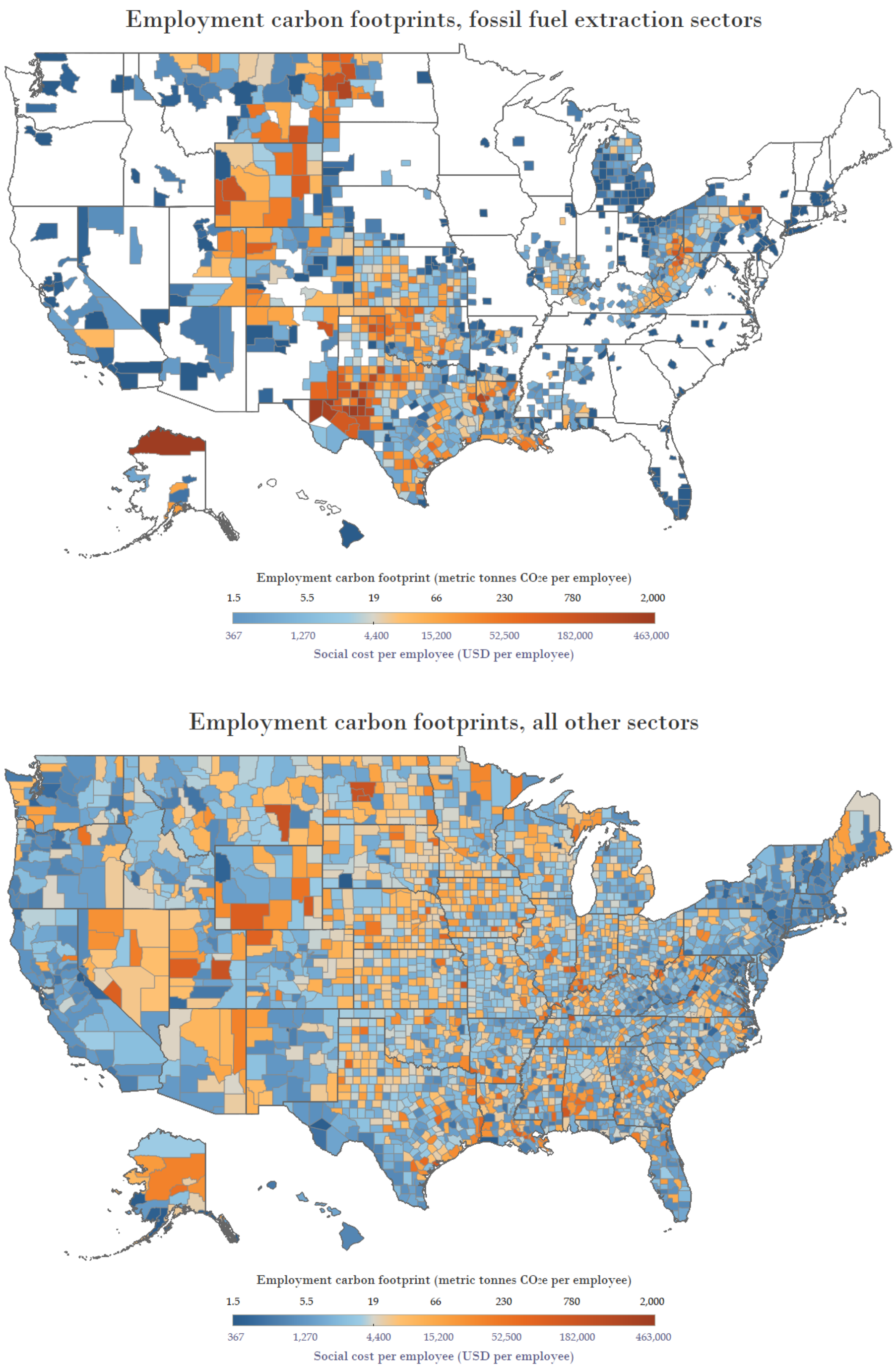
Figure 3.2: Distribution of Overall ECFs across U.S. states.

Along with the Overall ECF of each county, these figures display the social cost of firms' carbon emissions per employee. Strictly speaking, this cost represents the value to society in eliminating emissions from the employee's firm; however, in the context of just transition policy, it is helpful to characterize it in terms of the economic risk facing employees and the level of transition support required. If climate policy is implemented to address the externality of CO_2 emissions, this is the cost per employee that would be imposed on firms to internalize the social cost of their pollution. A higher social cost therefore indicates greater risk of job destruction or wage cuts in the face of climate policy. The most carbon-intensive counties have an average social cost per employee of over \$100,000 per year, far greater than median salaries in the area—this suggests that a climate policy that values the social cost of carbon at the EPA's \$190 per tonne will result in extensive job losses in these regions if commensurate policy support is not provided.

As mentioned, it is useful to understand the extent to which Overall ECFs are driven by fossil fuel extraction versus other activities given the inherently different pressures these sectors will face in a decarbonized economy. I therefore present maps that split counties' Overall ECFs into footprints from fossil fuel extraction and other sectors in Figure 3.3.

Consistent with previous studies measuring energy transition vulnerability across the U.S., the results identify counties in Appalachia, west Texas, Oklahoma, Wyoming, Montana, the Gulf Coast, western North Dakota and Alaska's North Slope as having high employment vulnerabilities—all areas with high levels of fossil fuel extraction.

However, I also find that there is a significant number of highly vulnerable counties that do not have local fossil fuel extraction industries, particularly in Nevada and large portions

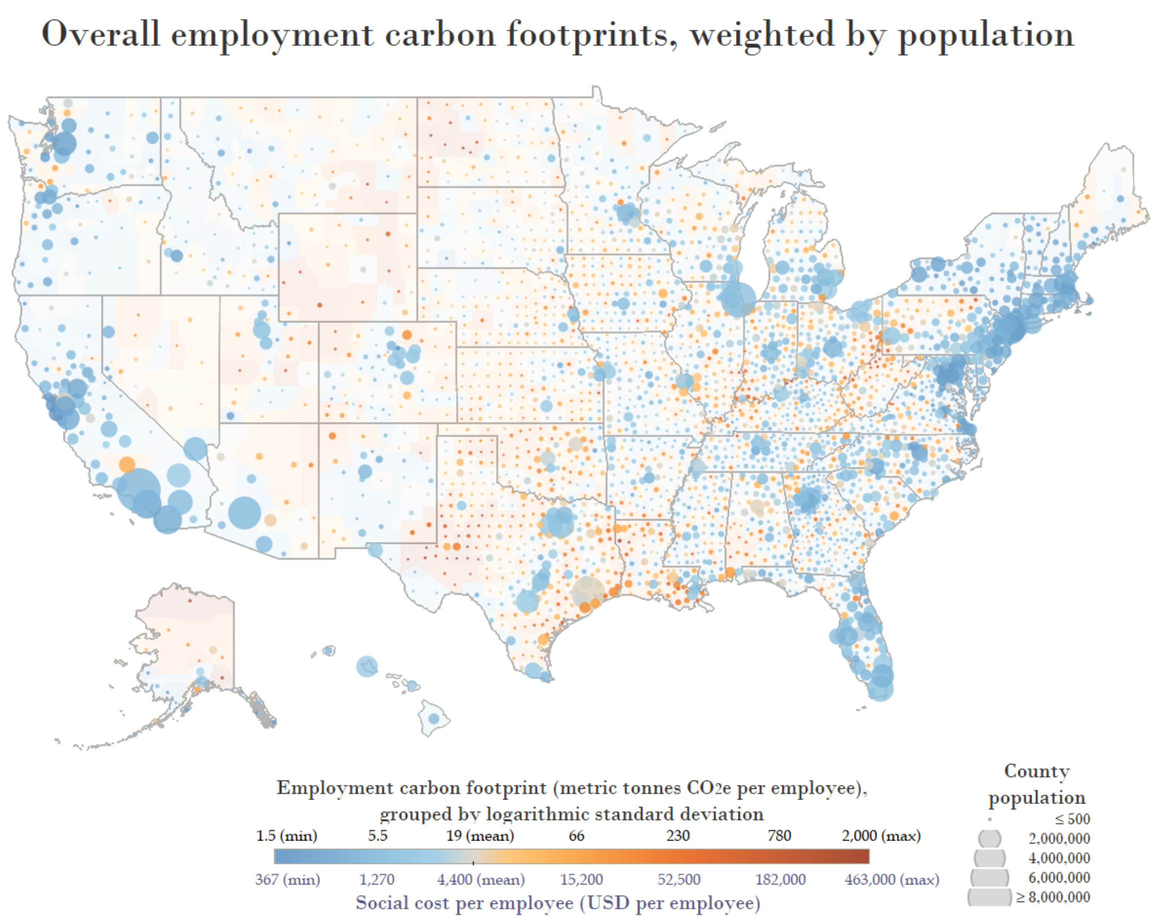


Notes: These maps split the Overall ECFs presented in Figure 3.1 into the emissions from fossil fuel extraction sectors (i.e. coal mining and oil and gas extraction) and the emissions from all other covered sectors. Specifically, the fossil fuel extraction map considers Scope 1, 2 and 3 emissions from NAICS 2111 - Oil and Gas Extraction, and NAICS 2121 - Coal Mining. It should be noted that both of these NAICS codes cover some activities that are not strictly extraction—for example, NAICS 2121 includes beneficiating (i.e. preparing) coal, and NAICS 2111 includes sulfur recovery from natural gas. As such, there are some counties that appear in the fossil fuel extraction map that do not appear in the Scope 3 ECF map in Figure 3.6—these are counties for which some activity was recorded in NAICS 2111 or NAICS 2121 that resulted in Scope 1 or 2 emissions, but no extraction of coal or oil and gas actually occurred. These two maps are presented on the same color scale as Figure 3.1 to compare the relative weight of extractive vs non-extractive emissions in contributing to a county's Overall ECF, with total county employment as the denominator for both sets of ECFs.

Figure 3.3: Overall employment carbon footprints for fossil fuel extraction sectors versus all other sectors.

of the Great Plains states. These areas are overlooked by previous estimates, and Figure 3.3 shows that their vulnerability is driven by the presence of other polluting industries outside of fossil fuel production, such as mining and carbon-intensive manufacturing. In many cases, the Overall ECFs of these communities are just as high as, if not higher than, those of nearby fossil fuel communities. The emergence of these vulnerable counties in the overall analysis is significant—it indicates that, while communities reliant on fossil fuel extraction are often the focus of just transition policy, areas that rely heavily on fossil fuel consumption may also be exposed to employment impacts as the economy shifts. Importantly, it shows that these counties may be left behind if just transition policy focuses exclusively on fossil fuel extraction communities.

Figure 3.4 shows the same county-level map as Figure 3.1, however each county is represented by a dot whose size corresponds to the population of the county. High-ECF counties have much lower populations on average, with only a few highly populous counties having Overall ECFs above average. This illustrates the fact that while 43% of counties have above-average employment carbon footprints, these counties only account for 17% of the total U.S. population.

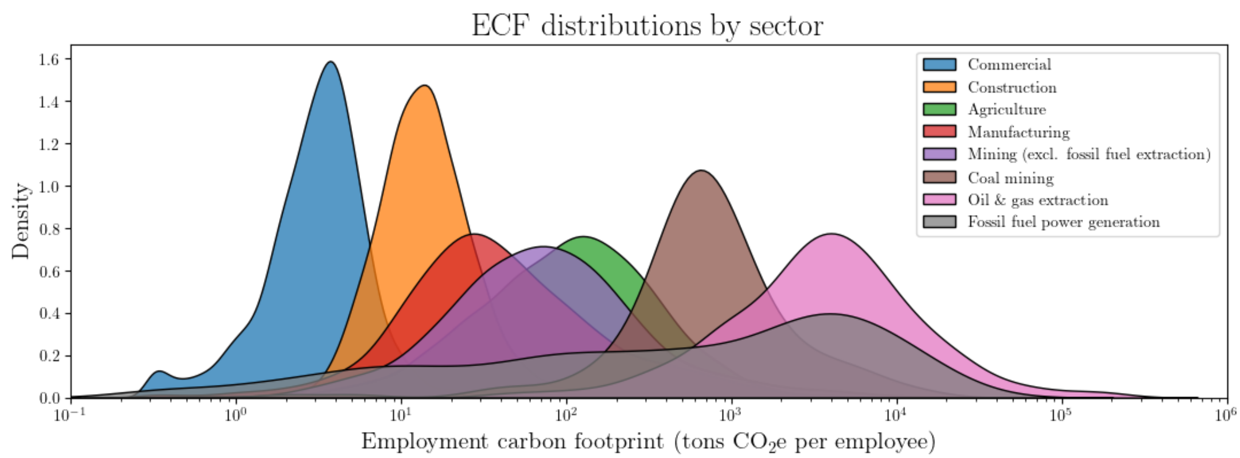


Notes: Each dot represents one county, with size reflecting the county's population and color representing the county's ECF.

Figure 3.4: Overall ECFs across U.S. counties, normalized by county population.

The Scope 1, 2 and 3 ECFs[1] used to create the Overall ECFs are shown in Figure 3.6. I find that the distributions of ECFs across geography are more or less consistent in the Overall, Scope 1, Scope 2, and Scope 3 cases. Notably, almost all of the counties on the Scope 3 map (i.e. counties with fossil fuel extraction) feature as highly vulnerable in the overall map, indicating that the presence of fossil fuel extraction industries has a particularly significant impact on the Overall ECF of the county.

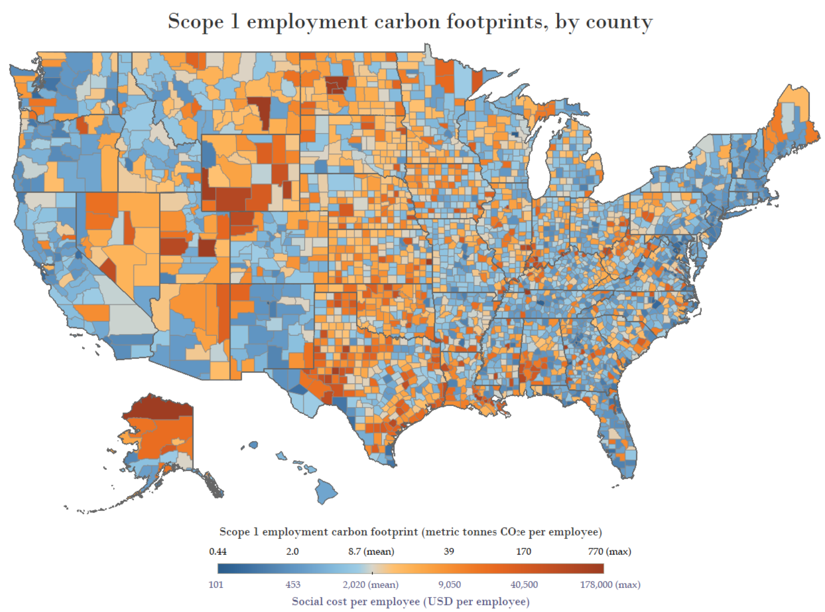
The carbon intensity of the high-level sectors covered in this analysis is presented in Figure 3.5, which displays the kernel distribution estimates of each Sectoral ECF. There are clear sectoral trends in carbon intensity, with variations between the cleanest sectors (commercial sectors) and dirtiest sectors (coal mining, oil & gas extraction, and fossil-fuel power generation) spanning several orders of magnitude. These differences give an indication of the extent to which between-county differences in sectoral prominence and workforce allocation may have on a county's Overall ECF. However, it is also notable that there is a significant degree of within-sector variation, even within relatively tightly defined sectors such as coal mining and oil & gas extraction. This indicates that, while some sectors will be harder hit by the energy transition than others, there will also be material distributed impacts *within* sectors, further highlighting the need for continuous measures of employment vulnerability when informing just transition policy. Figures 3.7 and 3.8 map these Sectoral ECFs across geography.

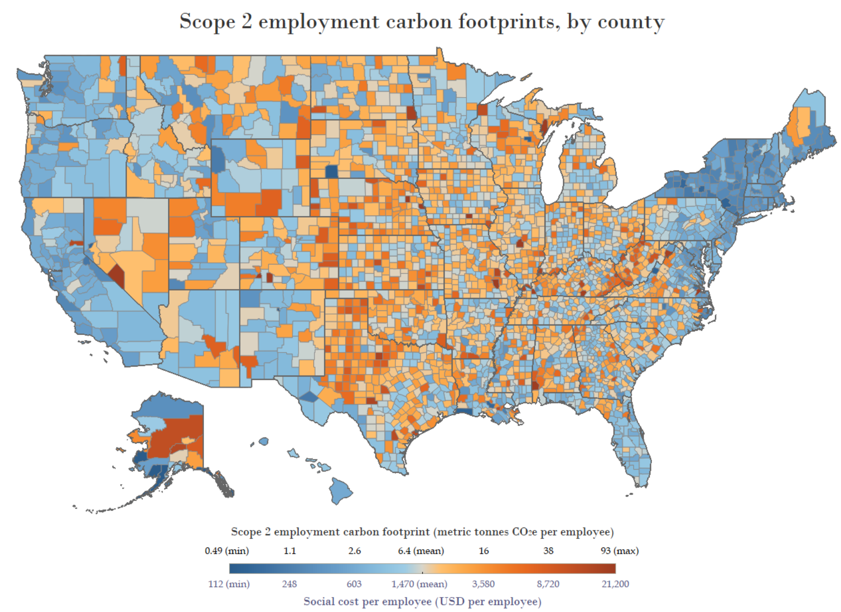


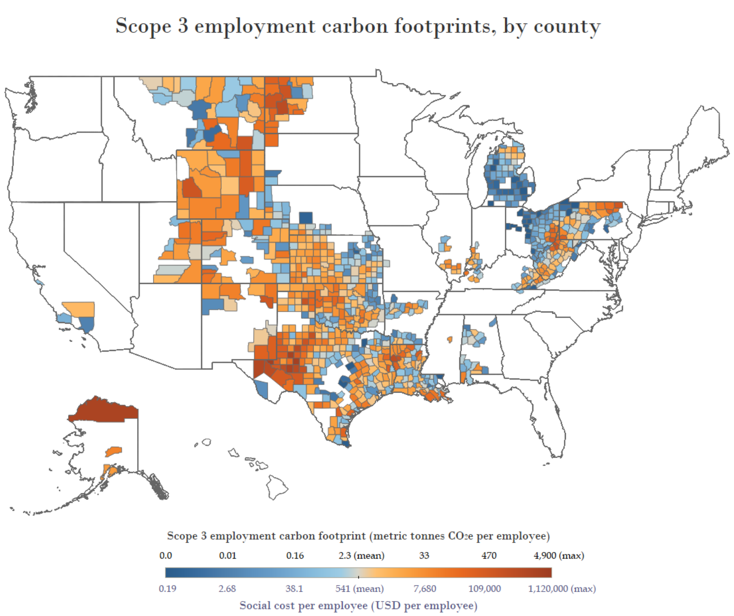
Notes: The kernel density estimates in this figure represent the ECF distributions across counties for each sectoral ECF (i.e. each county's carbon footprint for only those working in a given sector, as opposed to the entire county). The KDEs of the most carbon-intensive sectors sit at the right of the figure, including oil and gas, coal mining and fossil-fuel power generation.

Figure 3.5: Kernel density estimates of county-level ECF distributions for each covered sector.

1. Note that the denominator of each of these footprints is the same—namely, the total employment for the county. Also note that the Scope 3 plot has many missing counties—these are counties for which there was no fossil fuel production.

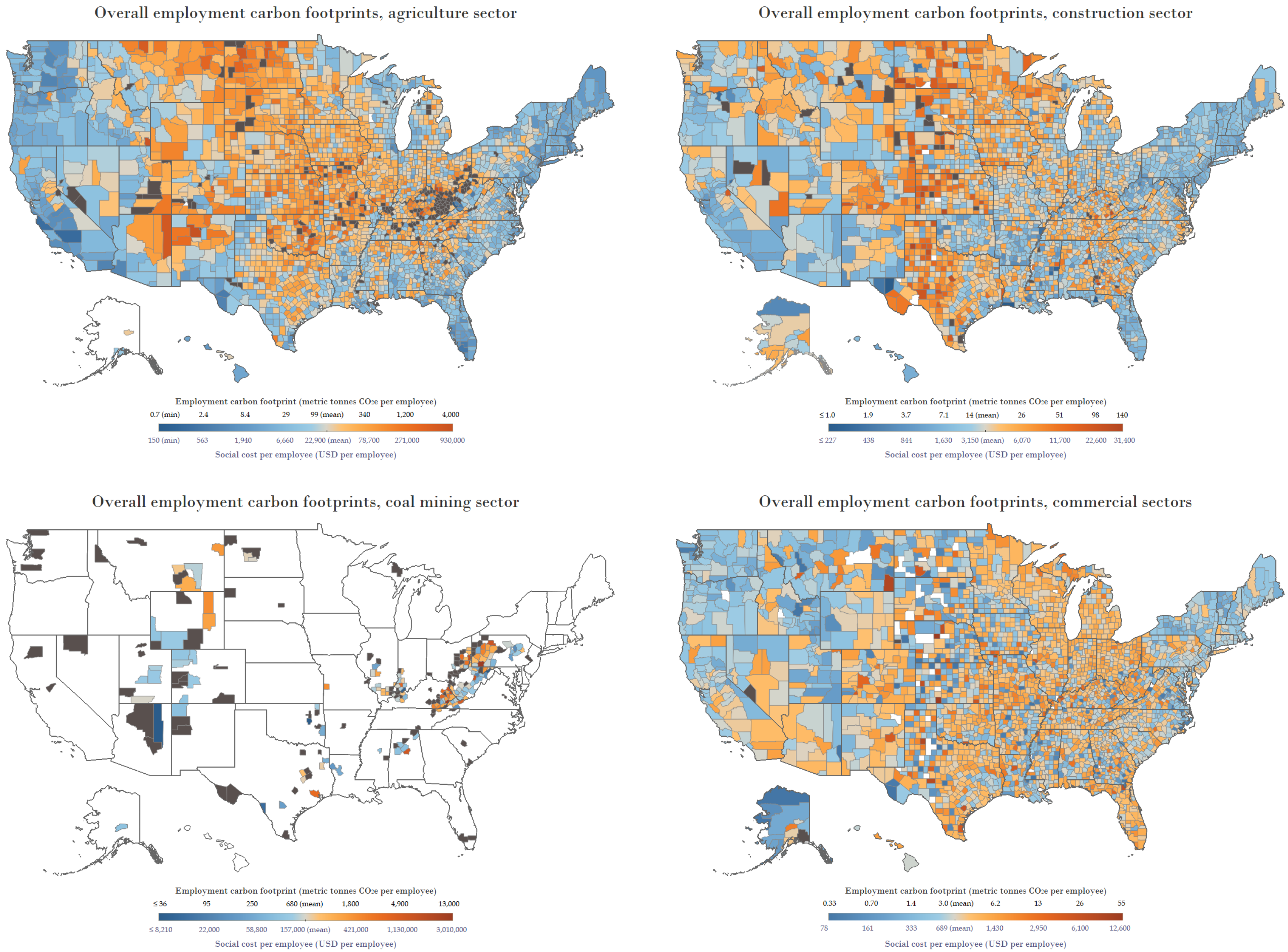






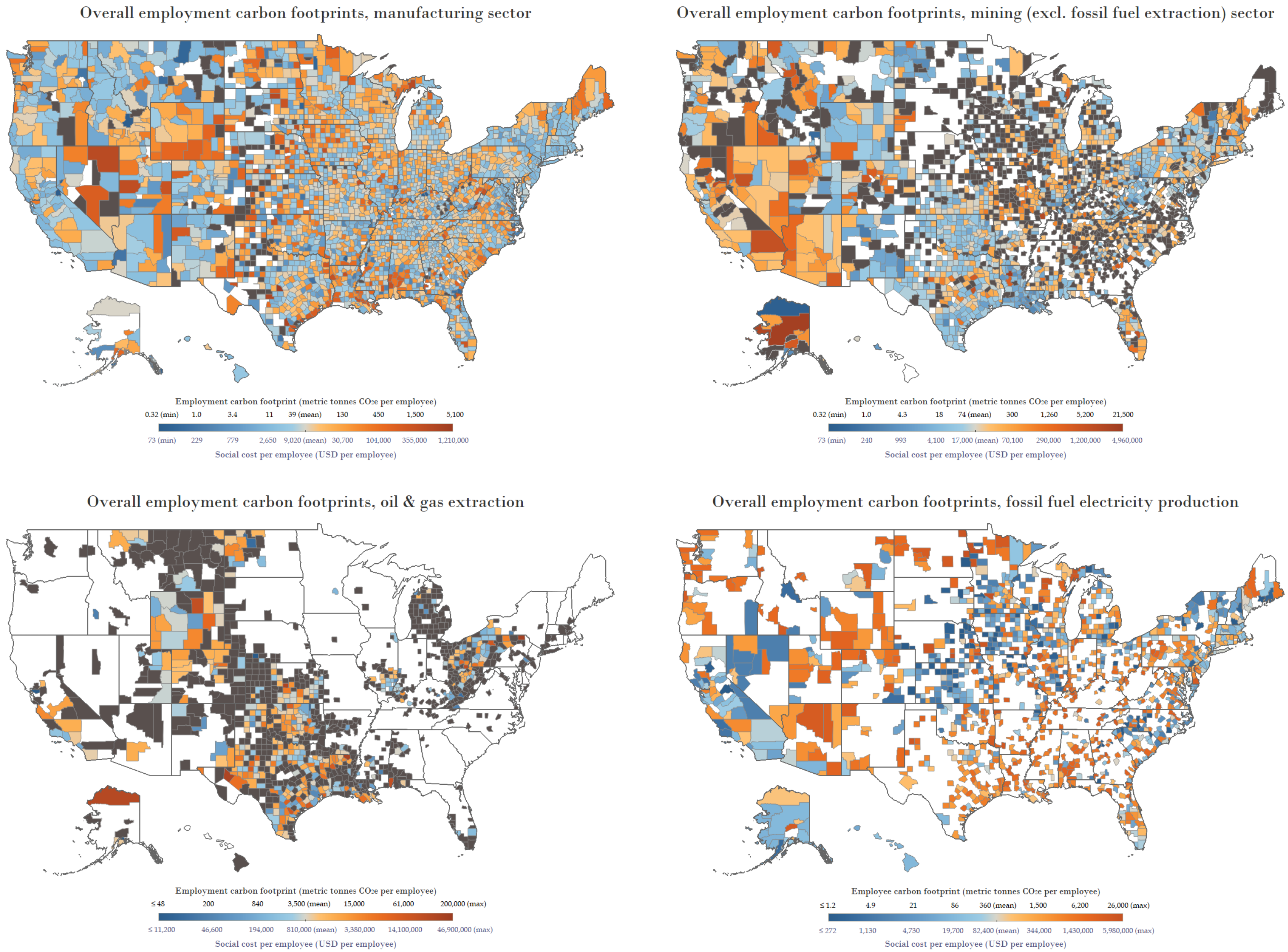
Notes: These maps display the Scope 1 (on-site emissions), Scope 2 (indirect emissions from electricity generation) and Scope 3 (defined in this paper as indirect emissions embedded in fossil fuel production) carbon footprints of each county. The denominator of each of these footprints is the same—namely, the total employment for the county. The white areas on the Scope 3 map represent those without fossil fuel production (i.e. without a coal mining or oil and gas industry). The "mean" ECF values on the legend of each map are the logarithmic mean of county ECF values for that Scope, as opposed to the logarithmic mean of overall ECF values as in Figures 3.1 and 3.4.

Figure 3.6: Scope 1, Scope 2 and Scope 3 ECFs across counties.



Notes: Each map represents counties' ECFs for a given sector (i.e. each county's carbon footprint for only those working in a given sector, as opposed to the entire county). White areas represent those without any activity in a given sector, and dark grey counties represent those for which publicly available employment data was not available for a given sector. The "mean" ECF values on the legend of each map are the logarithmic mean of county ECF values for that sector, and differ from average overall ECF values.

Figure 3.7: Distributions of sectoral ECFs—agriculture, construction, coal mining, commercial sectors.

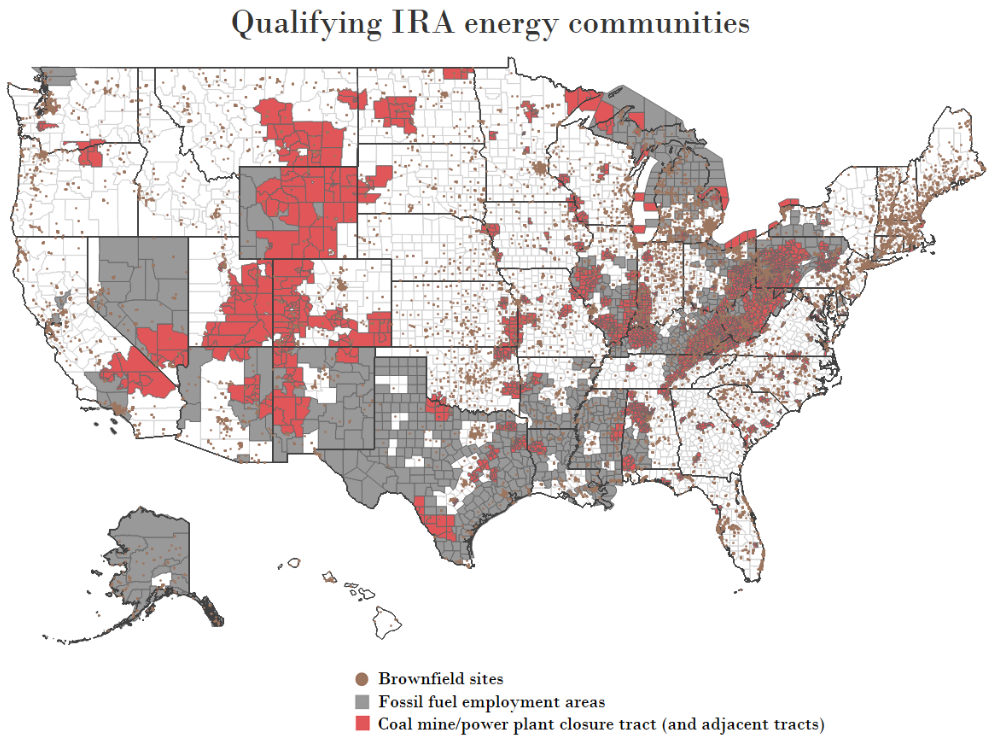


Notes: Each map represents counties' ECFs for a given sector (i.e. each county's carbon footprint for only those working in a given sector, as opposed to the entire county). White areas represent those without any activity in a given sector, and dark grey counties represent those for which publicly available employment data was not available for a given sector. The "mean" ECF values on the legend of each map are the logarithmic mean of county ECF values for that sector, and differ from average overall ECF values.

Figure 3.8: Distributions of sectoral ECFs—manufacturing, non-fossil mining, oil & gas, fossil-fuel power generation.

3.1.2 Comparison with IRA energy communities

Figure 3.9 displays areas designated as energy communities under the IRA for 2023 as implemented by the U.S. Department of Treasury and Internal Revenue Service (Interagency Working Group on Coal & Power Plant Communities & Economic Revitalization 2023). Figure 3.10 shows the differences in Overall ECFs for counties that contain at least one energy community[2] and counties that do not contain any qualifying energy communities. It is clear that while many of the most vulnerable counties are deemed energy communities, there is significant spread in Overall ECF within both qualifying and non-qualifying counties.

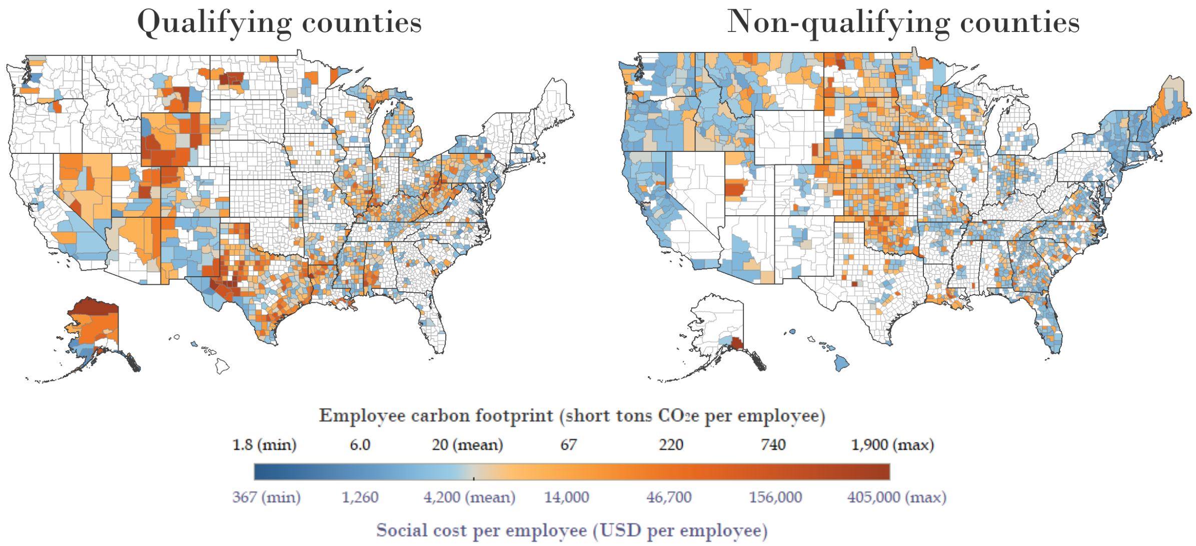


Notes: Colored areas represent those allocated energy community status for 2023 by the U.S. Department of Treasury and Internal Revenue Service under the Inflation Reduction Act. Shaded areas represent those that qualify under the fossil fuel employment criterion (grey) or the coal closure criterion (red)—the shapefiles for these areas were obtained from IWG (2023). Data on MSA/non-MSA tax revenue sources are currently unavailable, so areas that might qualify under the tax revenue criterion were not considered. The brown dots represent brownfield sites—note that these indicate points in space rather than holistic areas (brownfield sites are often limited to small, isolated parcels of land). Since IWG (2023) have yet to release data on eligible brownfield sites, these data were obtained from Raimi and Pesek (2022). Note that colored areas do not necessarily follow county boundaries due to the different geographic granularities of the qualifying criteria—fossil fuel employment areas are assessed at the MSA/non-MSA level, while the coal community criterion is assessed at the much smaller census tract level.

Figure 3.9: Qualifying energy communities for 2023 (IWG 2023, Raimi & Pesek 2022).

I focus the comparison on IRA energy communities that qualify under the fossil-fuel employment (FFE) criterion, as one would expect this metric to be similarly forward-looking to the Overall ECF measure (as opposed to coal closures, which are a retrospective measure). Figure 3.11 compares the Overall ECF distributions of counties that contain at least one

2. Counties were identified using geospatial analysis. Due to their very small geography, brownfield sites were excluded from this analysis. Since some energy communities are defined at the census tract level, I count any counties that contain a census tract-level energy community as a "qualifying county."

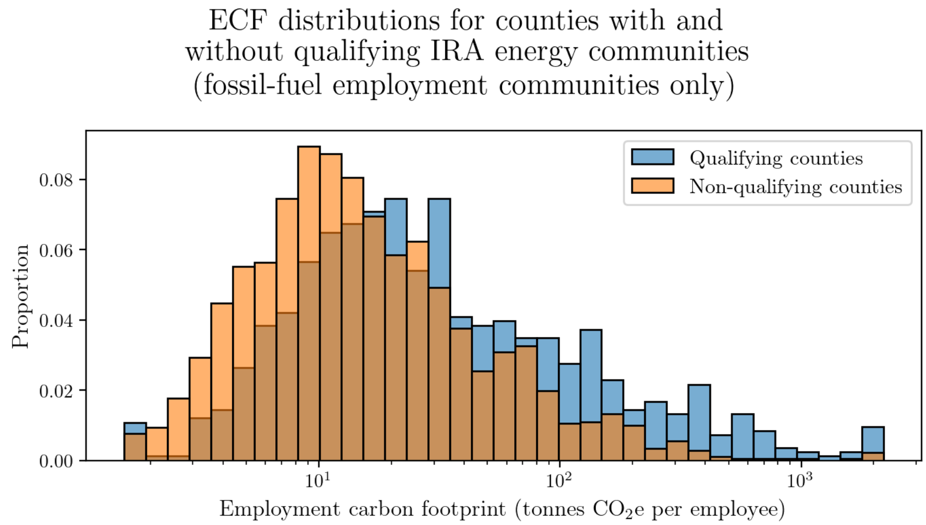


Notes: Counties are deemed to contain an energy community if any area of the county overlaps with some area of an energy community as designated by the U.S. Department of Treasury for 2023. Brownfield sites are not considered. Both maps measure county-level Overall ECFs against the national logarithmic average on the same color scale.

Figure 3.10: Overall ECFs of qualifying (left) and non-qualifying (right) counties that contain IRA energy communities (left) and counties that do not (right).

FFE energy community to that of counties that contain no FFE energy communities. If the FFE energy communities identified by the IRA were those with the highest ECFs, I would expect a negative skew in the ECF distribution for qualifying counties that would position it significantly to the right of the distribution for non-qualifying counties. By contrast, I observe that the two distributions are very similar, with the ECFs of qualifying counties only marginally higher than those of non-qualifying counties on average. While the majority of the most vulnerable counties qualify as FFE energy communities, there are still significant omissions ("false negatives")—124 counties with Overall ECFs in the 90th percentile do not qualify for the extra tax credit. Furthermore, many "false positives" remain, with 79 counties eligible for extra IRA funding having Overall ECFs in the bottom 20% and 26 having Overall ECFs in the bottom 10%.

Some of the reasons behind these anomalies have been unpacked by Raimi and Pesek (2022) and addressed in their proposed alternate methodology for identifying energy communities. The FFE criterion requires areas with high fossil fuel employment to also have an unemployment rate greater than the U.S. national unemployment rate in order to qualify. Raimi and Pesek (2022) find that this requirement means that some of the regions most reliant on carbon-intensive fossil fuel industries do not qualify as energy communities as their unemployment rate is not above the national average and could see areas float in and out of eligibility as their unemployment rate fluctuates. Furthermore, they find that the fossil fuel employment threshold of 0.17% is below the national average of 0.78%, meaning that some areas with below-average fossil fuel employment but above-average unemployment qualify. They also highlight that a binary classification of energy communities limits the ability to target the most vulnerable communities, and instead propose a stepped tax credit scaled by the extent of fossil fuel employment and coal industry presence in the area. Finally, they cri-



Notes: The orange histogram represents counties that contain at least one IRA energy community qualifying under the fossil-fuel employment criterion. The height of each bar represents the proportion of qualifying/non-qualifying counties that have a given employment carbon footprint. If the IRA's fossil-fuel employment criterion effectively targeted the most vulnerable communities, we would expect a greater proportion of qualifying counties to have high carbon footprints; instead, I find the two distributions are very similar, with the distribution for qualifying counties only slightly to the right of that for non-qualifying counties.

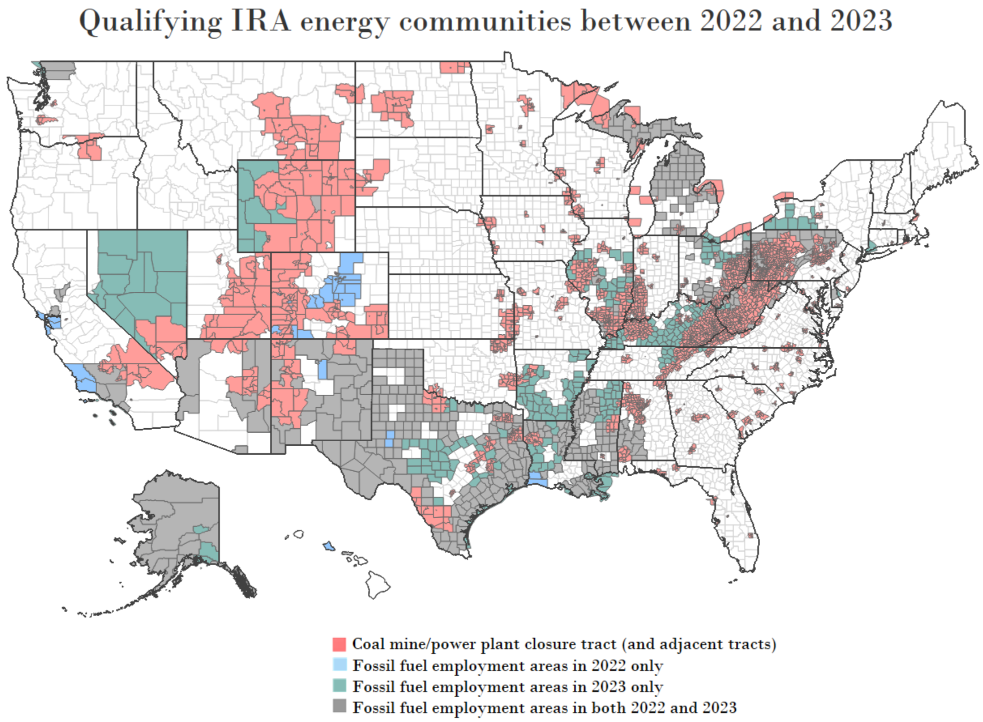
Figure 3.11: Overall ECF distributions for counties qualifying as energy communities under the fossil fuel employment criterion in the IRA, and non-qualifying counties.

tique the use of metropolitan and non-metropolitan statistical areas (MSAs and non-MSAs) as the geographic unit of analysis for the fossil fuel employment criterion, finding them to be too coarse to represent local employment dynamics and instead suggesting county-level estimates.

My results support these critiques, particularly around the unemployment threshold. According to the U.S. Department of Treasury's guidance, an MSA' or non-MSA's unemployment rate will be determined each calendar year by aggregating county-level unemployment data from the BLS' Local Area Unemployment Statistics (LAUS) for the previous year and comparing them to the national unemployment rate for the same year. Therefore, both an area's unemployment rate and the qualifying unemployment threshold—and therefore its energy qualification status—will be updated each calendar year with each set of new unemployment figures (generally released in April). This means that an area whose unemployment rate is close to the national rate could drop in and out of eligibility as its unemployment rate fluctuates. Furthermore, an increase in the *national* unemployment rate could cause a community to drop out of energy community status, even if the local economic circumstances of the area are unchanged.[3]

These effects can be significant. To investigate year-on-year changes in energy community

3. According to the IRS' and Treasury's rules, if a project was located in a qualifying energy community when construction began, the project continues to be eligible for its energy community tax credit bonus regardless of any changes to the energy community status of the location (U.S. Internal Revenue Service and U.S. Department of Treasury 2023). Therefore, this loss of eligibility would only apply to future projects in the area.

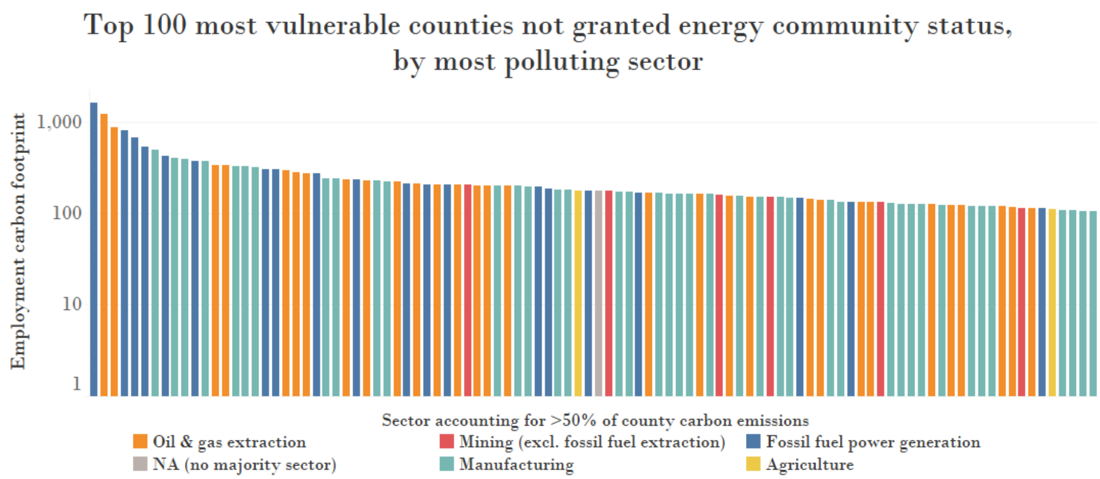


Notes: This figure shows how energy communities would have changed between 2022 and 2023 according to the language of the IRA and guidance from the Department of Treasury. Pink areas represent those allocated energy community status under the coal closure criterion, and are constant across 2022 and 2023. Grey areas represent those that qualify under the fossil fuel employment criterion in *both* 2022 and 2023, while green areas represent those that did not qualify in 2022 but qualified in 2023, and blue areas represent those that qualified in 2022 but dropped out of qualification in 2023. Results for 2023 were obtained from IWG (2023), while energy communities for 2022 were derived using the BLS Local Area Unemployment Statistics for 2022 and the Department of Treasury's methodology. Note that brownfield sites have been excluded from this figure for simplicity. Data on MSA/non-MSA tax revenue sources are currently unavailable, so areas that might qualify under the tax revenue criterion were not considered—however, one might expect similar volatility between years for these communities as they are also subject to the unemployment rate criterion.

Figure 3.12: Comparison of qualifying energy communities between 2022 and 2023

eligibility under the FFE criterion, I determined whether each MSA/non-MSA would qualify in 2022 (using 2021 LAUS data and the Treasury's method) and compared these results to the Treasury's designations for 2023. Figure 3.12 compares the two sets of energy communities. I find significant volatility in qualification status, with large areas (including over half of Texas, nearly all of Nevada, and large parts of Kentucky, Arkansas and Illinois) not qualifying in 2022 but qualifying in 2023, and other areas (such as central Colorado) dropping out of eligibility between 2022 and 2023 (see Figure S6). Some of the counties that would not have qualified in 2022, particularly those in west Texas, have some of the most carbon-intensive employment in the country, implying that the number of "false negatives" in Figure 3.11 could be even greater in future years. On the other hand, some areas dropped out of eligibility between 2022 and 2023, particularly in central Colorado. Such year-on-year volatility creates serious uncertainty and is a major concern for communities and clean energy investors alike.

Aside from communities with high levels of fossil fuel employment that do not pass the unemployment test, vulnerable communities are also left behind by the IRA's exclusive focus on fossil fuel extraction and processing sectors. Figure 3.13 depicts the most polluting sectors in each of the 100 most carbon-intensive counties that were not granted energy community status in 2023. Of this 100, 39 have high levels of fossil fuel employment (specifically in oil and gas extraction) but fail the unemployment rate test. But counties with high levels of carbon-intensive manufacturing are also missed, despite their high reliance on fossil fuels—such counties make up a third of the 100 most vulnerable counties overlooked by the IRA. Furthermore, the Department of Treasury's definition of fossil fuel employment does not include fossil fuel power generation (NAICS code 221112). This means that in many cases, no assistance is granted to counties with large power plants that are major sources of both pollution and employment, despite the coal closure criteria providing support to such communities after partial or complete closure of a coal-fired plant. 19 of the top 100 (and half of the top 10) most vulnerable overlooked counties fall into this category, a considerable oversight given that workers in coal-fired power plants are typically front-and-center of just transition discussions.

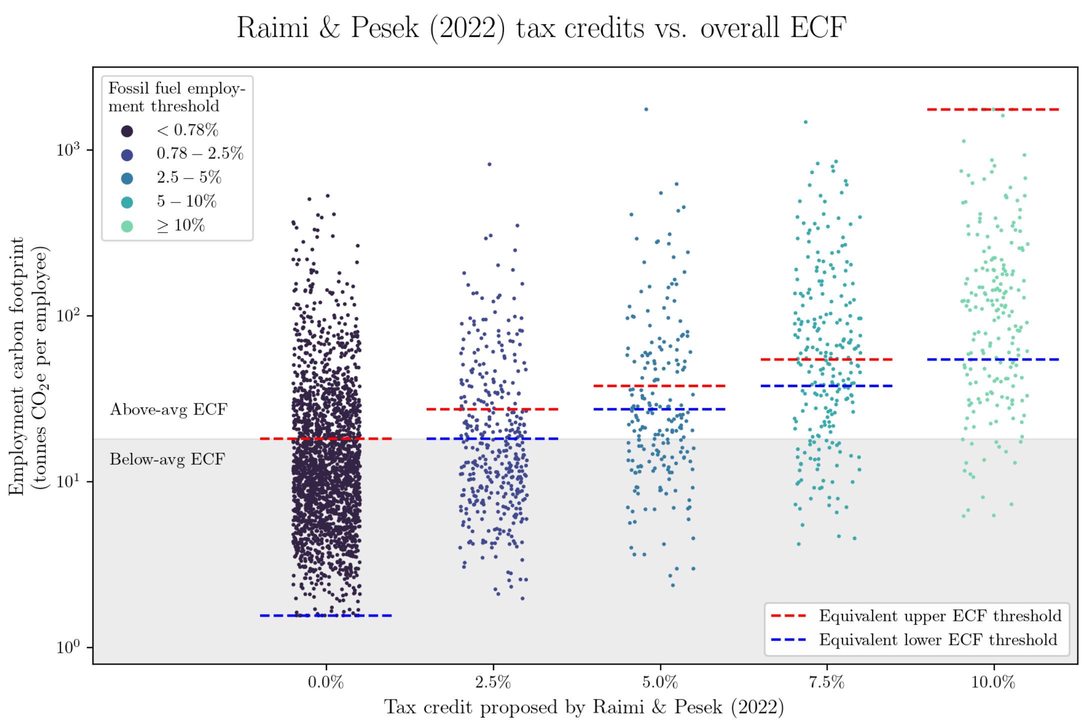


Notes: This figure depicts the 100 counties with the greatest Overall ECFs that were not granted energy community status by the Department of Treasury in 2023. Each bar represents one county. The relative share of each county's CO_2e emissions was calculated for each sector, and the most polluting sector for each county was identified as that which comprised over 50% of the county's carbon emissions.

Figure 3.13: Dominant sectors of 100 most carbon-intensive counties that are not 2023 ECs.

3.1.3 Comparison with the literature

My results also identify shortcomings with other methods of identifying vulnerable communities in the literature that focus exclusively on fossil fuel industries. Figure 3.14 compares the level of tax credit assigned to counties under Raimi and Pesek's (2022) proposed methodology with their corresponding Overall ECFs. Raimi and Pesek (2022) assigned tax credits on the basis of percent of fossil fuel employment share, coal production, and coal-fired power generation capacity, setting incremental thresholds for each level of the credit. To approximate the ECF levels equivalent to these qualifying thresholds, each of the FFE thresholds was converted to a Z-score based on the total distribution of fossil fuel employment shares across counties, and ECF values corresponding to these Z-scores were computed. These are the red and blue dashed lines on the figure, and indicate the bounds within which the Overall ECFs and Raimi and Pesek's (2022) tax credit levels are aligned. If a county sits above the red line, its Overall ECF indicates greater employment vulnerability than is accounted for by its proposed tax credit level; conversely, if it sits below the blue line, its tax credit level overestimates its employment vulnerability.

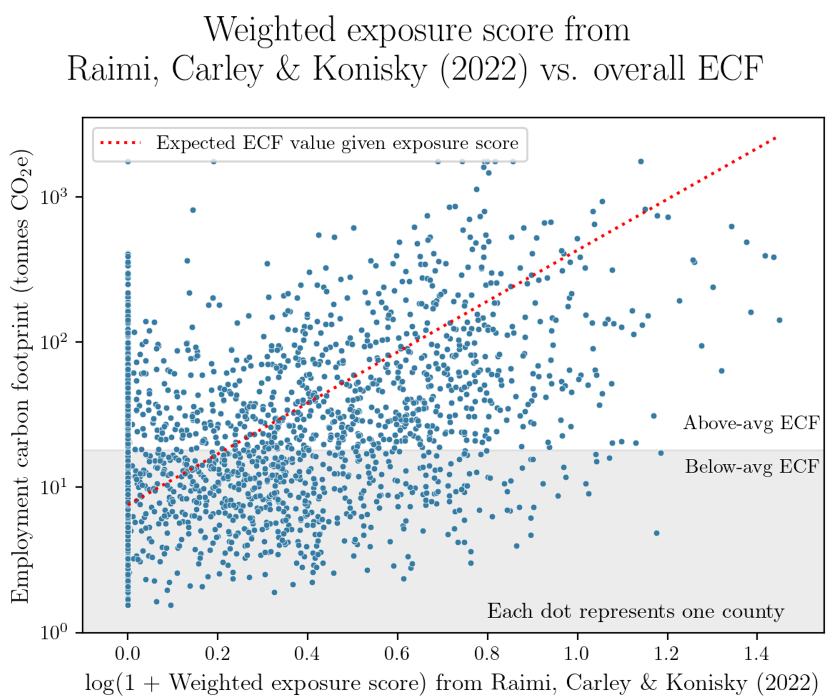


Notes: Each dot represents one county. Counties are separated by the tax credit they would receive under Raimi and Pesek's (2022) proposal and plotted vertically against their Overall ECF. Counties in the grey portion of the figure have ECFs below the national logarithmic average. The red and blue dotted lines represent the upper and lower bounds of the Overall ECFs one would expect counties to have if the proposed fossil fuel employment thresholds for each tax credit level were converted to equivalent points on the ECF distribution. If the level of support proposed by Raimi and Pesek (2022) aligned with Overall ECFs, one would expect all dots to be contained between the red and blue lines.

Figure 3.14: Comparison of tax credits assigned by Raimi and Pesek (2022) and ECFs.

While both the proposed tax credit levels and the Overall ECFs trend in the same direction, it is clear that there is significant variability in Overall ECF within each proposed tax credit bracket. 672 counties that have Overall ECFs above the national average would receive no tax credit under Raimi and Pesek's (2022) proposal, including 82 counties in the 90th percentile of carbon intensity. At the same time, a non-trivial number of counties that would receive some level of tax credit have below-average Overall ECFs. While this approach better targets carbon-intensive communities through its use of more continuous metrics, there remains significant heterogeneity that is not captured, again likely due to the exclusive focus on fossil-fuel sectors.

I perform a similar analysis on Raimi, Carley, and Konisky's (2022) calculation of county-level employment vulnerability scores, defined as a function of "exposure" and "sensitivity." Here exposure is not measured on the basis of employment share but rather the level of fossil fuel production and fossil fuel-fired power generation in the county. Because Overall ECFs are a measure of exposure, not sensitivity, I use the authors' methodology and data to derive exposure scores, and compare these to the Overall ECFs in Figure 3.15. I again find that while the measures trend in the same direction, the exposure scores miss a great deal of variability in employment carbon intensity. While the authors' exposure metrics cover natural gas and oil production, not just coal, they still do not capture economy-wide consumption of fossil fuels outside of the power generation sector. Additionally, these metrics are not normalized by population or employment in any way, which may lead to over- or under-estimation of the relative exposure of communities of different sizes. It should be noted that a significant contribution of Raimi, Carley, and Konisky's (2022) work is the incorporation of sensitivity measures into their overall employment vulnerability metric. While I do not consider these here, I observe a similar trend using the authors' overall vulnerability scores.



Notes: Each dot represents one county. Counties in the grey portion of the figure have Overall ECFs below the national logarithmic average. The red dotted line represents the point in the ECF distribution that corresponds with each point in the log(1+Weighted exposure score) distribution based on its Z-score. If ECFs identified the same counties as the exposure score, one would expect counties to follow the red line.

Figure 3.15: Comparison of ECFs and Raimi, Carley, and Konisky (2022) exposure scores.

In summary, efforts to identify communities with high employment vulnerability in both the IRA and the literature fail to capture the heterogeneity that observed in employment carbon footprints. The IRA's definition of energy communities excludes some high-ECF counties while including some with limited employment vulnerability, and exhibits volatile year-on-year changes in eligibility. While the literature has proposed several alternate, more continuous measures of transition vulnerability, theses efforts fail to capture economy-wide impacts and within-sector heterogeneity and thereby also exclude some at-risk areas.

3.2 Explained variance analysis

Table 3.1 presents the results of the explained variance analysis, displaying the R^2 scores for each regression. The first panel displays the results of separate regressions controlling for workforce allocation, demographics, power grid carbon intensity, climatic differences (heating and cooling degree days) and fuel mix. The second panel displays the results of a stepwise model that incrementally integrated each of these sets of controls (the regression coefficients of all variables in the stepwise model are provided in detail in Appendix B.2).

Table 3.1: Explained variance results

$n = 1547$	k	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Workforce allocation	8	0.539*						
Demographics	7		0.287*					
Politics	2			0.251*				
Power grid carbon intensity	1				0.070*			
Heating & cooling degree days	2					0.081*		
Fuel mix	48						0.522*	
Stepwise model	126	0.539*	0.603*	0.615*	0.659*	0.663*	0.723*	0.742*

Notes: * $p < 0.01$. This table presents the R^2 scores of the regressions performed during the explained variance analysis. The first panel shows the results of an individual regression analysis where each row controls for different sets of variables. The second panel shows the results of a stepwise regression where these sets of controls are progressively added to the model. In both panels, column (1) introduces each sector's share of total county employment, column (2) adds demographic variables (including an interaction term between population density and average personal income), column (3) adds political variables, column (4) introduces the average carbon intensity of the electricity grid in the county, column (5) introduces the 30-year average annual heating and cooling degree days for the county, and column (6) adds EF_{ss} values for each subsector within each high-level sector to control for fuel mix (at 3- or 4-digit NAICS granularity, depending on data availability). For the stepwise model, interaction terms were added in column (4) between power grid carbon intensity and sectoral employment share, column (6) between heating/cooling degree days and power grid carbon intensity and column (7) between sectoral employment share and EF_{ss} values within the same sector.

I find that more than half of the variance in counties' Overall ECFs is explained by the allocation of the workforce across the high-level sectors I consider. However, the other sets of variables appear to provide little extra information with which one could predict changes in ECF. Controlling for the carbon intensity of the grid or degree days explains comparatively negligible shares of the variance. Demographics alone explain just over 25% of the variance, however in the stepwise regression we see that this only translates to enough new information to increase the R^2 by 6 percentage points. Political variables, being highly correlated with demographics, increase this by only 1 percentage point. Similarly, while subsector fuel mix alone explains 52% of the variance, these data only increase the R^2 of the stepwise regression by 6 percentage points after the other variables (which are arguably easier to measure and obtain data for) are controlled for.

These results indicate that workforce allocation is, perhaps expectedly, the best single indicator of a county's Overall ECF. The shares of the workforce in the oil and gas and fossil fuel power generation sectors have particularly large effects, with regression coefficients of 1.187^{***} and 1.068^{***}, respectively, in regression 1 of the stepwise model (see Supporting Information for detailed regression coefficients).

In terms of other potential proxy variables, two of the demographic variables in stepwise regression 2 have statistically significant effects: tertiary educational attainment (-0.029^{***}) and unemployment rate (-0.065^{***}). Interestingly, the regression coefficient for unemployment rate is negative, indicating that employment vulnerability tends to decrease as unemployment rate increases (while the coefficient remains negative in subsequent stepwise regressions, it loses its statistical significance, with political variables gaining it instead). This runs directly counter to the definition of energy communities in the IRA, which requires a region to have higher than average unemployment to obtain energy community status.

The political variables of share of county voting Republican at the 2020 presidential election and whether the county is in a Republican state have relatively large statistically significant effects (0.487^{***} and 0.252^{***}, respectively, in stepwise regression (3)), and grid carbon intensity as well as many of the interaction terms between x_s and ef_{elec} also have significant (albeit small) effects. However, these variables are unlikely to be feasible measures through which policymakers could target communities, not only because they add relatively little information to that explained by workforce allocation. Using grid carbon intensity as a qualifying variable could create a perverse incentive for regions to slow power sector decarbonization effects in order to keep their power grid dirty enough to be eligible for additional funding, and policy that explicitly targets a specific political party is politically infeasible.

3.3 Distributive effects

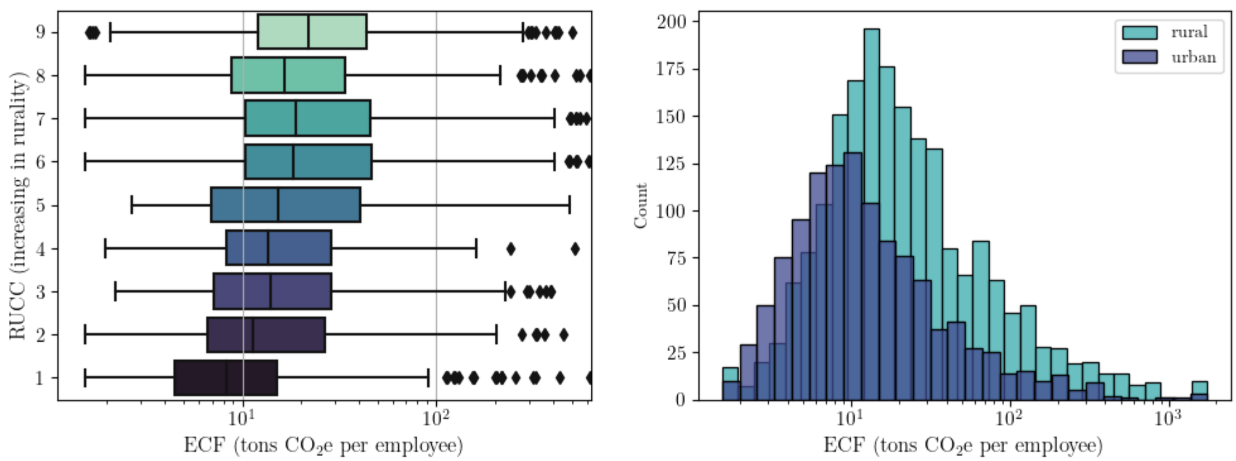
3.3.1 Urbanity & population density

One might expect that carbon-intensive industries and therefore carbon intensive employment are more likely to be located in rural areas, and therefore that the employment carbon footprints of rural counties would on average be higher than those of rural counties. Figure 3.16 supports this hypothesis, highlighting an increase in median employee carbon intensity as counties get more rural.

However, it is notable that significant variance in Overall ECFs exist across all urbanity classifications. As hypothesized, the share of employment in carbon-intensive sectors (defined here as coal mining, oil & gas extraction, and fossil-fuel power generation) is much higher in rural counties than in urban counties, as is demonstrated in Figure 3.17.

The shift in Overall ECF distribution for rural counties is more pronounced when comparing across standard deviation groupings of population density, arguably a more continuous measure of urbanity. Figure 3.18 shows that densely populated counties tend to have low

Distributions of ECFs across urbanity

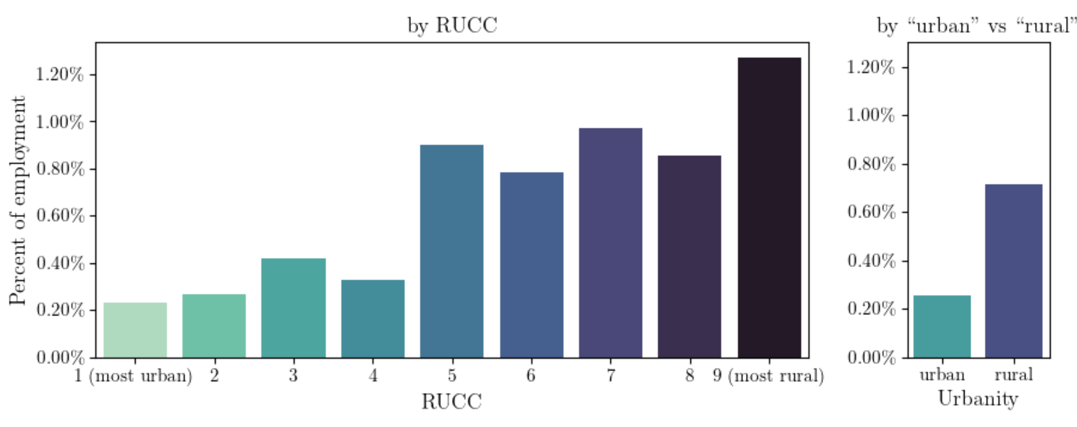


Notes: The left plot shows the ECF distribution of counties across Rural-Urban Continuum Codes (RUCCs), which classify counties by increasing rurality from 1 to 9. The right plot aggregates these RUCCs into "urban" and "rural" categories, where rural counties are those with RUCCs from 4 to 9.

Figure 3.16: Variation of ECF distributions across different levels of urbanity.

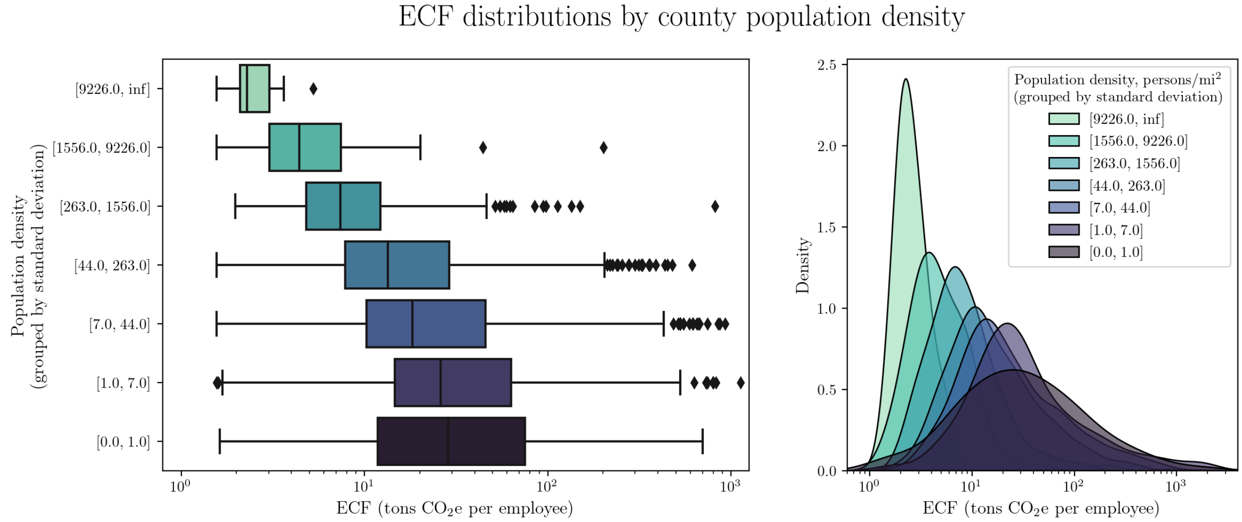
ECFs, while sparsely populated counties are much more likely to have high ECFs. It is notable that low-ECF counties exist across all population densities, illustrated by the "sloping" shape to the distributions in Figure 3.18. This stands to reason: while carbon-intensive jobs may be more likely to be located in rural counties, they are often geography dependent. By contrast, low-carbon intensity jobs such as retail are likely to exist in most counties.

Carbon-intensive employment share, by urbanity



Notes: The left plot shows the average share of county employment in carbon-intensive sectors—defined as coal mining, oil and gas, and fossil-fuel power generation—for different Rural-Urban Continuum Codes (RUCCs), which classify counties by increasing rurality from 1 to 9. The right plot aggregates RUCCs into "urban" and "rural" categories, where rural counties are those with RUCCs from 4 to 9.

Figure 3.17: Percentage of employment in carbon-intensive sectors for each urbanity category.



Notes: Both plots show the ECF distribution across counties for different levels of county population density. Lighter-hued marks indicate high population density, while darker marks indicate low population density. Counties are binned by population density, where the interval of each bin is equal to one standard deviation.

Figure 3.18: Variation in ECF distribution across county population density.

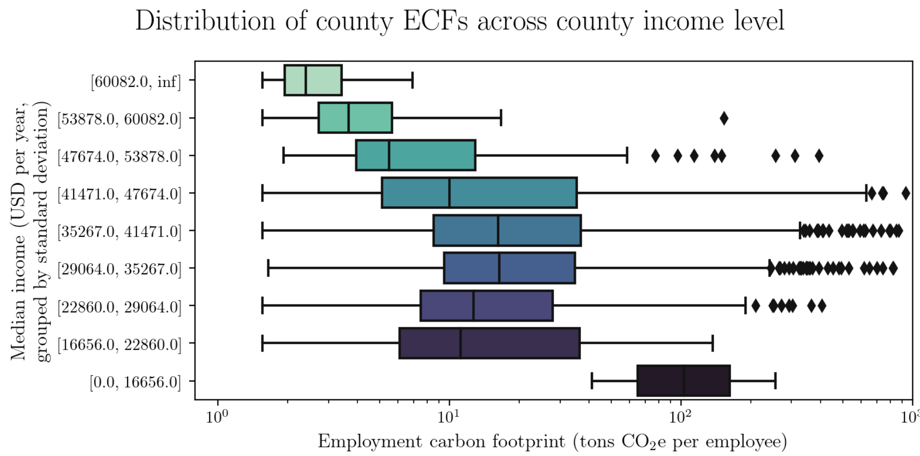
3.3.2 Income

It is important to understand whether low-income counties are particularly exposed to employment shocks from the energy transition. Figure 3.19 depicts the Overall ECF distributions for counties across nine brackets of median income. It shows a significant trend in which counties with high median incomes having substantially lower ECFs than those with average or below-average median incomes. However, when these distributions are separated by county urbanity as in Figure 3.20, it becomes clear that this trend is driven by urban counties, and that an opposite trend is observed in rural counties. We can also see that, in general, urban counties have higher median incomes than rural counties.

This trend is not overly surprising when considering the differences in sources of high-income employment between urban and rural counties. We have seen previously that carbon-intensive employment is more likely to be located in rural counties, and Figure 3.21 shows the distribution of county median income by sector, with jobs in carbon-intensive sectors (coal mining, oil & gas, and utilities) having higher salaries in most counties. The high-income, high-ECF trend in rural counties therefore suggests that carbon-intensive sectors are the primary source of well-paying jobs in rural counties. Conversely, in urban areas where there is less carbon-intensive employment, it is likely that the high incomes in richer counties come from employment in those low carbon intensity sectors that are still high-paying, such as finance, management and professional services.

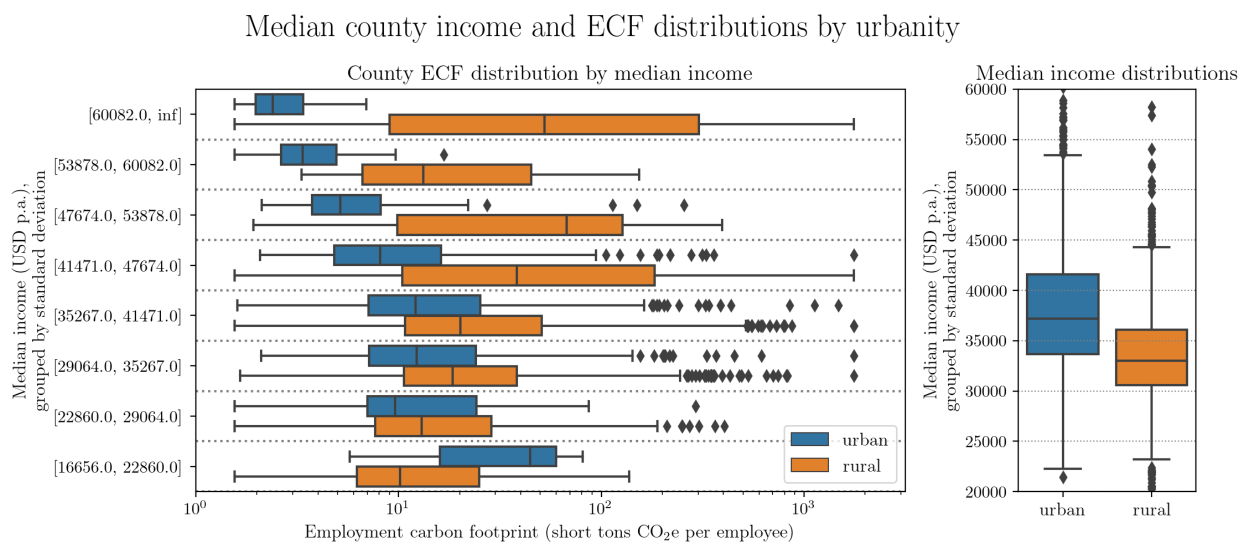
3.3.3 Race & Ethnicity

Environmental justice literature has consistently demonstrated racial disparities in pollution exposure, however it is not clear the extent to which employment in marginalized and minority communities is vulnerable to the energy transition. Figure 3.22 shows Overall ECF



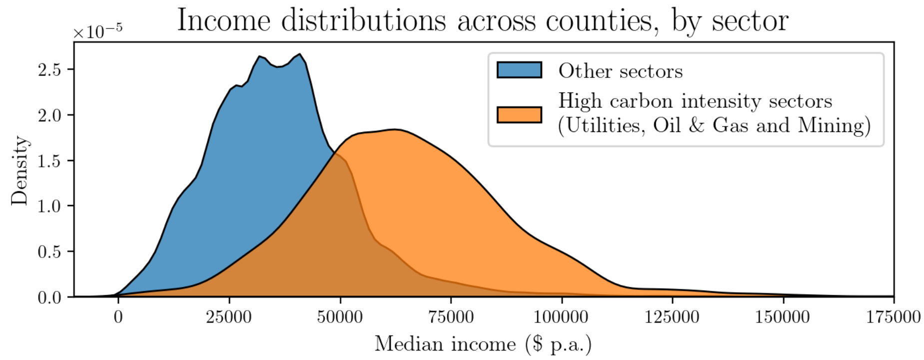
Notes: Counties are binned by median annual income, where the interval of each bin is equal to one standard deviation. Lighter-hued marks indicate high-income counties, while darker marks indicate low-income counties. Counties are binned by population density according to their standard deviation.

Figure 3.19: Overall ECF distributions for different county median income levels.



Notes: Orange boxes represent rural counties, while blue boxes represent urban counties. In the left plot, counties are binned by median annual income, and each box-whisker plot represents the Overall ECF distribution of counties within that income bin. In the right plot, counties are separated by urbanity, and the distributions of median annual income are plotted for urban and rural counties.

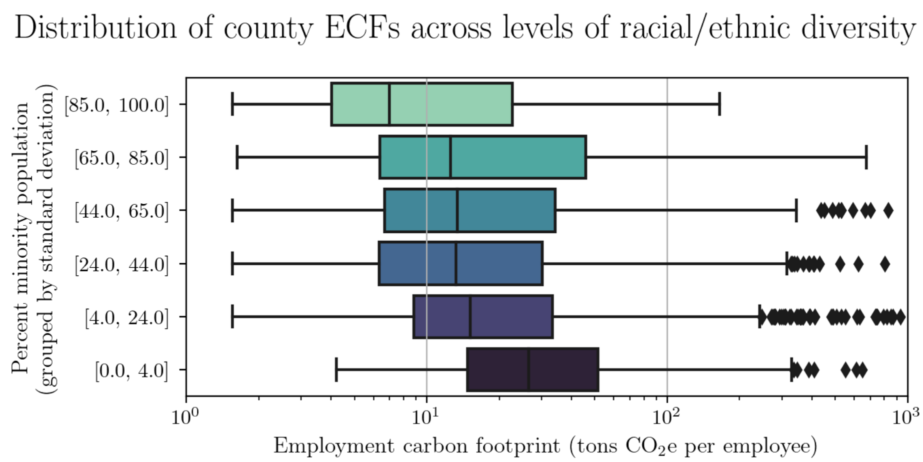
Figure 3.20: Distributions of Overall ECFs by median income level, broken out by urbanity (left). Median income distributions for urban and rural counties (right).



Notes: Data from the American Community Survey on the median annual income per county for employees in different sectors was used to calculate the average income for carbon-intensive employment (utilities, oil and gas and mining sectors) and other employment for each county. The KDEs of the distributions of median income for these two categories shows that employees in carbon-intensive sectors have higher median incomes than those in other sectors on average.

Figure 3.21: Distributions of county median salary for carbon-intensive and other sectors.

distributions across different levels of minority population share (defined as the share that is non-White or Hispanic), exhibiting a decrease in median ECF as racial and ethnic diversity increases. This trend is mostly consistent across Census Divisions and both urban and rural counties, although is particularly pronounced in urban counties (see Figure C.1 in Appendix C).



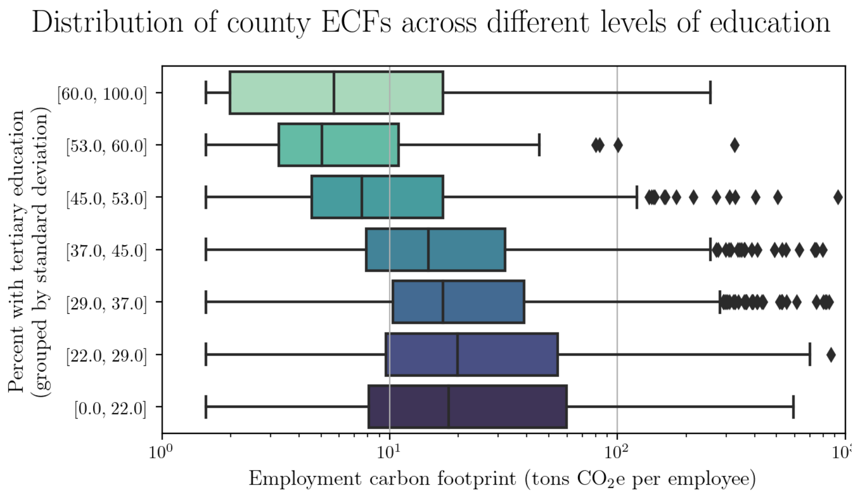
Notes: Counties were binned by share of the population that is non-White or Hispanic, where the interval of each bin is equal to one standard deviation. Lighter marks represent more racially/ethnically diverse counties.

Figure 3.22: Distributions of Overall ECFs across counties with differing minority population shares.

My results here show that the most polluting counties, which tend to have relatively high shares of polluting industry, are predominantly White and non-Hispanic. However, this overall trend is slight, and does not tell the full story. There are 58 counties where more than half the population are non-White or Hispanic that have Overall ECFs in the 90th percentile; some of the most carbon-intensive counties in the country, such as Reeves county in Texas, are over 75% non-White/Hispanic with significant migrant populations. At the same time, similarly carbon-intensive counties such as Billings county in North Dakota have minority populations shares of less than 1%. This highlights the need for just transition policies to be place-based and account for the specific sociodemographic contexts of communities. While similarly carbon-intensive, Billings county and Reeves county will clearly face distinct challenges in transitioning away from fossil fuels, and policy efforts should allow for flexibility that accounts for these differences.

3.3.4 Educational attainment

As discussed earlier, polluting jobs tend to be low-skilled, and Figure 3.23 shows that counties with higher degrees of tertiary education are likely to have lower Overall ECFs on average. Figure C.2 in Appendix C finds that this trend is particularly driven by urban counties.

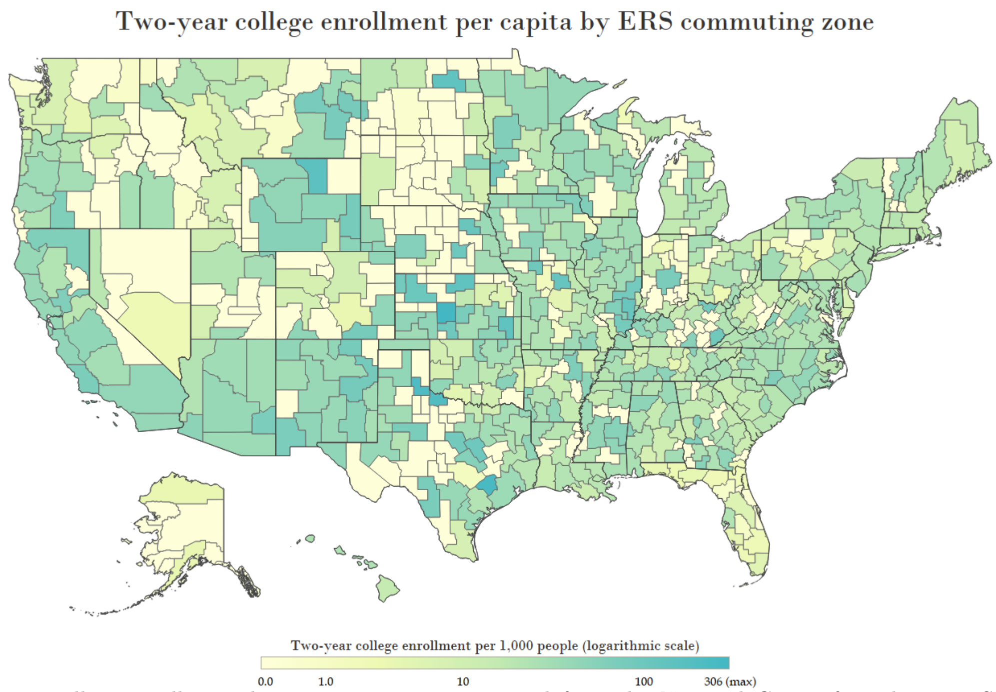


Notes: Counties were binned by share of the population with some level of tertiary education, where the interval of each bin is equal to one standard deviation. Lighter marks represent more educated counties.

Figure 3.23: Distributions of Overall ECFs across counties with different levels of tertiary education.

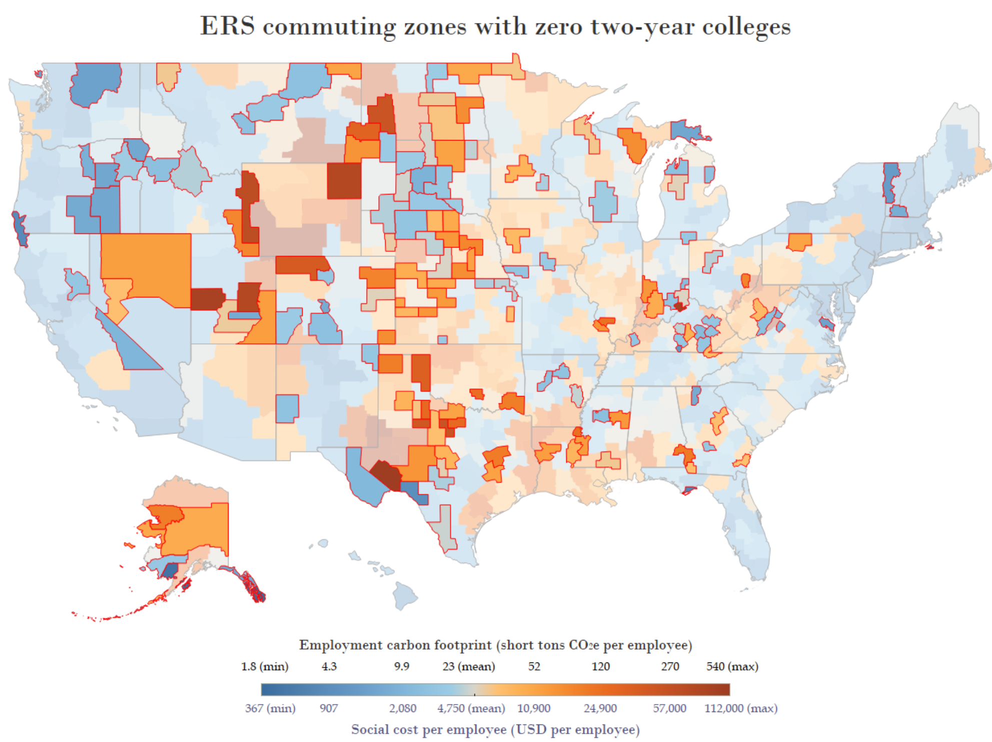
As has been explored in the literature, this skills gap presents a barrier to transitioning away from polluting industries that will require retraining and up-skilling to overcome. It is anticipated that apprenticeship and two-year community college institutions will have a significant role to play in this process (Ansolabehere et al. 2022), but such institutions may not be located close to where workers in polluting industries live and/or work, adding an additional barrier to their transition.

To investigate this further, I took data from the National Center for Education Statistics' Integrated Postsecondary Education Data System (IPEDS) on the number of and enrollment in two-year postsecondary institutions across counties. Since commuting between counties is common for work and education, I aggregated these data by ERS Commuting Zone (CZ) in order to cover areas within which it would be reasonable to commute to one of these institutions. I then computed enrollment per capita as a measure of the existing workforce development capacity in each CZ, and these results are displayed in Figure 3.24.



Notes: Two-year college enrollment data per county was retrieved from the National Center for Education Statistics and allocated to the nearest ERS commuting zone (CZ). This value was then normalized by the population of each ERS CZ. Lighter areas indicate CZs with little to no two-year/community college enrolment.

Figure 3.24: Two-year college enrollment per capita across 2010 ERS commuting zones.



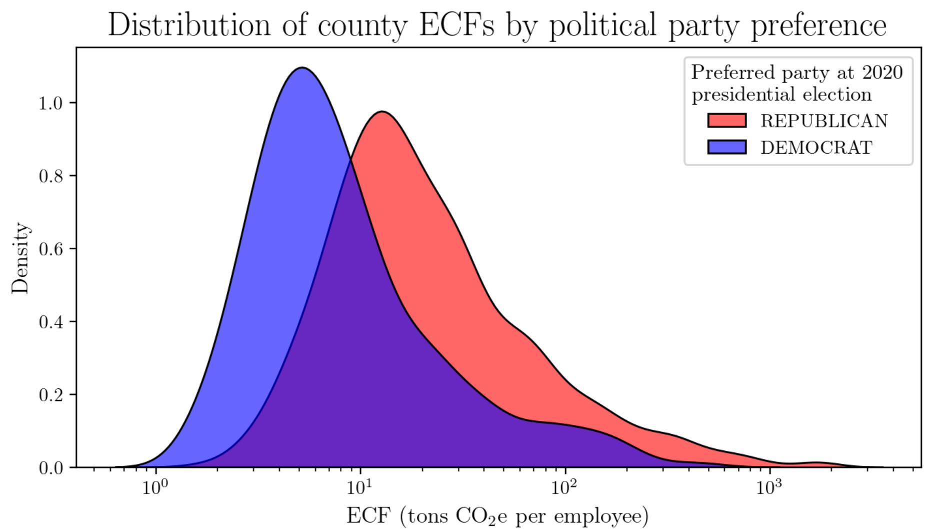
Notes: This figure shows the Overall ECFs of those ERS commuting zones (CZs) with zero two-year or community college enrollment according to the National Center for Education Statistics. To calculate CZ-level ECFs, county-level ECFs were aggregated to the CZ level as a population-weighted average.

Figure 3.25: Overall ECFs of commuting zones with no two-year colleges (red borders).

Notably, a significant portion of the CZs have zero existing two-year college capacity. Figure 3.25 shows how these CZs intersect with areas of high energy transition vulnerability using OverallvECFs aggregated to the CZ level. I find that many of the CZs with high employment vulnerability have no current workforce development capacity through two-year institutions, especially in the heartland states; comparison with Figure 3.24 shows that many of the CZs adjacent to these "education deserts" also have very limited enrollment capacity.

3.3.5 Political affiliation

In their analysis of household carbon footprints, Green and Knittel (2020) found that Republicans tended to have a slightly higher carbon footprint than Democrats. Figure 3.26 displays a similar result, with counties that voted Republican at the 2020 presidential election more likely to have high Overall ECFs than Democratic counties. Similarly, Figure C.3 in Appendix C shows that, when grouped by state, the states with most carbon-intensive Overall ECF distributions are overwhelming those that voted Republican.



Notes: Counties were separated based on which major party received the most votes in that county during the 2020 presidential election according to the MIT Election Lab.

Figure 3.26: Overall ECF distributions by political party preference in 2020 presidential election.

Part II

The political salience of employment & household vulnerability in climate politics

Chapter 4

Literature review

There is a growing literature analyzing the relationship between the climate policy preferences of political representatives and the costs and/or benefits their respective constituencies receive from climate and environmental policies. In the U.S. context, these preferences are most commonly analysed through the voting behavior of federal or state legislators on bills relating to climate or environmental issues. Holland et al. (2015) evaluated political support in the U.S. House of Representatives for the weakening of renewable fuel standards in favor of introducing cap-and-trade carbon policy, and find that members from districts with greater per-capita gains under cap-and-trade were more likely to vote in favor of the change, while those from districts with large gains under the existing policy were more likely to vote against. Cragg et al. (2013) argue that the “price” of voting in favor of carbon policy can be proxied using a congressional district’s per-capita carbon emissions and find that, all else equal, members from more carbon-intensive districts were less likely to vote in favor. This was particularly true in districts where heavy industry made up a large share of emissions. Numerous studies also highlight that legislators are more likely to vote in favor of climate policy following exposure of their districts to climate-related natural disasters or unusual weather, and that these districts are less likely to support anti-environment candidates after these events (Elliott et al. 2023; Herrnstadt and Muehlegger 2014; Liao and Ruiz Junco 2022).

As discussed previously in Section 1.2, employment impacts of climate and environmental policy are often perceived as the “price” of climate action/environmental goods (Kahn and Matsusaka 1997) and influence public support for such policies accordingly. This “jobs versus environment” divide has resulted in the public often viewing climate policies as negative for employment (Vona 2019; Evans and Phelan 2016; Graff, Carley, and Konisky 2018; Tvinnereim and Ivarsflaten 2016). This effect is especially prominent in areas where local employment is more reliant on fossil fuels, and demonstrates that local employment impacts are a salient issue for communities in determining their support for climate policy.

In addition to employment impacts, public support for climate policies is also driven by the costs they impose on households, particularly in the form of increased energy costs. In a large-scale survey spanning the U.S., U.K., Germany and France, Bechtel and Scheve (2013) found that respondents’ support for global climate cooperation was highly sensitive to resulting increases in average household costs. Similar studies have found that climate policies with higher direct financial costs, such as those that increase electricity/gasoline prices or reduce purchasing power, tend to be less supported than similar but less directly costly policies (Maestre-Andrés, Drews, and Bergh 2019; Lam 2015; Drews and Bergh 2016; Brannlund and Persson 2012). This effect remains significant even when policies compensate the public for these cost increases, such as through the recycling of revenue generated from carbon pricing (Jenkins 2014). There is also evidence to suggest that the public's general aversion to taxation, well-documented in the fiscal policy literature, also extends to environmental policy; studies have found that carbon pricing policies labelled taxes are less likely to be supported than identical policies with different labels (Klenert et al. 2018; Brannlund and Persson 2012).

If climate policy penalizes the use of fossil fuels, households with larger carbon footprints are likely to incur greater costs than low-carbon footprint households and are therefore more economically vulnerable, all else equal, to these policies. One might expect such vulnerability to further drive communities' support for climate policies. However, there is also evidence to suggest that constituencies that support climate policy adjust their consumer choices to reflect "green" beliefs, thereby reducing their carbon footprint (Costa and Kahn 2013). Both Kahn (2007) and Kahn and Morris (2009) show that people with green beliefs are more likely to engage in green transportation practices, even when controlling for demographics and effects of the built environment. Similarly, Kahn and Vaughn (2009) find that, holding community demographics constant, communities in green zip codes (as determined by their political choices) are more likely to purchase green products (namely, LEED-certified buildings and the Toyota Prius).

The extent to which public opinion on climate policy is represented in the voting behavior of political representatives is not clear. While some studies have found economic and social policy to be responsive to the public's views (Caughey and Warshaw 2018), analyses on environmental issues are less conclusive. Kim and Urpelainen (2017) find that the increased polarization of environmental policy in U.S. politics reflects differences between Republican and Democratic political elites rather than the preferences on environmental policy of the median voter they represent—this significant partisanship effect has been corroborated by numerous other studies (Kono 2020; Cragg et al. 2013; Hogan 2021; Coley and Hess 2012). McAlexander and Urpelainen (2020) show that legislators understand this disconnect, with members of congress more likely to vote in favor of environmental legislation in the lead up to a close election. However, while they do still identify a significant partisan effect, Vandeweerdt, Kerremans, and Cohn (2016) show that, even when controlling for the presence of interest groups, campaign finance, and political party and ideology, U.S. members of congress are still more likely to vote in favor of cap-and-trade legislation if their constituents support climate action (Wynes et al. (2022) present a similar result). Yet another set of literature has found that campaign contributions from both polluting industries and environmental groups have consistent and significant effects on legislator voting behavior (Goldberg et al. 2020; Ard, Garcia, and Kelly 2017; Holland et al. 2015; Gao and Huang 2023; Hogan 2021; Kahane 2016).

Regardless of one's view on the mechanism through which legislator policy preferences are incentivized, the literature has consistently shown correlations between employment in polluting industries and political representative votes against climate policy. Many studies have used employment in fossil fuel industries as a measure interest group presence in a region, and have found significant and negative correlations between levels of employment and pro-environment legislator voting, even when controlling for party, ideology, constituency demographics and campaign finance (Vandeweerdt, Kerremans, and Cohn 2016; Kahane 2016; Coley and Hess 2012; Anderson 2011; Kono 2020). These findings suggest that community concerns around the employment impacts of climate policy are shared by their elected officials. Such concerns can be observed qualitatively in the discourse of political actors around the world, which often frames the impacts of climate policy in terms of the costs or benefits to local employment (Vona 2019; Evans and Phelan 2016; Diamond and Zhou 2022; Kalt 2021; Räthzel and Uzzell 2011). This political salience of the issue of job losses is also prominent in other policy areas such as trade and taxation (Margalit 2011; Zatoński et al. 2023; Crosbie and Florence 2022).

If employment and household impacts are both salient issues for the public and politicians, which have a larger effect on political support for climate policy? The employment carbon footprint dataset derived in Part I of this thesis and the household carbon footprint dataset from Green and Knittel (2020) (outlined in more detail in the following section) allow me to address this question, and add to the literature in two ways. Firstly, as outlined in Part I, the Overall ECF represents a much more holistic measure of employment vulnerability to the energy transition than was previously available—most studies that control for employment effects measure a congressional district's share of employment in a set of chosen industries (for example, mining, oil and gas, and manufacturing), which fails to capture within-sector differences in vulnerability. Similarly, in contrast to other studies that investigate correlations with specific consumption choices such as transportation, the HCF represents a comprehensive measure of household carbon consumption encompassing transportation practices, consumer choices and energy consumption. No study to the author's knowledge has used a continuous measure of household cost vulnerability to explain public support for climate policy. Together, these two datasets allow for a more holistic representation of potential employment and household impacts of climate policy than has been incorporated into the literature to date.

The second, and most significant, contribution of this work is to understand the relative effects of these two issues. While the literature outlined above has investigated the political salience of these two issues in isolation, no study to the author's knowledge has attempted to compare the relative significance of these effects. This work therefore brings empirical evidence to an open question in the political economy literature.

Chapter 5

Methodology

5.1 Overview

This analysis aims to understand the relative effects of employment carbon footprint and household carbon footprint on representative voting behavior on climate policy. I address this question through a series of regressions of congressional pro-climate voting on carbon footprints. I hypothesize that, all else equal, members of congress from high-ECF districts will be more likely to vote against climate legislation. Given the apparent salience of jobs as an issue for elected officials, I also hypothesize that this effect will be larger than any correlation between household carbon footprints and voting behavior.

It is also useful to better understand how carbon footprints relate to public opinion on climate action, so I also analyze regressions of public climate opinion on carbon footprints. In line with the literature that finds household costs to be negatively correlated with climate policy support, I hypothesize that communities with high household carbon footprints will be less likely to support climate policy, controlling for socioeconomic and demographic conditions.

The following sections outline the data used in this analysis and specify the models used in more detail.

5.2 Data

The carbon footprint data used in this analysis come from two pieces of work from the MIT Center for Energy & Environmental Policy Research. Employment vulnerability was represented by the Overall ECF data derived in Part I (for clarity, I will refer to Overall ECFs as simply "ECFs" for the remainder of Part II). Household vulnerability was represented by a similar measure, the household carbon footprint (HCF), derived by Green and Knittel (2020). These census tract-level footprints were derived using data on energy consumption, consumer behavior, and transportation from representative samples of U.S. households. For each of these samples, a machine learning model was trained to predict consumption from household demographics, geographic characteristics and weather data, and these models were used to project out the carbon footprints of households across all census tracts. Given that the congressional district is the unit of analysis for congressional voting behavior, district-level ECF and HCF data were generated by weighting the county- and tract-level figures, respectively, by population share. Figure 5.1 displays the district-level ECFs and HCFs used in my analysis. County-level HCF estimates are displayed in Appendix D.

Data on congressional voting behavior was taken from the League of Conservation Voters (LCV) National Environmental Scorecard, which tracks the voting records on environmental issues of members of congress. In consultation with experts from environmental organizations, the LCV identifies each vote on an environment-related issue that occurred in a given year, determines the "pro-environment" and "anti-environment" positions for each vote, and scores the votes of each member of congress (League of Conservation Voters 2023). Pro-environment votes are scored 1 and anti-environment votes (as well as absentee votes) are scored 0, and the average score for each member is transformed in an annual score (hereafter, "the LCV score") on a scale of 0 (anti-environment) to 100 (pro-environment) (League of Conservation Voters 2023). Each vote is also coded by its general environmental topic—for example, "clean energy," "water, oceans, and drilling," and "transportation."

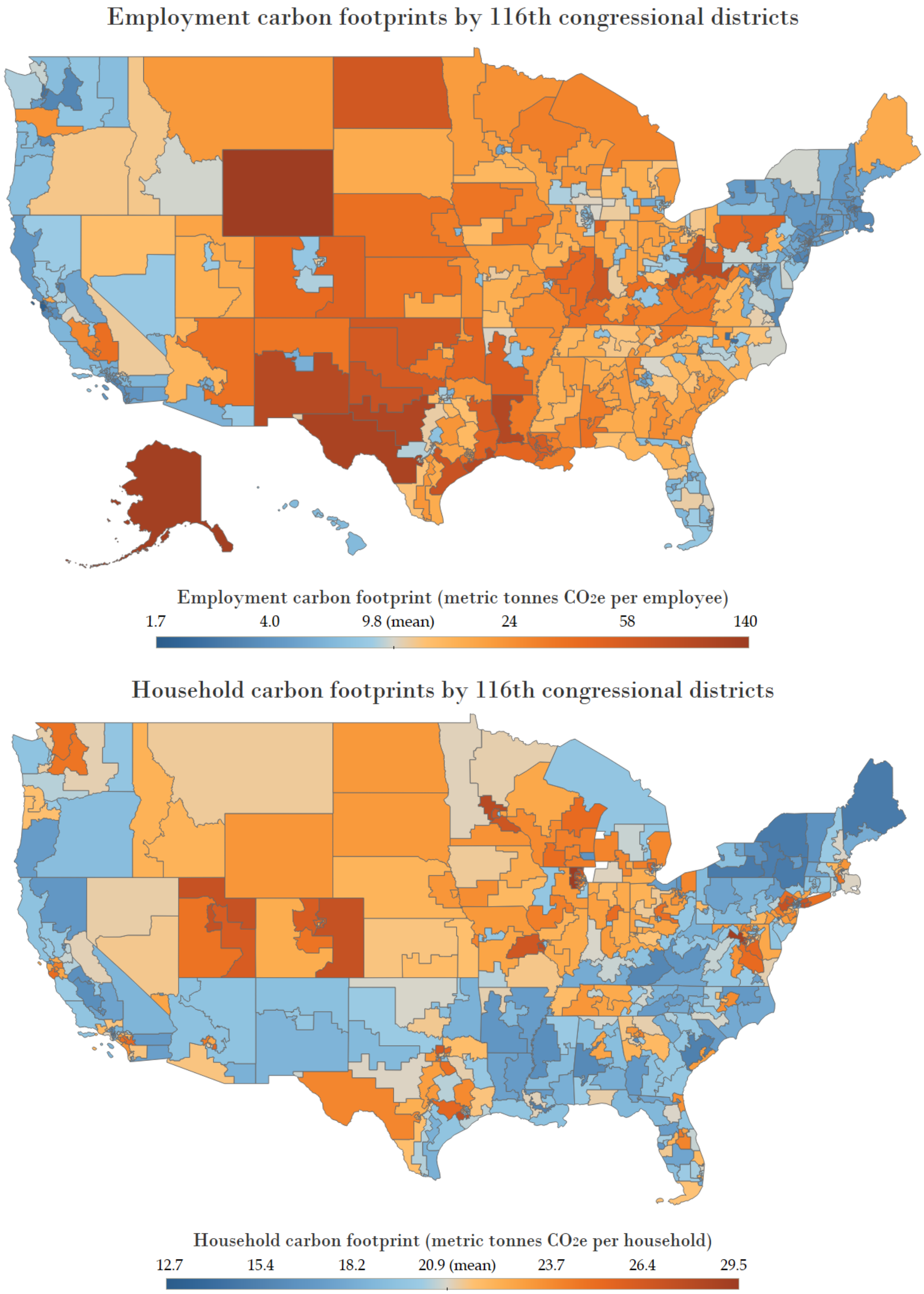
I considered environmental votes that occurred in the House of Representatives from the start of 2018 up until the 2022 mid-terms. The models described below used both LCV scores and binary pro-/anti-climate vote scores as the outcome variable. When using the LCV score as the outcome variable, I averaged the LCV scores from 2018 to 2022 for each congressional district—if the representative for a given district changed in that period, LCV scores were averaged between the representatives.[1] When the outcome variable was individual vote scores, I considered only bills that were coded as relating to "climate change," "clean energy" or "dirty energy."

Data on public opinion on climate change was obtained from the Yale Climate Opinion Maps, generated by the Yale Program on Climate Change Communication, which outlines estimates of climate change beliefs at high geographic granularity across the U.S. based on largescale survey data collected between 2008 and 2021 (Howe et al. 2015). The climate opinion dataset reports a range of estimates—as has been done in the literature (Wynes et al. 2022), the most relevant variable to use as a measure for climate change opinion in this analysis was "Estimated percentage who think Congress should be doing more/much more to address global warming." I isolated estimates of this variable from 2018 to 2021 at both the county and congressional district level, and as with the LCV scores computed the average across that timeframe.

I controlled for demographic and geographical factors using 5-year and 1-year estimates from the American Community Survey at the geographic granularity of interest (U.S. Census Bureau 2023a). Specifically, the demographic variables considered were: Black population share; Hispanic population share; rate of tertiary education attainment; median age; and median household income. The geographic variable of interest was population density, as a proxy for urbanity.

In addition the political party of a representative, I control for each representatives ideology using the DW-Nominate scores developed by Lewis et al. (2021). This measure analyzes all congressional roll call votes of each member of congress and scores them on a continuous

1. A key control in my models is whether a member of congress belongs to the Republican party. In cases were the representative of a district changed from one party to another between 2018 and 2022, I coded the political party of the district to be whichever party held the district for the longest.



Notes: These maps show the average employment (top) and household (bottom) carbon footprints of each congressional district, calculated as population-weighted estimates from county- and census tract-level data, respectively. Since employment carbon footprints are highly skewed, the ECFs are displayed on a logarithmic scale. Note that Alaska and Hawaii are missing from the HCF map, as this dataset does not cover these states.

Figure 5.1: District-level employment (top) and household (bottom) carbon footprints

scale from -1 to 1, where 1 is most conservative and -1 is most liberal. For data on political party preference at the county level, I used voting data from the 2020 U.S. presidential election from the MIT Election Lab (MIT Election Data and Science Lab 2020).

Finally, several studies have demonstrated a relationship between political donations to congressional representatives and their voting record on environmental issues (Ard, Garcia, and Kelly 2017; Goldberg et al. 2020). As has been done in the literature, I control for campaign finance effects using data from OpenSecrets (OpenSecrets 2023) by computing the share of a congressional representative's total campaign contributions that came from fossil fuel industries (coal mining and oil and gas extraction) in each cycle from 2018 to 2022, and computing the average of these shares across those years.

5.3 Model design

I conduct three regression models: two ordinary least squares (OLS) estimations and one probit estimation. For each set of regressions, both non-standardized and standardized coefficients were computed.

I begin by investigating the effects of a community's carbon footprints on its approval of congressional action on climate policy ("climate opinion score"). I conduct a set of OLS regressions (with robust standard errors) of average climate opinion score on employment and household carbon footprints. Since more liberal districts are more likely to support climate policy, I use a binary control variable for whether the county voted majority Republican in the 2020 presidential election, and add a control for the percentage of the county that voted Republican in later regressions. Since richer districts are more likely to support climate legislation (Cragg et al. 2013; Kono 2020) I also control for the median household income of the district for each regression. As demographic characteristics including race/ethnicity, age, and particularly level of tertiary education attainment have been shown to correlate with support for climate policy (Hogan 2021; Kono 2020), I add controls for these variables in progressive regressions. Given the findings in Part I of this thesis that indicate that ECFs are correlated with population density, I also control for population per square kilometer. I run these models at both the congressional district level and at the county level, as the climate opinion data are available at both and the ECF and HCF data are most representative at the county level. Summary statistics for the county-level model are presented in Table 5.1.

I next conduct the more substantive portion of this analysis, investigating the effects of the carbon footprints of a constituency on the environmental voting record of its representative in the U.S. House of Representatives. Using OLS regression with robust standard errors, I regress each representative's average LCV score onto their constituency's employment and household carbon footprints. Table 5.2 displays the summary statistics for the variables used in the average LCV score OLS estimations. I again control for income and political ideology, this time using the representative's political party and DW-Nominate score. I add the same demographic characteristics as with the climate opinion regressions.

Importantly, in an attempt to gain insight into the mechanisms by which constituency preferences or vulnerabilities might be translated into congressional voting behavior, I also control for public opinion on climate action and political donations from fossil fuel industries. There is evidence to suggest that district-level gains and losses from climate policy are translated into political incentives for legislators through campaign contributions (Holland et al. 2015). Similarly, legislators have been shown to shift their voting behavior in response to constituent opinion on climate change (Vandeweerdt, Kerremans, and Cohn 2016; Wynes et al. 2022; McAlexander and Urpelainen 2020). Controlling for these variables allows me not only to corroborate this literature, but also to understand whether legislators would take heed of the potential costs of climate policy to their constituents without political pressure from the public or campaign finance.

Finally, to validate the OLS results from the average LCV scores, I run a set of probit regressions where the outcome variable is whether or not a given representative voted in the pro-climate position on a given bill relating to "climate change," "clean energy" or "dirty energy." I considered each vote on every bill relating to these topics between 2018 and the 2022 midterms as a datapoint, for a total of 18,391 votes.

Between 2018 and 2022, the League of Conservation Voters considered several votes related to non-environmental issues around democracy and social justice, including voting rights, abortion access and marriage equality, and coded these bills as relating to "justice and democracy." While views on these issues are clearly partisan and therefore likely correlated the political party and/or ideology of each representative, they also provide a useful avenue to check that carbon footprints are not simply correlated with various variables not captured in my analysis. I repeat the probit estimation on 7,234 votes relating to "justice and democracy" between 2018 and 2022, where the pro-justice position (as coded by the LCV) is the outcome variable. If I find that carbon footprints are correlated with both pro-climate voting and pro-justice voting, I will conclude that any effect of carbon footprints on climate voting is the result of spurious correlation with other unobserved variables.

Table 5.1: Summary statistics for variables in county-level OLS estimation of average climate opinion scores

Variable ($n = 3,101$)	Mean	Std.	Min	Max
Average climate opinion score	54.65	5.57	42.25	78.14
ECF (tonnes CO_2e per employee)	46.40	125.62	1.56	1,755.15
HCF (tonnes CO_2e per household)	19.46	3.55	10.73	32.01
Median household income ($)	54,849.50	14,566.24	22,292.00	147,111.00
Republican	0.83	0.38	0.00	1.00
Percent voting Republican	65.12	15.98	8.73	96.18
Black population share (%)	10.04	14.65	0.00	88.04
Hispanic population share (%)	9.62	13.99	0.00	98.90
Tertiary education attainment (%)	37.14	7.74	5.12	69.39
Median age	41.61	5.45	22.20	68.00
Population per km^2	103.25	695.18	0.07	27,763.60

Table 5.2: Summary statistics for variables in OLS estimation of average LCV scores

Variable ($n = 479$)	Mean	Std.	Min	Max
Average LCV score	52.84	43.55	0.00	100.00
ECF (tonnes CO_2e per employee)	14.35	16.94	1.56	124.69
HCF (tonnes CO_2e per household)	21.10	3.16	12.71	29.47
Median household income ($)	68,723.68	18,957.18	32,582.00	146,441.00
Republican	0.50	0.50	0.00	1.00
Black population share (%)	13.81	13.70	1.19	67.76
Hispanic population share (%)	18.17	18.15	1.10	87.98
Tertiary education attainment (%)	42.39	7.25	19.06	67.02
Median age	38.66	3.60	28.40	55.70
Population per km^2	919.29	2,585.87	3.43	28,851.83
Average climate opinion score	60.85	6.00	47.95	79.49
Fossil fuel donations (average % of total)	1.85	2.11	0.00	11.21
DW-Nominate	0.12	0.44	-0.68	0.87

Chapter 6

Results

6.1 Constituency climate opinion

Table 6.1 displays the results of regressions of county-level public support for congressional climate action. Standardized regression coefficients are available in Table D.1 in Appendix D. In column (1), I find that ECF, HCF, whether the county voted majority Republican, and median household income all have statistically significant effects on the average climate opinion score of the county. Richer counties are more likely to support further congressional action on climate change, while Republican counties and counties with higher carbon footprints are more likely to oppose.

These effects remain significant in column (2), where demographic variables are added. This column shows that counties that are younger, more urban, more educated, and more diverse are more likely to support climate action, echoing findings in the literature (Lee et al. 2015; Hogan 2021; Holian and Kahn 2015). However, age, education and Black population share lose their statistical significance in column (3) when a continuous measure on political ideology (the percent of the county that voted Republican in the 2020 election) is added, and interestingly the effect of population density becomes negative, presumably due to the correlation between conservatism and rurality.

Both the non-standardized and standardized results in column (3) show that, holding all else constant, household carbon footprint has a greater effect on climate opinion than employment carbon footprint. A doubling of a county's HCF reduces its support for climate action by nearly 2 percentage points, whereas doubling a county's ECF reduces support by only 0.28 percentage points. However, these effects are both smaller than that of political ideology—a standard deviation increase in the logarithms of ECF and HCF only reduce a county's climate opinion by 0.48 and 0.50 percentage points, respectively, while a standard deviation increase in the percent of a county's population that voted Republican reduces climate opinion by 4.6 percentage points. These findings are similar in the congressional district-level analysis, the results of which are displayed in Tables D.2 and D.3.

While the direction of the effect of HCF on climate opinion cannot be ascertained from these results, I offer two potential causal mechanisms, each implying opposite directions of the effect. First, it is possible that communities with high carbon footprints are less likely to support climate policy because of the perceived costs it could impose on them such as

Table 6.1: OLS estimation results for average climate opinion score, county level

	Dependent variable: Avg. climate opinion score		
Variable	(1)	(2)	(3)
log(ECF)	-0.894***	-0.730***	-0.402***
	(0.057)	(0.053)	(0.037)
log(HCF)	-5.823***	-5.844***	-2.787***
	(0.515)	(0.534)	(0.370)
Republican	-9.381***	-6.638***	-0.778***
	(0.180)	(0.203)	(0.183)
Median household income ('000)	0.077***	0.039***	0.027***
	(0.007)	(0.007)	(0.006)
Median age		-0.062***	0.010
		(0.016)	(0.010)
Percent tertiary educated		0.144***	-0.014
		(0.011)	(0.009)
Percent Black		0.077***	0.003
		(0.005)	(0.004)
Percent Hispanic		0.082***	0.048***
		(0.005)	(0.004)
log(Population density)		0.396***	-0.146***
		(0.046)	(0.036)
Percent voting Republican			-0.288***
			(0.005)
Intercept	78.003***	71.899***	81.971***
	(1.253)	(1.855)	(1.170)
Observations	3,101	3,101	3,100
R^2	0.605	0.682	0.852
Adjusted R^2	0.604	0.681	0.851
Residual Std. Error	3.504	3.147	2.143
F Statistic	1080.453***	706.479***	1303.320***
Note:		*p<0.05; **p<0.01; ***p<0.001	

increased energy costs. There is evidence to suggest that living a carbon-intensive lifestyle increases the short-run marginal price of supporting climate policy (Holian and Kahn 2015), implying that one's views on climate policy are, in part, driven by one's consumption choices.

However, a second possible explanation is that those who hold "green" beliefs and are more likely to support climate policy are also more likely to change their lifestyle and consumption to reduce their personal carbon footprint. Several studies have identified this effect in California (Kahn 2007; Kahn and Morris 2009; Kahn and Vaughn 2009)—in contrast to the explanation above, this would imply that one's beliefs on climate change drive their carbon footprint, not the other way around.

6.2 Representative climate voting

Having established an effect between both household and employment carbon footprints and constituency opinion on congressional climate action, I now turn to their effects on congressional voting behavior. Table 6.2 shows the results of the regression of the average LCV scores of members of the House of Representatives (standardized results in Table D.4 in Appendix D).

Table 6.2: OLS estimation results for average LCV score

	Dependent variable: Average LCV score			
Variable	(1)	(2)	(3)	(4)
log(ECF)	-3.069***	-1.757*	-2.194***	-1.568*
	(0.616)	(0.696)	(0.648)	(0.735)
log(HCF)	-6.301	-0.357	-3.143	3.119
	(4.013)	(4.996)	(4.086)	(4.149)
Republican	-81.828***	-79.842***	-76.423***	-76.616***
	(1.349)	(1.754)	(2.329)	(2.235)
Median household income ('000)	0.047	0.034	0.053	0.016
	(0.031)	(0.042)	(0.032)	(0.039)
Median age		0.382**		0.413**
		(0.137)		(0.139)
Percent tertiary educated		-0.106		-0.094
		(0.093)		(0.084)
Percent Black		-0.026		-0.043
		(0.040)		(0.031)
Percent Hispanic		0.009		0.009
		(0.035)		(0.031)
log(Population density)		-0.140		-0.217
		(0.324)		(0.288)
Climate opinion score		0.563*		0.563***
		(0.254)		(0.145)
log(1+ Fossil fuel donation share)			-0.946	-0.158
			(0.880)	(0.990)
Conservative ideology score			-8.042***	-5.454*
			(2.263)	(2.154)
Intercept	116.839***	52.208*	103.850***	40.445*
	(10.845)	(25.827)	(11.218)	(17.588)
Observations	487	487	479	479
R^2	0.957	0.960	0.959	0.961
Adjusted R^2	0.957	0.959	0.959	0.960
Residual Std. Error	9.023	8.793	8.824	8.683
F Statistic	6032.489***	2967.992***	5027.261***	2891.764***
Note:				*p<0.05; **p<0.01; ***p<0.001

Column (1) uses the same variables as column (1) of Table 6.1 on climate opinion. The effects of employment carbon footprint and of a given legislator being Republican are statistically significant. Notably, even just this model specification with no additional controls yields an R^2 value of 0.957. Also notable is the size of the effect of being a Republican on pro-climate voting—the average LCV scores of Republican legislators is 81.8 points lower than those of Democrats, all else equal. Given the scores range from 0 to 100, this corroborates findings in the literature of a significant partisan divide on climate policy that is reflected is legislator voting behavior.

Column (2) adds demographic variables as well as the district's climate opinion score, given the strong correlations between the two identified in the previous analysis. Both median age and climate opinion have statistically significant effects on pro-climate voting. Interestingly, age is positively correlated with pro-climate voting in this regression. This could be due to the fact that older constituents typically have greater voter turnout and political participation than other age groups, controlling for other demographic factors (Verba and Nie 1987; Campbell 2011)—therefore, when controlling for climate opinion, one might expect legislators to be more responsive to older constituents given they are more likely to express their preferences through voting.

Column (3) aims to assess an alternate mechanism of legislator position formation on climate issues: campaign finance. It replaces the demographic and climate opinion controls with the share of campaign contributions from fossil fuel industries, as well as the DW-Nominate conservative ideology score to ensure that any effect of fossil fuel donations is not just correlated with the conservatism of a particular legislator. While ideology is statistically significant, fossil fuel donation share is not, despite the discussion of this effect in the literature. This could be due to the significance of the effect of employment carbon footprint on pro-climate voting. Previous work has found that fossil fuel companies "reward" legislators who take anti-environment positions (Goldberg et al. 2020), and ECFs and fossil fuel donations are quite highly correlated in the data ($r = 0.62$)—therefore, if legislators' anti-climate voting positions are responsive to their constituents' employment carbon footprints, we might expect ECF to explain much of the same variance as fossil fuel donations. I find some evidence to support this theory: when rerunning regression (3) without log(ECF), fossil fuel donations have a statistically significant effect of -2.082***.

Column (4) combines these controls, with the same variables having significant effects. Altogether, these results yield two notable findings. Firstly, I find that, all else equal, legislators from districts with higher employment carbon footprints are less likely to vote in favor of climate policy, while increasing a district's average household carbon footprint does not have this effect. This supports my hypothesis that jobs are a more salient issue for elected officials than household energy costs. Importantly, the results indicate that legislators are more likely to vote against climate policy as employment vulnerability in their district increases even if their constituents' desires for more or less congressional action on climate change, and their political donations from the fossil fuel industry, remain unchanged.

Secondly, the results show that partisanship and political ideology are the most influential factors on the climate-related voting behavior of legislators. While I do find evidence that legislators take their constituents' beliefs on climate action into account, with legislators from districts that support climate action statistically more likely to vote in favor of climate legislation, this effect is marginal compared to the divide between "partisan elites." The pro-climate voting score of a Republican legislator will be 76 points lower than that of an equally-conservative Democrat, even if they both represent constituencies with the same carbon footprints, beliefs on climate change, and demographics. This partisan effect is so significant that if the Republican variable in column (4) is removed, the R^2 drops from 0.961 to 0.679. The implication is concerning, but perhaps unsurprising: legislators' positions on climate policy are more a function of partisan politics than of constituency representation.

I replicate the regressions of LCV scores with probit regressions on each climate-related vote between 2018 and the 2022 midterms, where each vote a representatives casts in that time period on a climate-related issue is considered a datapoint. Table 6.3 displays the results from these regressions. Columns (1) to (4) show the base regression coefficients for climate-related votes, and column (5) displays the coefficients for justice-related votes as a check for the effects of carbon footprints on voting on other issues. The corresponding average marginal effects of each variable are displayed in Table D.5 in Appendix D. Standardized regression coefficients and standardized marginal effects are also presented in Appendix D in Tables D.6 and D.7, respectively.

Table 6.3: Probit estimation results for votes on individual bills

	Dependent variable: Pro-climate vote				Justice vote
Variable	(1)	(2)	(3)	(4)	(5)
log(ECF)	-0.217***	-0.109***	-0.107***	-0.094**	0.084
	(0.025)	(0.029)	(0.027)	(0.032)	(0.056)
log(HCF)	-0.712***	-0.181	-0.281*	-0.072	-0.305
	(0.137)	(0.152)	(0.142)	(0.159)	(0.365)
Republican	-2.930***	-2.782***	-1.220***	-1.224***	-1.861***
	(0.034)	(0.041)	(0.105)	(0.110)	(0.197)
Median household income ('000)	0.007***	0.004*	0.007***	0.003*	0.011**
	(0.001)	(0.002)	(0.001)	(0.002)	(0.004)
Median age		0.029***		0.022***	-0.023*
		(0.005)		(0.005)	(0.010)
Percent tertiary educated		0.002		0.009*	0.017*
		(0.004)		(0.004)	(0.008)
Percent Black		0.002***		0.002***	-0.007***
		(0.000)		(0.000)	(0.001)
Percent Hispanic		0.003**		0.005***	-0.006*
		(0.001)		(0.001)	(0.003)
log(Population density)		0.002		-0.004	-0.038
		(0.013)		(0.014)	(0.030)
Climate opinion score		0.036***		0.004	0.031**
		(0.005)		(0.006)	(0.012)
log(1+ Fossil fuel donation share)			-0.144***	-0.127***	-0.066
			(0.030)	(0.032)	(0.054)
Conservative ideology score			-2.131***	-2.124***	-2.416***
			(0.131)	(0.147)	(0.221)
Intercept	3.530***	-1.729**	1.339***	-0.710	0.704
	(0.361)	(0.626)	(0.378)	(0.660)	(1.396)
Observations	18,969	18,969	18,391	18,391	7,234
Pseudo R^2	0.690	0.695	0.709	0.710	0.775
Note:					*p<0.05; **p<0.01; ***p<0.001

As with the average LCV score regressions, employment carbon footprint, legislator party and ideology, and median constituency age all have statistically significant effects in columns (1)–(4). According to the marginal effects presented in Table D.5, an increase in a district's ECF from the 25th to the 75th percentile (4.88 to 17.1 metric tonnes CO_2e per employee) decreases the probability its legislator votes in favor of climate legislation by 1.6 percentage points, holding all else constant. The significant partisan divide remains: Democratic legislators are 13 percentage points more likely to support climate policy than Republican legislators from the same district. Similarly, a standard deviation increase in a legislator's conservative ideology score sees a 10 percentage point decrease in the likelihood they support climate policy (see standardized marginal effects in Table D.7).

The probit model finds several additional demographic and socioeconomic variable effects—median household income, tertiary educational attainment, Black population share and Hispanic population share all have positive and statistically significant effects on the likelihood that the legislator from a given district votes in favor of climate policy. While the probit model finds a statistically significant effect of HCF on pro-climate voting in columns (1) and (3), this effect loses its significance when controlling for demographic variables.

In contrast to the LCV regressions, the effect of fossil fuel donations on pro-climate is significant in the probit estimation. Comparing the 25th and 75th percentile of fossil fuel donation shares, a legislator that takes 0.2% of their campaign finance from fossil fuel industries is 3.4 percentage points more likely to vote for climate legislation than one who takes 2.5% from fossil fuel industries. While public climate opinion is statistically significant in column (2), it loses its significance when fossil fuel donations and conservative ideology score are included.

In the estimation of pro-justice voting in column (5), neither ECF or HCF have a statistically significant effect on pro-justice voting, and nor is an effect observed for fossil fuel donations. This suggests that the effects of employment carbon footprints and fossil fuel donations on legislator voting behavior is specific to climate legislation and not merely correlated with unobserved variables.

Given the degree to which political party explains the climate voting record of legislators, I repeat both the OLS and probit estimations described above with separate models for Democratic and Republican legislators in order to understand how the identified effects differ between parties. Table 6.4 and Table 6.5 display these results for LCV scores and votes on climate-related bills, respectively.

These models have relatively low R^2 values compared to the original OLS and probit models, again highlighting the significance of partisanship in explaining voting behavior. For the OLS models, ECF has a statistically significant effect for Democrats in columns (1)–(3), but loses its significance in column (4). For Republicans, both ECF and HCF have significant negative effects without controls, however these lose their significance once controls are added. For the probit models, I observe an effect of ECF in columns (5)–(7) but the effect loses its significance when all controls are combined. Interestingly, ECF is not significant for Democrats, but HCF is, with a significant effect observed for Democrats in columns (1)–(4) and in columns (5)–(6) for Republicans. The contradiction of these results (both with each other and the earlier models) combined with the low R^2 values makes it difficult to ascertain the validity of these results on carbon footprint effects, however the observed partisan difference might be a question for future research.

Table 6.4: OLS estimation results for average legislator LCV score, by political party

Dependent variable: Avg. LCV score	Democrat				Republican			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(ECF)	-2.517**	-1.431*	-1.502*	-0.422	-2.698**	-0.752	-2.051	-1.499
	(0.781)	(0.628)	(0.719)	(0.601)	(0.944)	(1.070)	(1.070)	(1.200)
log(HCF)	-3.224	-0.390	-3.851	-1.131	-17.257*	-6.336	-7.632	-0.137
	(3.763)	(3.200)	(3.626)	(3.280)	(8.614)	(8.511)	(7.475)	(7.948)
Median household income ('000)	0.003	-0.013	0.007	0.004	0.198*	0.167	0.112	0.076
	(0.022)	(0.026)	(0.024)	(0.027)	(0.100)	(0.122)	(0.092)	(0.115)
Median age		0.232		0.188		0.345		0.378
		(0.141)		(0.135)		(0.229)		(0.223)
Percent tertiary educated		0.106		0.045		-0.364		-0.170
		(0.060)		(0.063)		(0.190)		(0.184)
Percent Black		0.049		0.046		-0.230**		-0.095
		(0.038)		(0.039)		(0.076)		(0.071)
Percent Hispanic		0.058		0.056		-0.088		-0.017
		(0.042)		(0.043)		(0.061)		(0.049)
log(Population density)		0.444		0.415		-0.789		-0.512
		(0.258)		(0.263)		(0.593)		(0.570)
Climate opinion score		0.090		0.144		1.354***		0.837***
		(0.093)		(0.084)		(0.297)		(0.244)
log(1+ Fossil fuel donation share)			-3.203***	-3.415***			-0.472	0.983
			(0.823)	(0.845)			(1.221)	(1.320)
Conservative ideology score			0.529	2.178			-27.336***	-21.639***
			(1.282)	(1.194)			(6.447)	(6.252)
Intercept	109.689***	76.178***	111.134***	78.651***	57.759*	-47.203	45.304*	-33.081
	(10.146)	(12.238)	(9.342)	(10.868)	(23.337)	(32.849)	(20.128)	(28.668)
Observations	241	241	238	238	246	246	241	241
R^2	0.076	0.117	0.112	0.154	0.117	0.254	0.321	0.364
Adjusted R^2	0.064	0.082	0.093	0.113	0.106	0.226	0.307	0.333
Residual Std. Error	6.564	6.499	6.494	6.422	10.804	10.053	9.599	9.415
F Statistic	3.848*	1.811	4.830***	3.177***	6.457***	5.319***	7.363***	6.123***

Note: *p<0.05; **p<0.01; ***p<0.001

Table 6.5: Probit estimation results for votes on individual bills, by political party

Dependent variable: Pro-climate vote	Democrat				Republican			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(ECF)	-0.056	-0.034	0.023	-0.013	-0.414***	-0.130*	-0.305***	-0.073
	(0.034)	(0.041)	(0.037)	(0.043)	(0.048)	(0.054)	(0.047)	(0.055)
log(HCF)	-0.745***	-0.418*	-0.499**	-0.426*	-0.929***	-0.619*	0.073	-0.228
	(0.161)	(0.187)	(0.170)	(0.202)	(0.253)	(0.294)	(0.256)	(0.289)
Median household income ('000)	0.009***	0.005**	0.009***	0.006**	0.006*	0.005	-0.002	-0.004
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Median age		0.020*		0.016		0.016*		0.001
		(0.008)		(0.008)		(0.008)		(0.008)
Percent tertiary educated		0.013**		0.012*		0.001		0.024***
		(0.005)		(0.005)		(0.006)		(0.007)
Percent Black		0.009***		0.009***		-0.007***		-0.006***
		(0.001)		(0.001)		(0.001)		(0.001)
Percent Hispanic		0.008***		0.009***		-0.004		-0.002
		(0.002)		(0.002)		(0.002)		(0.002)
log(Population density)		0.057***		0.044*		-0.028		0.008
		(0.016)		(0.017)		(0.025)		(0.025)
Climate opinion score		-0.014*		-0.032***		0.103***		0.060***
		(0.006)		(0.008)		(0.009)		(0.009)
log(1+ Fossil fuel donation share)			-0.232***	-0.281***			0.004	-0.016
			(0.036)	(0.041)			(0.052)	(0.056)
Conservative ideology score			-1.181***	-1.170***			-2.904***	-2.585***
			(0.188)	(0.224)			(0.193)	(0.212)
Intercept	3.174***	1.244	1.964***	2.278*	1.837**	-6.063***	0.280	-3.786***
	(0.416)	(0.817)	(0.463)	(0.910)	(0.665)	(1.037)	(0.648)	(1.009)
Observations	9,900	9,900	9,391	9,391	9,069	9,069	9,000	9,000
Pseudo R^2	0.017	0.049	0.036	0.066	0.063	0.131	0.152	0.185

Note: *p<0.05; **p<0.01; ***p<0.001

However, both the OLS ad probit models observe an interesting effect of fossil fuel donations. In both sets of regressions, fossil fuel donations have no observable effect on Republican voting behavior but do have a statistically significant negative effect on the pro-climate voting of Democrats. This result is intriguing, and calls for further research into whether Democratic legislators' voting on climate issues is more "up for sale" (i.e. responsive to campaign contributions) than Republican legislators, or if fossil fuel industries are more discerning for Democrats than Republicans when targeting anti-environment legislators to donate to.

Part III

Discussion & conclusion

Chapter 7

Discussion & policy implications

The energy transition is necessary to address climate change and will benefit the U.S. on the whole, but will impose costs on a concentrated few whose employment is reliant on fossil fuels. Just transition policy is needed to support these groups, however my results demonstrate that current efforts to target policies to the communities that need them most are inadequate. I find that several communities with high employment carbon footprints are at risk of being left behind if policymakers do not quickly adopt holistic measures of employment vulnerability to the energy transition that span the entire economy, are continuous, and consider both fossil fuel production and consumption. The need for such measures is all the more urgent given my findings on the political salience of employment vulnerability for legislators—without adequate measures to identify and provide support to areas where jobs are at-risk, we can expect political resistance to climate policy on the basis of job impacts to continue.

Employment vulnerability is not distributed evenly. I find that job impacts of the energy transition will be born by the inland states, particularly in fossil fuel-producing counties in west Texas, Appalachia, Wyoming, Oklahoma, the Gulf Coast and western North Dakota, as well as Alaska's North Slope. However, counties in Nevada and the Great Plains states that do not produce fossil fuels but rely greatly on their consumption will also heavily impacted, and these communities are largely missed by analyses in both the literature and policy sphere.

Most consequentially, many of these communities are missed by the United States' most significant piece of climate legislation, the Inflation Reduction Act. My analysis finds that the IRA's definition of "energy communities" is insufficient in identifying the most vulnerable, carbon-intensive communities. Not only are some of the country's most vulnerable regions excluded, but areas that I find are not particularly vulnerable are included. This is potentially a billion-dollar oversight, with the IRA at risk of funneling clean investment away from the regions that desperately need to move away from fossil fuels.

I echo some of the recommendations from the literature on how to improve measures to identify vulnerable communities, and put forward several of my own. Firstly, measures should be proactive, not reactive. The IRA's definition requires a region to have above-average unemployment to qualify under the fossil fuel employment criterion, however this excludes communities that are highly reliant on fossil fuels but where unemployment impacts may not yet have been felt. In fact, my explained variance analysis suggests that counties with high unemployment tend to have *less* carbon-intensive jobs. I demonstrate that it also introduces significant year-on-year volatility and thereby uncertainty into a community's energy community status, as changes in both national and local unemployment cause areas to swing in and out of qualification. Similar critiques can be made of the coal closure criterion. Previous studies have shown that just transition efforts need to begin before closures have impacted a region (Harrahill and Douglas 2019), not solely afterwards, and I note that employment in coal-fired power plants is not counted towards the fossil-fuel employment criterion in the IRA—meaning these communities can only qualify once jobs have been lost. Secondly, measures should be continuous and proportional to the level of employment vulnerability a community faces. As recommended by Raimi and Pesek (2022), policies (such as the IRA's tax credits) could be scaled according to a community's employment vulnerability, but only if the employment vulnerability measure is also continuous. Finally, in contrast to the literature, I highlight the importance of considering employment vulnerability across the entire economy and capturing fossil fuel consumption as well as fossil fuel production. Failing to do so overlooks regions where energy-intensive sectors that consume a lot of fossil fuels, such as heavy manufacturing or non-fossil mining, are significant contributors to the local economy; indeed, I find that nearly half of the most carbon intensive counties that are not granted energy community status are heavily reliant on carbon-intensive manufacturing.

It is worth pausing here to note that the Inflation Reduction Act is, first and foremost, an investment incentive package for clean energy. While I have interpreted the energy communities provision as a just transition policy and thereby identified its shortcomings, this is not the overall objective of the IRA, and it could be argued that the energy communities provision is equally focused on replacing aging fossil fuel infrastructure with clean energy projects as it is supporting the communities they reside in. However, the fact remains that the IRA is the only major piece of U.S. federal policy that integrates some just energy transition policy measures, and until additional policy efforts are introduced these measures will be insufficient. Future just transition policy that not only incentivizes investment but supports workforce development and social and cultural transition is required, and to identify which communities need this assistance policymakers must use metrics of transition vulnerability that are continuous, proactive, and economy-wide.

My target measure, the employment carbon footprint (ECF), satisfies these criteria, and could be used by policymakers to inform future decision-making on where to provide targeted policy support for the just transition. It is particularly important for policymakers to consult the supplemental maps that draw out the differences in vulnerability between fossil fuel-extracting and fossil fuel-consuming communities, as the impacts of decarbonization on these industries will take very different forms and require unique policy approaches to address (Sovacool et al. 2021; Moniz and Kearney 2022).

To this point, while the Overall ECF effectively highlights where policy support may be needed to mitigate employment impacts from the energy transition, it does not prescribe the form that this support should take. Communities with similar carbon intensities will invariably face unique challenges—these could be a function of the local industrial make-up (Sovacool et al. 2021; Moniz and Kearney 2022), cultural identities inextricably tied to certain industries (Carley, Evans, and Konisky 2018; Evans and Phelan 2016; Cha 2020) or the compounding effects of other vulnerabilities such as local pollution exposure, educational disadvantage or energy insecurity (Graff, Carley, and Konisky 2018; Carley and Konisky 2020; Carley et al. 2018). To begin to understand the intersection of these vulnerabilities, my metric could be incorporated into more holistic frameworks of vulnerability in the literature (Turner et al. 2003; Carley et al. 2018) that capture not only economic but also environmental, health and physical risks associated with climate change and the energy transition and include assessments of sensitivity and adaptability to these risks. Within such frameworks, supplementing ECFs with retrospective measures of fossil fuel reliance (such as the IRA's coal closures measure) could capture historical harms and ensure that restorative justice concerns are also accounted for during policymaking. However, it may be unwise for policymakers to rely on such metrics alone during policy design—studies have consistently demonstrated that local, bottom-up initiatives that facilitate active community involvement in decision-making are more successful, more effective at building trust with stakeholders, and more positively perceived by the public (Graff, Carley, and Konisky 2018; Carley and Konisky 2020; Harrahill and Douglas 2019).

In terms of what drives differences in Overall ECFs between communities, I find that the largest contributing factor is the allocation of the workforce across sectors. Oil and gas, coal mining and fossil-fuel power generation have the highest sectoral ECFs on average, and naturally counties with high shares of employment in these sectors tend to have higher Overall ECFs. Policy efforts to reduce energy transition vulnerability should therefore focus on helping diversify local economies away from these polluting sectors.

However, there is also substantial within-sector variation in Overall ECFs, even when controlling for subsector employment share, fuel mix and grid carbon intensity. Future work should seek to understand this more thoroughly, but these results suggest that a non-trivial amount of an employee's vulnerability to the energy transition is driven by the total factor carbon emissions efficiency of their firm. In hard-to-abate sectors, this could signal that policy incentives to increase emissions efficiency while maintaining productivity may be an effective way to reduce employee vulnerability.

The degree of unexplained variance in Overall ECFs indicates that it may be unwise for policymakers to rely solely on proxy variables such as workforce allocation when attempting to target the communities whose employment is most vulnerable to the energy transition. Workforce allocation alone accounts for only 50% of the variance in employment vulnerability between counties, meaning that policies that use fossil fuel employment rates as a key measure may still miss at-risk communities—even without other inhibiting criteria like the unemployment threshold I critique in the IRA. This presents a challenge for policymakers in situations where data-driven measures such as ECFs can't be legislated—how do we proxy for employment vulnerability to replicate the results we see in the data? My analysis suggests that data on workforce allocation should be part, but not all, of the solution, and that demographics, climatic conditions and power grid carbon intensity are largely ineffective as proxies. Future work might consider whether explainability is increased with more granular workforce allocation data, however this was unavailable for my analysis and may well also be unavailable to policymakers given the strict disclosure requirements for U.S. Census Bureau employment data.

The distributional analysis of employment carbon footprints finds that areas with high Overall ECFs tend to be more rural, less racially and ethnically diverse, less educated, and more likely to vote Republican. However, there is significant variability across all of these demographics—for example, while on average high-ECF counties tend to have less racial and ethnic diversity, there are many counties that are both highly diverse and highly vulnerable. There are also significant differences between urban and rural areas in these trends—for example, I find that while high-ECF counties in urban areas tend to be lower-income, the opposite is true for rural counties, supporting the literature that finds carbon-intensive employment to be the best (if not only) source of high-income employment in regional areas.

In addition to low levels of tertiary education, I find that many vulnerable regions have little to no capacity for local retraining and re-skilling through two-year and community colleges. This is concerning—even if new, "green" jobs were to emerge in these regions, research has shown that there are significant skill gaps between these and more polluting jobs that will require workforce development (Vona et al. 2018). Without local retraining capacity, vulnerable employees looking to transition to cleaner industries may be forced to relocate; given what we know about the importance of social fabric and cultural identity in the just transition, such an imposition presents a significant barrier to workforce development and may be untenable for many communities. Expanding retraining capacity in regions where it is constrained must be a priority for just transition policy if it is to ensure that new clean jobs are filled by those whose industries made way for them during the energy transition.

An outstanding question is whether there are disparities in employment carbon footprints along racial or ethnic lines *within* a given county. Ash and Boyce (2018) find that minority populations tend not to hold polluting (and often high-paying) jobs despite bearing the majority of the pollution impacts, and with more granular data on sectoral employment share by race/ethnicity future work could determine whether this translates into lower employment vulnerability to the energy transition. If this were to be the case, then just transition policy efforts would need to be careful to focus not only on transitioning workers in polluting industries but also on ensuring that racial and ethnic disparities in access to high-paying employment are eliminated in new opportunities the energy transition might generate.

Altogether, the distributional analysis makes the case for just transition policy that is place-based and tailored to the unique circumstances and needs of the community it strives to serve. Broad brush approaches, such as investment incentives like the IRA's tax credits, only address part of the transition challenge—new clean energy projects in a community do not necessarily mean new clean jobs for those living in the community, and do nothing on their own to address the loss of cultural identity that may result in a transition away from a history of carbon-intensive industry. While my results are primarily aimed at helping policymakers identify communities that need assistance, they also demonstrate the diversity of contexts these communities exist within, and I recommend that policymakers adopt differentiated transition policy approaches, based on the demographic characteristics of the area (across the dimension of urbanity, for example) but also in consultation with the community itself.

With Part I of this thesis analyzing how employment vulnerability is distributed across the U.S., Part II allowed me to interrogate a separate question: how does employment vulnerability affect the politics of climate policy? I find that both the beliefs of the public and the actions of political representatives are affected by the carbon intensity of jobs in a community. Importantly, I find that while the public's support for further action on climate change is more correlated with household carbon consumption than employment carbon footprints, members of the U.S. House of Representatives do not take these household consumption patterns into account when voting on climate policy. Instead, they prioritize the preservation of carbon-intensive jobs for their constituents, with representatives from high-ECF districts more likely to vote against climate legislation.

While I do find that representatives are partially responsive to their constituents' views on climate policy, this effect of employment vulnerability remains even when this public opinion (as well as donations from fossil fuel industries) is controlled for. This presents an interesting implication: that legislators view carbon-intensive employment and climate policy as in tension, and that they tend to prioritize the protection of these jobs above climate action even if this does not reflect the views of the majority of citizens they represent. It also suggests that this prioritization of employment is not (at least solely) driven by donations from the fossil fuel industry, although I am unable to completely control for industrial interest group pressure of other forms such as informal lobbying.

However, despite identifying effects of employment vulnerability, public climate opinion, and constituency demographics on voting behavior, I find that whether a legislator votes in favor of climate policy is overwhelmingly explained by a simple binary: their political party. The employment and household carbon footprint data I use in this analysis provides deeper insight into the economic implications of climate policy for congressional districts than has previously been accounted for in most of the literature—even still, the effects of these and other variables are marginal compared to the effect of a legislator being Republican. This disturbing (but perhaps not overly surprising) finding supports a growing theory in the literature: that the positions of political representatives on climate policy are increasingly being driven by divides between partisan elites instead of the economic interests and political beliefs of the citizens they represent.

Nevertheless, this work brings further evidence to the claim that jobs are a particularly salient issue for politicians, and this finding has important implications for the just transition. In a political environment where climate politics is partisan, every vote counts, and mitigating legislator concerns about job impacts will likely be crucial in securing support for any future climate policy. The history of the Inflation Reduction Act is the perfect case study of this phenomenon. Originally part of the Biden administration's "Build Back Better" plan, the legislation was whittled away and eventually defeated by Democratic senator Joe Manchin of West Virginia, whose vote held the balance of power in the Senate and who represented some of the communities with the most carbon-intensive employment in the country. Manchin's concerns centered around the economic implications of the legislation (Manchin 2021), and while he eventually supported the passing of the IRA, its scope had been drastically reduced due to his interventions.

Could more targeted, efficacious just transition policy have won Manchin's support for the original Build Back Better climate agenda? While it's impossible to say, previous work has shown that generous welfare benefits for carbon-intensive workers increases the likelihood that legislators from carbon-intensive districts vote in favor of climate policy (Kono 2020; Gazmararian 2022a). This, along with our findings on the political salience of the employment impacts of the energy transition, suggests that just transition policy might not only do right by carbon-intensive communities, but also partially nullify the political incentive to vote down climate legislation in the name of protecting workers. But for such policy to be effective, it will have to be sufficiently targeted, and measures such as the ECF will be essential in ensuring this.

Chapter 8

Conclusion

While the just transition is increasingly becoming a policy priority in the fight against climate change, work to identify which communities need assistance is nascent. This thesis fills this gap by deriving a continuous, economy-wide metric of employment vulnerability to the energy transition—the employment carbon footprint (ECF). Using mostly public data, I derive ECFs for every county in the United States. Communities with high employment carbon footprints are heavily reliant on fossil fuel in their local economies, either through high levels of fuel consumption or the presence of fossil fuel extraction industries, and are those in most dire need of policy support as the energy transition progresses.

I find that both the literature and the Inflation Reduction Act exclude several high-ECF regions with significant employment vulnerability due to insufficiently proactive metrics, a sole focus on fossil-fuel sectors, a lack of continuity, and a lack of consideration for fossil fuel consumption in addition to fossil fuel production. Policy efforts need to ensure that data-driven measures of employment vulnerability are used in order to target the communities most at-risk and ensure that they are not left behind during the energy transition.

I find that while the prevalence of carbon-intensive sectors is the greatest driver of a county's ECF, there are significant within-sector differences in ECF that are unexplained by sectoral employment allocation, demographics and politics, grid carbon intensity and sub-sector fuel mix. This suggests that non-trivial differences in total factor carbon emissions efficiency between firms may contribute to differences in communities' employment vulnerability, and that using a region's level of fossil fuel employment as a proxy variable presents an incomplete picture of the region's employment vulnerability to the energy transition.

This thesis finds that highly vulnerable areas tend to be more rural, less racially and ethnically diverse, more likely to vote Republican and less educated, however also highlights the significant variability in all of these trends and the need for just transition policy to consider the specific economic, demographic and sociocultural characteristics of vulnerable communities. I draw particular attention to the need to rapidly expand retraining capacity in two-year and community colleges in high-ECF areas where it is constrained.

Furthermore, I demonstrate that the voting behavior of members of the U.S. Congress on climate issues is correlated with the employment carbon footprints of their districts, and argue that this provides empirical evidence of the political salience of the issue of employment for climate policy. While both household-level reliance on fossil fuels and ECFs are negatively correlated with public opinion on climate policy, the household carbon footprints of their constituents do not factor into legislators' calculus when voting on climate legislation. Importantly, I also identify a significant partisan divide on climate voting, even when this does not represent the views of the public.

I recommend that policymakers use the ECF results, particularly the distributions of Overall ECFs across the United States, in future attempts to identify communities with high employment vulnerability to the energy transition. I argue that, given the aforementioned salience of jobs as an issue for politicians, mitigating employment impacts and supporting communities is crucial in securing political support for climate policy at large, and such efforts need to effectively target the right communities to be effective. More generally, this work demonstrates the need for policymakers to take sufficient care (and possess the requisite data) when determining who should benefit from policy support. The criteria that determine a community's eligibility to assistance during the energy transition should be informed by data and reflective of the goals of the policy, not considered as an afterthought. After all, the perfectly designed policy is useless if it neglects the very communities it was designed to serve.

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Part IV

Appendices

Appendix A

Detailed ECF calculation methodology & assumptions

A.1 Price elasticity calculations

Pass-through rates (ρ) used to distribute effective carbon emissions across the energy supply chain were calculated using the price elasticities of the fuel in question for a given sector, as per Equation 2.3. Price elasticities for a given fuel and sector were taken from the literature—where a range of values where provided by the literature, maximum and minimum values were taken and used to calculate maximum and minimum values for ρ. Average values for ρ were then calculated as the average of the maximum and minimum values, and these average values were the ones used in the analysis. Table A.1 displays the elasticity figures taken from the literature. In some cases, price elasticity data were not available and values were assumed based on the price elasticities of similar fuels.

Table A.1: Price elasticity values used in analysis

Source	Fuel	Sector	NERC Region	PED min	PED max	PES min	PES max
Burke and Liao (2015)	Coal	Industry		-0.7	-0.3		
Erickson and Lazarus (2018)	Coal	All				2.6	2.6
U.S. Energy Information Administration (2012)	Coal	Power	FRCC	-0.53	-0.53		
			MRO	-0.11	-0.11		
			NPCC	-0.23	-0.23		
			RFC	-0.18	-0.18		
			SERC	-0.22	-0.22		
			SPP	-0.02	-0.02		
			TRE	-0.02	-0.02		
			WECC	-0.14	-0.14		
			ASCC	-0.11	-0.11		
			HICC	-0.11	-0.11		
	Natural gas	Power	FRCC	-0.16	-0.16		
			MRO	-0.31	-0.31		
			NPCC	-0.21	-0.21		
			RFC	-0.60	-0.60		
			SERC	-0.41	-0.41		
			SPP	-0.02	-0.02		
			TRE	-0.02	-0.02		
			WECC	-0.05	-0.05		
			ASCC	-0.29	-0.29		
			HICC	-0.29	-0.29		
	Residual fuel oil	Power	FRCC	-2.16	-2.16		
			MRO	-0.70	-0.70		
			NPCC	-1.26	-1.26		
			RFC	-1.13	-1.13		
			SERC	-1.53	-1.53		
			SPP	-1.28	-1.28		
			TRE	-0.05	-0.05		
			WECC	-0.64	-0.64		
			ASCC	-1.26	-1.26		
			HICC	-1.26	-1.26		
Ponce and Neumann (2014)	Natural gas	All				0.76	0.76
	LPG	All				0.76[a]	0.76[a]
Labandeira, Labeaga, and López-Otero (2017)	Natural gas	Industry		-0.053	-0.053		
	Natural gas	Commercial		-0.292			
	Natural gas	Residential		-0.042	-0.042		
	Diesel	Industry		-0.741	-0.741		
	Residual fuel oil	Industry		-0.741[b]			
	Heating oil	Commercial			-0.185		
	LPG	Commercial			-0.185[c]		
	Electricity	Industry			-0.145		

[a] Assumed same as natural gas.
[b] Assumed same as diesel.
[c] Assumed same as heating oil.

Source	Fuel	Sector	NERC Region	PED min	PED max	PES min	PES max
Antón (2020)	Crude oil	Industry		-0.6	-0.03		
	Residual fuel oil	Industry			-0.6[d]		
Smith (2009)	Crude oil	All				0.10	
Gately (2004)	Crude oil	All					0.58
Brons et al. (2008)	Gasoline	Transport		-0.84	-0.84		
	Diesel	Transport		-0.84[e]	-0.84[e]		
Coyle, DeBacker, and Prisinzano (2012)	Gasoline	All				0.29	2.0
	Diesel	All				0.29[e]	2.0[e]
	Heating oil	All				0.29[e]	2.0[e]
	Residual fuel oil	All				0.29[e]	2.0[e]
	Jet fuel	All				0.29[e]	2.0[e]
Sobieralski (2012)	Jet fuel	Transport		-0.15	-0.10		
	Residual fuel oil	Transport		-0.15[f]	-0.10[f]		
U.S. Energy Information Administration (2021c)	Natural gas	Commercial			-0.28		
	Heating oil	Commercial		-0.30			
	Heating oil	Residential		-0.24	-0.24		
	LPG	Commercial		-0.30[c]			
	Electricity	Residential		-0.50	-0.50		
	Electricity	Commercial			-0.18		
Burke and Abayasekara (2018)	Electricity	Commercial		-0.60			
Ros (2017)	Electricity	Industry		-0.60			
Calculated using data from Deetjen and Azevedo (2019), see Appendix A.2	Electricity	All	FRCC			1.180	1.180
			MRO			0.985	0.985
			NPCC			2.673	2.673
			RFC			1.651	1.651
			SERC			1.550	1.550
			SPP			0.985	0.985
			TRE			4.022	4.022
			WECC			1.597	1.597
			ASCC			1.830	1.830
			HICC			1.830	1.830

[c] Assumed same as heating oil.
[d] Assumed as the same as the lower bound of global crude oil PED.
[e] Assumed same as gasoline.
[f] Assumed same as jet fuel.

A.2 PES of electricity calculation

We calculate an estimate of the price elasticity of supply of electricity for each NERC region by estimating the supply curve of power for each fuel type (coal, natural gas or oil) and then estimating the number of hours each power generation technology is on the margin each year. We use EIA Form EIA-860 and Form EIA-923 data on annual power plant electricity generation and fuel consumption to calculate the heat rate of every power plant in the U.S., and estimate the marginal costs of these plants as the product of the heat rate and the price per MMBtu of the plant's fuel (price data was also obtained from the EIA). In each NERC region, we used these marginal cost estimates and each plant's nameplate capacity to construct a supply curve for each fossil-fuel fired electricity generation technology (i.e. coal-, gas-, and oil-fired generation). We use linear regression to estimate the gradient of the supply curves, and then calculate the PES at each "step" of the supply curves according to the below:

$$PES = \frac{dQ}{dMC}\frac{MC}{Q} = \frac{1}{gradient} \times \frac{MC}{Q}. \tag{A.1}$$

Finally, we use results from the power sector hourly dispatch model developed by Deetjen and Azevedo (2019) to identify, for each NERC region, the total demand and the fuel type of the marginal generator for each hour of the year, and match these data to the previously calculated PES values according to where the demand intersects with our derived supply curves. We then average these hourly PES estimates over the entire year to derive the average PES of electricity for each NERC region.

Appendix B

Regression details from explained variance analysis

B.1 Subsectors considered

The extent to which we can control for subsector emissions factor variables is constrained by the availability of county-level data on subsector fuel mix. The availability of these data varies between sectors. Table B.1 outlines all of the subsectors used as independent variables EF_{ss} and the high-level sectors they belong too. Emissions data for the commercial sector are available on the basis of building types rather than industry codes, the emissions factors for the commercial sector were by building type. Therefore, for the commercial sector the building types considered are outlined in the “subsector NAICS code" column, with the NAICS codes corresponding to each building type detailed in the “subsector name" column for reference (this NAICS-building type crosswalk is displayed for reference, however note that the emissions data used to derive EF_{ss} was available by building type only, not NAICS codes).

Table B.1: Subsectors considered for EF_{ss} during explained variance regressions, for each high-level sector

Sector	Subsector granularity	Subsector NAICS code	Subsector name
Agriculture	4-digit	1111	Oilseed and grain farming
		1112	Vegetable and melon farming
		1113	Fruit and tree nut farming
		1114	Greenhouse, nursery, and floriculture production
		1119	Other crop farming
		1121	Cattle ranching and farming
		1122	Hog and pig farming
		1123	Poultry and egg production
		1124	Sheep and goal farming
		1125	Aquaculture
		1129	Other animal production
Construction	3-digit	236	Construction of buildings
		237	Heavy and civil engineering construction
		238	Specialty trade contractors
Manufacturing	3-digit	311	Food manufacturing
		312	Beverage and tobacco product manufacturing
		313	Textile mills
		314	Textile product mills
		315	Apparel manufacturing
		316	Leather and allied product manufacturing
		321	Wood product manufacturing
		322	Paper manufacturing
		323	Printing and related support activities
		324	Petroleum and coal products manufacturing
		325	Chemical manufacturing
		326	Plastics and rubber products manufacturing
		327	Nonmetallic mineral product manufacturing
		331	Primary metal manufacturing
		332	Fabricated metal product manufacturing
		333	Machinery manufacturing
		334	Computer and electronic product manufacturing
		335	Electrical equipment, appliance, and component manufacturing
		336	Transportation equipment manufacturing
		337	Furniture and related product manufacturing
		339	Miscellaneous manufacturing
Mining (excl. fossil)	4-digit	2122	Metal ore mining
		2123	Nonmetallic mineral mining and quarrying
		2131	Support activities for mining
Coal mining	4-digit	2121	Coal mining
Oil & gas	3-digit	211	Oil and gas extraction
Fossil-fuel power generation	6-digit	221112	Fossil fuel electric power generation
Commercial	Varied	office	Information (NAICS 51)
			Finance and insurance (NAICS 52)
			Real estate and rental and leasing (NAICS 53)

Sector	Subsector granularity	Subsector NAICS code	Subsector name
			Professional, scientific, and technical services (NAICS 54)
			Management of companies and enterprises (NAICS 55)
			Administrative and support services (NAICS 561)
			Wholesale electronic markets and agents and brokers (NAICS 425)
			Public administration (NAICS 92)
		retail	Retail trade (NAICS 44-45)
		warehousing & storage	Merchant wholesalers, durable goods (NAICS 423)
			Merchant wholesalers, nondurable goods (NAICS 424)
			Wholesale electronic markets and agents and brokers (NAICS 425)
		restaurants	Food services and drinking places (NAICS 722)
		accommodation	Accommodation (NAICS 721)
		schools	Elementary and secondary schools (NAICS 6111)
		hospitals	Hospitals (NAICS 622)
		outpatient	Ambulatory health care services (NAICS 621)

B.2 Explained variance analysis stepwise regression coefficients

Table B.2 below contains the linear regression coefficients for each of the independent variables in the six runs of the stepwise model conducted during the explained variance analysis. Numbers in subscript indicate NAICS codes of subsectors—where words are in subscript (e.g. “accommodation") this indicates a subclass of commercial building (in the absence of subsectoral data for commercial buildings).

Table B.2: Regression coefficients for independent variables in explained variance analysis.

Dependent variable: $\log ECF$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	2.062***	5.462**	2.660	1.174	0.355	-3.389	-2.978
	(0.286)	(2.649)	(2.660)	(2.695)	(2.845)	(2.807)	(2.970)
CDD					0.001***	0.001***	0.001**
					(0.000)	(0.000)	(0.000)
$CDD \cdot ef_{elec}$					-0.000***	-0.000**	-0.000
					(0.000)	(0.000)	(0.000)
PercentTertiaryEd		-0.029***	-0.020***	-0.017***	-0.016***	-0.016***	-0.016***
		(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
EF_{1111}						-1.764*	-3.608***
						(0.950)	(1.154)
EF_{1112}						-0.849	-0.437
						(1.267)	(1.723)
EF_{1113}						-0.805	-0.954
						(1.399)	(1.887)
EF_{1114}						-2.785**	-2.183
						(1.223)	(1.671)
EF_{1119}						2.164	3.300
						(3.284)	(3.928)
EF_{1121}						-0.706	-1.578
						(3.514)	(4.319)
EF_{1122}						-1.672*	-1.601
						(0.949)	(1.218)
EF_{1123}						1.894	3.719**
						(1.209)	(1.584)
EF_{1124}						0.383	2.071
						(1.597)	(2.285)
EF_{1125}						-6.267*	-8.725*
						(3.774)	(4.536)
EF_{2122}						-0.748	0.006
						(1.954)	(2.123)
EF_{2123}						-2.132**	-4.814***
						(1.018)	(1.280)
EF_{2131}						0.176	0.403
						(0.790)	(0.815)
EF_{236}						-2.720	-5.863*
						(2.011)	(3.463)
EF_{237}						1.059	0.426
						(1.207)	(1.933)
EF_{238}						-16.027*	-11.554
						(8.329)	(9.747)
EF_{311}						1.472	2.481
						(1.117)	(2.016)
EF_{312}						-1.180	-2.007
						(1.153)	(2.328)
EF_{313}						-0.677	-2.027
						(1.576)	(3.285)
EF_{314}						-1.767*	-2.580
						(0.903)	(1.735)
EF_{315}						-2.624**	-0.381
						(1.328)	(2.546)
EF_{316}						-1.434	-4.866
						(3.020)	(5.611)

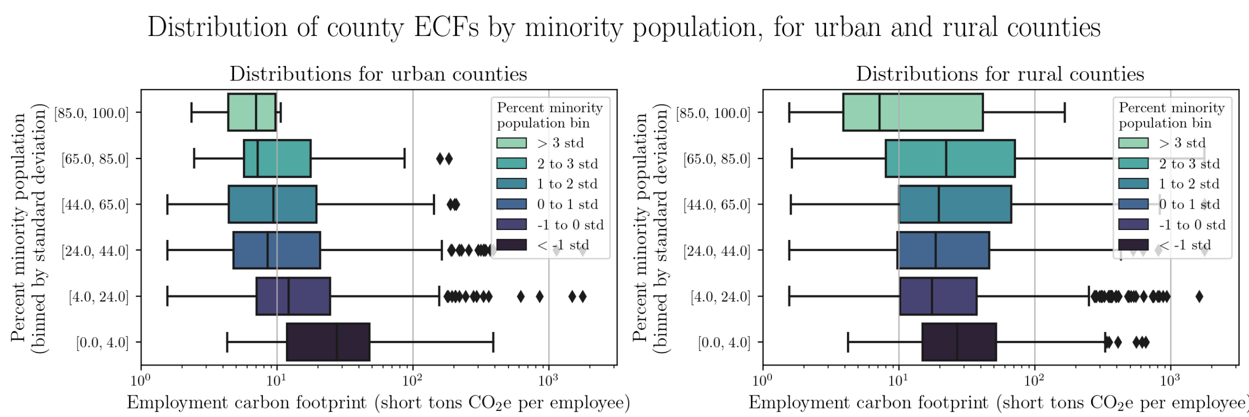
Dependent variable: $\log ECF$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
EF_{321}						0.589	-4.651
						(1.656)	(3.047)
EF_{322}						10.019***	3.329
						(1.120)	(2.556)
EF_{323}						-1.236	-3.089
						(1.990)	(3.559)
EF_{324}						-0.415	2.626
						(0.840)	(1.675)
EF_{325}						7.450***	3.549*
						(0.899)	(1.846)
EF_{326}						-3.048	1.071
						(2.302)	(4.437)
EF_{327}						3.029***	4.306**
						(0.851)	(1.839)
EF_{331}						1.342	0.465
						(1.181)	(2.447)
EF_{332}						-4.178**	-0.722
						(2.123)	(3.276)
EF_{333}						2.254	6.716**
						(1.832)	(3.213)
EF_{334}						-1.814	1.422
						(4.141)	(8.537)
EF_{335}						-4.486**	-4.136
						(2.022)	(3.881)
EF_{336}						-1.989	-1.293
						(1.622)	(3.625)
EF_{337}						-4.378**	-7.767**
						(1.800)	(3.636)
EF_{339}						-1.672	-3.900
						(1.292)	(2.414)
$EF_{accommodation}$						-3.121*	-4.225
						(1.826)	(8.785)
$EF_{hospital}$						2.612	24.406*
						(2.730)	(14.532)
EF_{office}						1.847	-5.729
						(2.105)	(8.124)
$EF_{outpatient}$						0.890	13.543
						(4.212)	(21.172)
$EF_{restaurant}$						-3.468**	9.099
						(1.596)	(7.836)
EF_{retail}						-6.625***	-33.733***
						(2.507)	(9.588)
EF_{school}						1.000	-4.173
						(1.470)	(6.557)
$EF_{warehouse\&storage}$						-1.291	16.089
						(3.213)	(14.274)
EF_{coal}						-1.616	-0.968
						(3.588)	(4.367)
EF_{og}						5.566*	5.219
						(2.888)	(3.287)
EF_{pwr}						1.535	1.895
						(1.142)	(1.247)
ef_{elec}				0.001***	0.002**	0.001*	0.001
				(0.000)	(0.001)	(0.001)	(0.001)
HDD					0.000	0.000**	0.000
					(0.000)	(0.000)	(0.000)
HDD$\cdot$ ef_{elec}					-0.000	-0.000	-0.000
					(0.000)	(0.000)	(0.000)
PersonalIncome		0.000	0.000	0.000	0.000	-0.000	-0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PovertyRate		-0.006	-0.003	0.001	0.001	-0.003	-0.006
		(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
UnemploymentRate		-0.065**	-0.032	-0.014	-0.013	-0.009	-0.008
		(0.027)	(0.027)	(0.026)	(0.026)	(0.024)	(0.024)
PercentRepublican			0.525**	0.470**	0.487**	0.394*	0.147
			(0.211)	(0.204)	(0.222)	(0.219)	(0.226)
log(1+PercentMinority)		0.006	0.031	0.035	0.016	-0.045	-0.080*
		(0.036)	(0.038)	(0.037)	(0.043)	(0.044)	(0.046)
log(1+PopulationDensity)		-0.021	-0.171	-0.355	-0.334	-0.707**	-0.721**
		(0.296)	(0.293)	(0.295)	(0.296)	(0.297)	(0.317)

Dependent variable: $\log ECF$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(1+PopulationDensity·PersonalIncome)		-0.187	-0.016	0.109	0.090	0.510*	0.546*
		(0.285)	(0.282)	(0.282)	(0.284)	(0.283)	(0.302)
$\log(1 + x_{ag})$	0.258***	-0.048	-0.011	0.264***	0.272***	0.095	0.038
	(0.030)	(0.036)	(0.036)	(0.061)	(0.061)	(0.070)	(0.164)
$\log(1 + x_{ag} \cdot EF_{1111})$							0.639**
							(0.309)
$\log(1 + x_{ag} \cdot EF_{1112})$							-0.218
							(0.329)
$\log(1 + x_{ag} \cdot EF_{1113})$							0.117
							(0.365)
$\log(1 + x_{ag} \cdot EF_{1114})$							-0.184
							(0.345)
$\log(1 + x_{ag} \cdot EF_{1119})$							-1.162
							(1.055)
$\log(1 + x_{ag} \cdot EF_{1121})$							0.185
							(0.995)
$\log(1 + x_{ag} \cdot EF_{1122})$							-0.049
							(0.286)
$\log(1 + x_{ag} \cdot EF_{1123})$							-0.480
							(0.329)
$\log(1 + x_{ag} \cdot EF_{1124})$							-0.634
							(0.464)
$\log(1 + x_{ag} \cdot EF_{1125})$							1.720*
							(1.002)
$\log(1 + x_{ag} \cdot ef_{elec})$				-0.140***	-0.137***	-0.034	-0.014
				(0.030)	(0.030)	(0.036)	(0.046)
$\log(1 + x_{cn})$	0.276***	0.320***	0.268***	0.240**	0.274**	0.038	0.002
	(0.054)	(0.054)	(0.054)	(0.122)	(0.121)	(0.151)	(0.333)
$\log(1 + x_{cn} \cdot EF_{236})$							0.672
							(0.749)
$\log(1 + x_{cn} \cdot EF_{237})$							0.086
							(0.370)
$\log(1 + x_{cn} \cdot EF_{238})$							-0.446
							(0.977)
$\log(1 + x_{cn} \cdot ef_{elec})$				0.030	-0.008	0.149	0.126
				(0.083)	(0.083)	(0.111)	(0.134)
$\log(1 + x_{coal})$	0.503***	0.431***	0.431***	0.310*	0.318*	0.153	0.313
	(0.108)	(0.103)	(0.101)	(0.174)	(0.173)	(0.185)	(0.356)
$\log(1 + x_{coal} \cdot EF_{coal})$							-0.414
							(1.082)
$\log(1 + x_{coal} \cdot ef_{elec})$				0.026	0.023	0.060	0.034
				(0.031)	(0.031)	(0.050)	(0.066)
$\log(1 + x_{comm})$	-0.294***	-0.095	-0.095	-0.241	-0.151	-0.101	-0.420
	(0.061)	(0.060)	(0.059)	(0.198)	(0.201)	(0.193)	(0.287)
$\log(1 + x_{comm} \cdot EF_{accommodation})$							0.026
							(0.277)
$\log(1 + x_{comm} \cdot EF_{hospital})$							-0.599
							(0.401)
$\log(1 + x_{comm} \cdot EF_{office})$							0.257
							(0.275)
$\log(1 + x_{comm} \cdot EF_{outpatient})$							-0.351
							(0.539)
$\log(1 + x_{comm} \cdot EF_{restaurant})$							-0.466*
							(0.279)
$\log(1 + x_{comm} \cdot EF_{retail})$							1.038***
							(0.349)
$\log(1 + x_{comm} \cdot EF_{school})$							0.186
							(0.236)
$\log(1 + x_{comm} \cdot EF_{warehouse\&storage})$							-0.554
							(0.415)
$\log(1 + x_{comm} \cdot ef_{elec})$				0.112	0.080	0.088	0.204*
				(0.078)	(0.079)	(0.076)	(0.105)
$\log(1 + x_{mf})$	0.385***	0.349***	0.334***	0.485***	0.496***	0.422***	0.395***
	(0.028)	(0.031)	(0.031)	(0.057)	(0.057)	(0.057)	(0.089)
$\log(1 + x_{mf} \cdot EF_{311})$							-0.089
							(0.178)
$\log(1 + x_{mf} \cdot EF_{312})$							0.043
							(0.199)
$\log(1 + x_{mf} \cdot EF_{313})$							0.118
							(0.266)

Dependent variable: $\log ECF$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\log(1 + x_{mf} \cdot EF_{314})$							0.094
							(0.163)
$\log(1 + x_{mf} \cdot EF_{315})$							-0.226
							(0.235)
$\log(1 + x_{mf} \cdot EF_{316})$							0.421
							(0.470)
$\log(1 + x_{mf} \cdot EF_{321})$							0.596^{**}
							(0.262)
$\log(1 + x_{mf} \cdot EF_{322})$							0.664^{***}
							(0.239)
$\log(1 + x_{mf} \cdot EF_{323})$							0.193
							(0.279)
$\log(1 + x_{mf} \cdot EF_{324})$							-0.349^{**}
							(0.170)
$\log(1 + x_{mf} \cdot EF_{325})$							0.391^{**}
							(0.173)
$\log(1 + x_{mf} \cdot EF_{326})$							-0.336
							(0.337)
$\log(1 + x_{mf} \cdot EF_{327})$							-0.149
							(0.183)
$\log(1 + x_{mf} \cdot EF_{331})$							0.097
							(0.221)
$\log(1 + x_{mf} \cdot EF_{332})$							-0.408
							(0.326)
$\log(1 + x_{mf} \cdot EF_{333})$							-0.427
							(0.294)
$\log(1 + x_{mf} \cdot EF_{334})$							-0.254
							(1.025)
$\log(1 + x_{mf} \cdot EF_{335})$							-0.040
							(0.290)
$\log(1 + x_{mf} \cdot EF_{336})$							0.024
							(0.325)
$\log(1 + x_{mf} \cdot EF_{337})$							0.284
							(0.286)
$\log(1 + x_{mf} \cdot EF_{339})$							0.201
							(0.202)
$\log(1 + x_{mf} \cdot ef_{elec})$				-0.094^{***}	-0.096^{***}	-0.073^{***}	-0.076^{***}
				(0.025)	(0.025)	(0.025)	(0.029)
$\log(1 + x_{mn})$	0.494^{***}	0.326^{***}	0.314^{***}	0.294^{***}	0.302^{***}	0.234^{***}	0.173
	(0.043)	(0.042)	(0.041)	(0.059)	(0.059)	(0.062)	(0.130)
$\log(1 + x_{mn} \cdot EF_{2122})$							-0.550
							(0.397)
$\log(1 + x_{mn} \cdot EF_{2123})$							1.104^{***}
							(0.320)
$\log(1 + x_{mn} \cdot EF_{2131})$							-0.256
							(0.322)
$\log(1 + x_{mn} \cdot ef_{elec})$				-0.003	-0.002	0.025	0.046^{**}
				(0.011)	(0.011)	(0.016)	(0.021)
$\log(1 + x_{og})$	1.187^{***}	1.063^{***}	1.010^{***}	0.655^{***}	0.681^{***}	0.778^{***}	0.602^{*}
	(0.077)	(0.073)	(0.073)	(0.096)	(0.096)	(0.114)	(0.312)
$\log(1 + x_{og} \cdot EF_{og})$							0.928
							(1.370)
$\log(1 + x_{og} \cdot ef_{elec})$				0.060^{***}	0.058^{***}	-0.004	0.003
				(0.014)	(0.015)	(0.035)	(0.045)
$\log(1 + x_{pwr})$	1.068^{***}	1.072^{***}	1.064^{***}	0.540^{***}	0.558^{***}	0.688^{***}	0.645^{**}
	(0.079)	(0.074)	(0.073)	(0.098)	(0.098)	(0.099)	(0.268)
$\log(1 + x_{pwr} \cdot EF_{pwr})$							0.406
							(0.990)
$\log(1 + x_{pwr} \cdot ef_{elec})$				0.089^{***}	0.089^{***}	0.046^{**}	0.042^{*}
				(0.012)	(0.012)	(0.021)	(0.025)
RepublicanState			0.252^{***}	0.210^{***}	0.188^{***}	0.176^{***}	0.169^{***}
			(0.050)	(0.048)	(0.050)	(0.053)	(0.053)
Observations	1,420	1,420	1,420	1,420	1,420	1,420	1,420
R^2	0.539	0.603	0.615	0.659	0.663	0.723	0.742
Adjusted R^2	0.536	0.599	0.610	0.652	0.656	0.707	0.717
Residual Std. Error	0.847	0.788	0.776	0.733	0.730	0.673	0.662
F Statistic	206.300^{***}	142.076^{***}	131.617^{***}	103.403^{***}	91.116^{***}	44.831^{***}	29.527^{***}

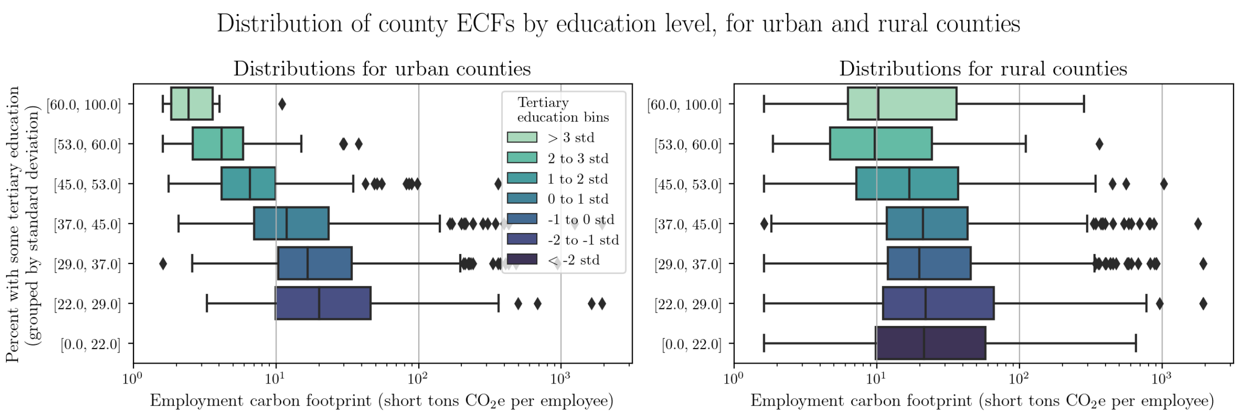
Appendix C

Supplementary figures & tables from Part I



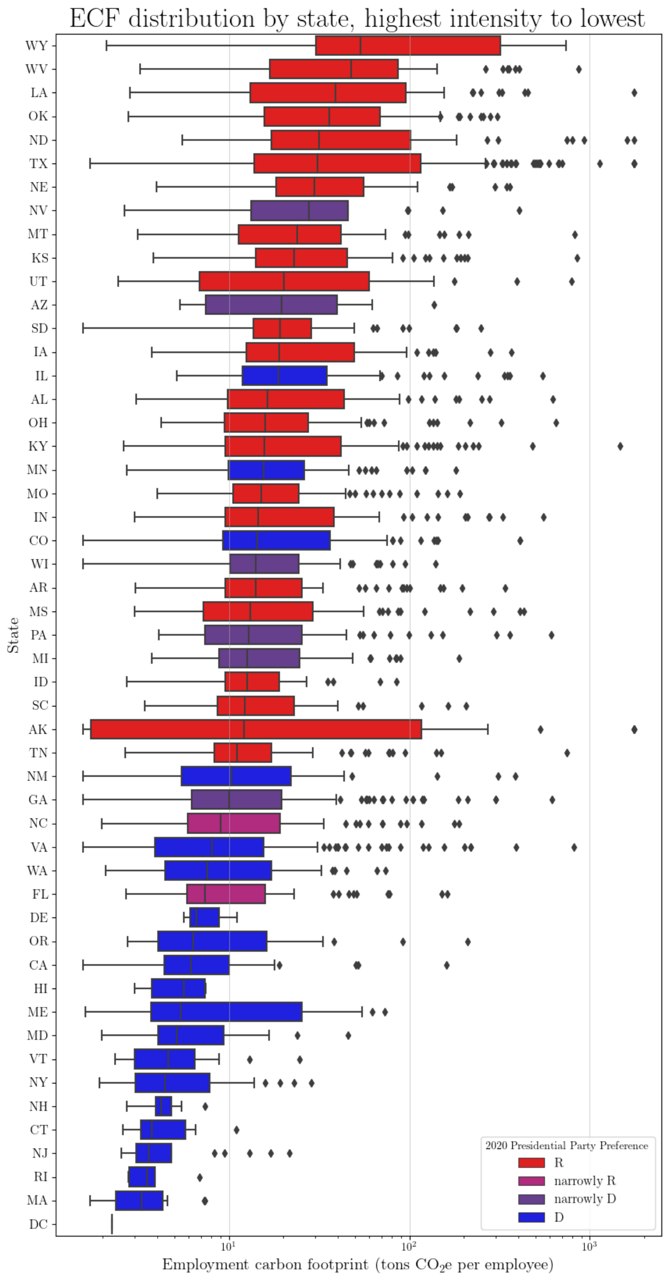
Notes: Counties were binned by share of the population that is non-White or Hispanic, where the interval of each bin is equal to one standard deviation. Lighter marks represent more racially/ethnically diverse counties.

Figure C.1: Distributions of ECFs across counties with differing shares of minority population, for urban and rural counties.



Notes: Counties were binned by share of the population with some level of tertiary education, where the interval of each bin is equal to one standard deviation. Lighter marks represent more educated counties. The left figure represents urban counties, while the right represents rural counties.

Figure C.2: Overall ECF distributions at different levels of educational attainment, for urban and rural counties.

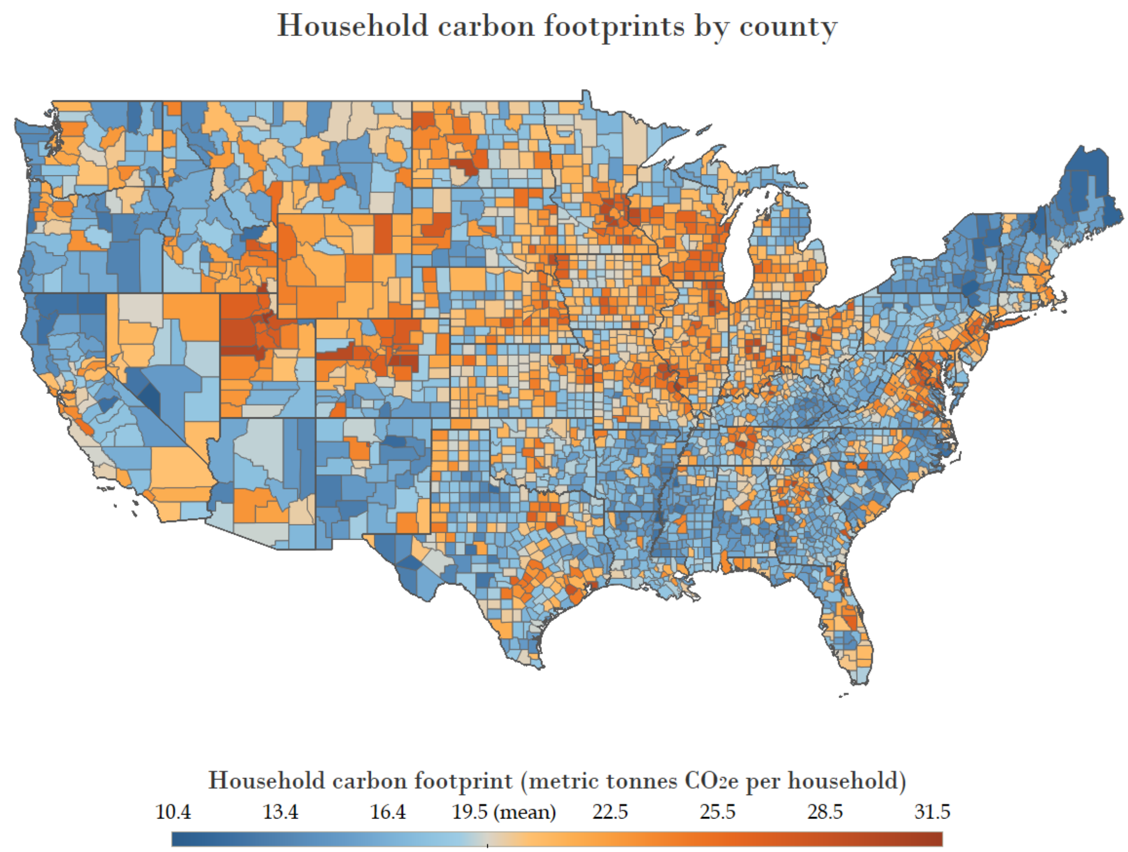


Notes: Each box plot represents the distribution of Overall ECFs across counties in a given state, and the color of each box reflects the party that received the most votes in that state during the 2020 presidential election according to the MIT Election Lab.

Figure C.3: Overall ECF distribution by state, colored according to political affiliation in 2020 presidential election.

Appendix D

Supplementary figures & tables from Part II



Notes: This figure displays the average household carbon footprint of each county, calculated as a population-weighted estimate from the census tract-level data derived by Green and Knittel (2020).

Figure D.1: Distribution of household carbon footprints across U.S. counties.

Table D.1: Standardized OLS results for average climate opinion score, county level

	Dependent variable: Avg. climate opinion score		
Variable	(1)	(2)	(3)
log(ECF)	-0.191***	-0.156***	-0.086***
	(0.012)	(0.011)	(0.008)
log(HCF)	-0.187***	-0.188***	-0.090***
	(0.017)	(0.017)	(0.012)
Republican	-1.670***	-1.181***	-0.139***
	(0.032)	(0.036)	(0.033)
Median household income ('000)	0.200***	0.103***	0.070***
	(0.018)	(0.020)	(0.015)
Median age		-0.060***	0.010
		(0.016)	(0.010)
Percent tertiary educated		0.199***	-0.019
		(0.016)	(0.013)
Percent Black		0.202***	0.007
		(0.012)	(0.010)
Percent Hispanic		0.203***	0.118***
		(0.013)	(0.009)
log(Population density)		0.125***	-0.046***
		(0.014)	(0.011)
Percent voting Republican			-0.824***
			(0.015)
Intercept	1.372***	0.965***	0.106***
	(0.029)	(0.031)	(0.028)
Observations	3,101	3,101	3,100
R^2	0.605	0.682	0.852
Adjusted R^2	0.604	0.681	0.851
Residual Std. Error	0.624	0.560	0.381
F Statistic	1080.453***	706.479***	1303.320***

Note: *p<0.05; **p<0.01; ***p<0.001

Table D.2: OLS results for average climate opinion score, congressional-district level

Variable	Dependent variable: Avg. climate opinion score (1)	(2)	(3)
log(ECF)	-2.929***	-1.496***	-1.033***
	(0.312)	(0.254)	(0.219)
log(HCF)	-8.191**	-5.703*	-6.303***
	(2.653)	(2.715)	(1.129)
Republican	-5.098***	-3.302***	-0.173
	(0.349)	(0.321)	(0.352)
Median household income ('000)	0.030	0.020	0.034**
	(0.022)	(0.022)	(0.013)
Median age		0.056	-0.003
		(0.065)	(0.037)
Percent tertiary educated		0.090*	0.148***
		(0.039)	(0.027)
Percent Black		0.075***	0.080***
		(0.017)	(0.010)
Percent Hispanic		0.080***	0.079***
		(0.011)	(0.010)
log(Population density)		0.953***	0.816***
		(0.117)	(0.094)
Conservative ideology score			-5.096***
			(0.411)
Intercept	92.729***	68.342***	67.722***
	(6.718)	(8.112)	(3.755)
Observations	487	487	480
R^2	0.619	0.733	0.843
Adjusted R^2	0.616	0.728	0.840
Residual Std. Error	3.812	3.209	2.402
F Statistic	151.237***	147.850***	206.291***

Note: *p<0.05; **p<0.01; ***p<0.001

Table D.3: Standardized OLS estimation results for average climate opinion score, congressional-district level

	Dependent variable: Avg. climate opinion score		
Variable	(1)	(2)	(3)
log(ECF)	-0.418***	-0.214***	-0.148***
	(0.045)	(0.036)	(0.031)
log(HCF)	-0.204**	-0.142*	-0.157***
	(0.066)	(0.068)	(0.028)
Republican	-0.830***	-0.538***	-0.028
	(0.057)	(0.052)	(0.057)
Median household income ('000)	0.091	0.060	0.105**
	(0.068)	(0.068)	(0.040)
Median age		0.033	-0.002
		(0.038)	(0.022)
Percent tertiary educated		0.106*	0.173***
		(0.046)	(0.031)
Percent Black		0.167***	0.179***
		(0.038)	(0.023)
Percent Hispanic		0.236***	0.232***
		(0.033)	(0.029)
log(Population density)		0.291***	0.249***
		(0.036)	(0.029)
Conservative ideology score			-0.366***
			(0.030)
Intercept	0.416***	0.266***	0.026
	(0.043)	(0.030)	(0.032)
Observations	487	487	480
R^2	0.619	0.733	0.843
Adjusted R^2	0.616	0.728	0.840
Residual Std. Error	0.621	0.523	0.391
F Statistic	151.237***	147.850***	206.291***

Note: *p<0.05; **p<0.01; ***p<0.001

Table D.4: Standardized OLS estimation results for average LCV score

	Dependent variable: Average LCV score			
Variable	(1)	(2)	(3)	(4)
log(ECF)	-0.062***	-0.035*	-0.044***	-0.032*
	(0.012)	(0.014)	(0.013)	(0.015)
log(HCF)	-0.022	-0.001	-0.011	0.011
	(0.014)	(0.018)	(0.014)	(0.015)
Republican	-1.882***	-1.836***	-1.757***	-1.762***
	(0.031)	(0.040)	(0.054)	(0.051)
Median household income ('000)	0.020	0.015	0.023	0.007
	(0.013)	(0.018)	(0.014)	(0.017)
Median age		0.032**		0.034**
		(0.011)		(0.011)
Percent tertiary educated		-0.018		-0.015
		(0.015)		(0.014)
Percent Black		-0.008		-0.014
		(0.013)		(0.010)
Percent Hispanic		0.004		0.004
		(0.014)		(0.013)
log(Population density)		-0.006		-0.009
		(0.014)		(0.012)
Climate opinion score		0.079*		0.079***
		(0.036)		(0.021)
log(1+ Fossil fuel donation share)			-0.013	-0.002
			(0.012)	(0.014)
Conservative ideology score			-0.082***	-0.055*
			(0.023)	(0.022)
Intercept	0.948***	0.926***	0.886***	0.887***
	(0.015)	(0.021)	(0.026)	(0.026)
Observations	487	487	479	479
R^2	0.957	0.960	0.959	0.961
Adjusted R^2	0.957	0.959	0.959	0.960
Residual Std. Error	0.207	0.202	0.203	0.200
F Statistic	6032.489***	2967.992***	5027.261***	2891.764***

Note: *p<0.05; **p<0.01; ***p<0.001

Table D.5: Marginal effects of probit estimation for votes on climate-related bills

	Dependent variable: Pro-climate vote			
Variable	(1)	(2)	(3)	(4)
log(ECF)	-0.0245***	-0.0122***	-0.0114***	-0.0100**
	(0.0028)	(0.0033)	(0.0029)	(0.0034)
log(HCF)	-0.0804***	-0.0202	-0.0299*	-0.0077
	(0.0154)	(0.0169)	(0.0151)	(0.0168)
Republican	-0.3305***	-0.3098***	-0.1300***	-0.1298***
	(0.0047)	(0.0052)	(0.0112)	(0.0116)
Median household income ('000)	0.0008***	0.0004*	0.0007***	0.0003*
	(0.0001)	(0.0002)	(0.0001)	(0.0002)
Median age		0.0032***		0.0023***
		(0.0006)		(0.0006)
Percent tertiary educated		0.0003		0.0010*
		(0.0004)		(0.0004)
Percent Black		0.0002***		0.0002***
		(0.0000)		(0.0000)
Percent Hispanic		0.0004**		0.0005***
		(0.0001)		(0.0001)
log(Population density)		0.0002		-0.0005
		(0.0014)		(0.0015)
Climate opinion score		0.0040***		0.0005
		(0.0006)		(0.0006)
log(1+ Fossil fuel donation share)			-0.0153***	-0.0134***
			(0.0032)	(0.0034)
Conservative ideology score			-0.2271***	-0.2252***
			(0.0142)	(0.0158)
Observations	18,969	18,969	18,391	18,391
Pseudo R^2	0.690	0.695	0.709	0.710
Note:		*p<0.05; **p<0.01; ***p<0.001		

Table D.6: Standardized probit estimation results for votes on individual bills

	Dependent variable: Pro-climate vote				Justice vote
Variable	(1)	(2)	(3)	(4)	(5)
log(ECF)	-0.217***	-0.109***	-0.107***	-0.094**	0.084
	(0.025)	(0.029)	(0.027)	(0.032)	(0.056)
log(HCF)	-0.712***	-0.181	-0.281*	-0.072	-0.305
	(0.137)	(0.152)	(0.142)	(0.159)	(0.365)
Republican	-2.930***	-2.782***	-1.220***	-1.224***	-1.861***
	(0.034)	(0.041)	(0.105)	(0.110)	(0.197)
Median household income ('000)	0.007***	0.004*	0.007***	0.003*	0.011**
	(0.001)	(0.002)	(0.001)	(0.002)	(0.004)
Median age		0.029***		0.022***	-0.023*
		(0.005)		(0.005)	(0.010)
Percent tertiary educated		0.002		0.009*	0.017*
		(0.004)		(0.004)	(0.008)
Percent Black		0.002***		0.002***	-0.007***
		(0.000)		(0.000)	(0.001)
Percent Hispanic		0.003**		0.005***	-0.006*
		(0.001)		(0.001)	(0.003)
log(Population density)		0.002		-0.004	-0.038
		(0.013)		(0.014)	(0.030)
Climate opinion score		0.036***		0.004	0.031**
		(0.005)		(0.006)	(0.012)
log(1+ Fossil fuel donation share)			-0.144***	-0.127***	-0.066
			(0.030)	(0.032)	(0.054)
Conservative ideology score			-2.131***	-2.124***	-2.416***
			(0.131)	(0.147)	(0.221)
Intercept	3.530***	-1.729**	1.339***	-0.710	0.704
	(0.361)	(0.626)	(0.378)	(0.660)	(1.396)
Observations	18,969	18,969	18,391	18,391	7,234
Pseudo R^2	0.690	0.695	0.709	0.710	0.775

Note: *p<0.05; **p<0.01; ***p<0.001

Table D.7: Standardized marginal effects of probit estimation for votes on climate-related bills

	Dependent variable: Pro-climate vote			
Variable	(1)	(2)	(3)	(4)
log(ECF)	-0.0245***	-0.0122***	-0.0114***	-0.0100**
	(0.0028)	(0.0033)	(0.0029)	(0.0034)
log(HCF)	-0.0804***	-0.0202	-0.0299*	-0.0077
	(0.0154)	(0.0169)	(0.0151)	(0.0168)
Republican	-0.3305***	-0.3098***	-0.1300***	-0.1298***
	(0.0047)	(0.0052)	(0.0112)	(0.0116)
Median household income ('000)	0.0008***	0.0004*	0.0007***	0.0003*
	(0.0001)	(0.0002)	(0.0001)	(0.0002)
Median age		0.0032***		0.0023***
		(0.0006)		(0.0006)
Percent tertiary educated		0.0003		0.0010*
		(0.0004)		(0.0004)
Percent Black		0.0002***		0.0002***
		(0.0000)		(0.0000)
Percent Hispanic		0.0004**		0.0005***
		(0.0001)		(0.0001)
log(Population density)		0.0002		-0.0005
		(0.0014)		(0.0015)
Climate opinion score		0.0040***		0.0005
		(0.0006)		(0.0006)
log(1+ Fossil fuel donation share)			-0.0153***	-0.0134***
			(0.0032)	(0.0034)
Conservative ideology score			-0.2271***	-0.2252***
			(0.0142)	(0.0158)
Observations	18,969	18,969	18,391	18,391
Pseudo R^2	0.690	0.695	0.709	0.710
Note:		*p<0.05; **p<0.01; ***p<0.001		