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Measuring the Spectrum of Occupational Emissions[*]

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Abstract

Understanding how occupations differ in their exposure to emissions-intensive activities is fundamental for analyzing labor market risks amid changes in the energy mix. We develop new, data-driven measures of occupational emissions intensity that capture heterogeneity across and within industries. Our baseline Occupational Emissions Score (OES), along with wage- and concentration-adjusted variations (WOES and COES), highlights substantial differences in emissions exposure across the U.S. workforce. Applying these measures, we document several new facts: emissions are highly concentrated in a small set of occupations; emissions intensity has declined over time; and even within industries, workers' exposure varies significantly by occupation. Higher-emission occupations are disproportionately held by older, male, native-born, and less-educated workers, and are concentrated in particular regions. While higher-emission occupations tend to experience lower employment growth, they show higher hourly wages and vacancy growth. An event study of coal mine closures further shows that high-emission occupations are more exposed to structural shocks. Together, our measures provide a comprehensive, granular framework for understanding occupational risk and adjustment during major economic shifts.

Keywords: Occupations, Emissions, Labor Market Dynamics, Regional Differences, Coal, Energy

JEL Codes: J23, J24, J62, Q52, Q54, R11

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1. Introduction

The evolving energy landscape represents one of the most significant economic transformations currently underway, with potentially substantial implications for labor markets. Like earlier structural changes—such as the China Shock, which triggered persistent employment losses in U.S. manufacturing regions (Autor et al., 2013, 2016)—changes in the energy mix is expected to impose significant and uneven adjustment costs (Hanson, 2021; Walker, 2013; Hanson, 2023). However, unlike trade and globalization shocks, this shift is largely foreseeable, offering an opportunity to anticipate its labor market consequences and design more effective responses.[1]

Identifying which workers are most exposed to the risks and opportunities arising from a shift shock is particularly important and requires careful attention. While industries are a natural unit for analyzing economic activity, focusing solely on industries risks overlooking substantial heterogeneity in workers' exposure to risks. In the context of a shift in the energy mix, many occupations are distributed across multiple industries with varying emissions profiles, and even within a single industry, workers in different occupations may experience markedly different levels of exposure. Our paper places occupations at the center of the analysis. This approach is consistent with recent research showing that occupation-specific factors—not just industry affiliation—play a dominant role in shaping workers' labor market outcomes. For instance, Traiberman (2019) finds that occupations explain a substantially larger share of lifetime earnings losses from import competition than industries. Kambourov and Manovskii (2009) similarly show that human capital is largely occupation-specific, with occupational mobility being a key driver of wage dynamics and inequality. Building on these insights, we develop novel, data-driven, continuous measures of occupational emissions exposure, offering a granular perspective based on emissions intensity.

Our baseline measure, the Occupational Emissions Score (OES), reflects the average emissions associated with an occupation based on its industry distribution. We extend this with two refinements: the Concentration-Adjusted Occupational Emissions Score (COES), which adjusts for how concentrated an occupation is within specific industries, and the Wage-Adjusted Occupational Emissions Score (WOES), which incorporates wage differences to proxy for variations in decision-making influence over emissions. These scores move beyond binary classifications (Vona et al., 2018; Saussay et al., 2022; Curtis and Marinescu, 2023; Bluedorn et al., 2023), providing a richer and more nuanced characterization of occupational emissions exposure and offering several advantages. By constructing continuous scores for the entire U.S. workforce based on observed data from the Environmental Protection Agency (EPA) and the Census American Community Survey (ACS), we capture the full spectrum of emissions-related risks facing workers. Unlike approaches relying on subjective perceptions or narrow subsets of jobs, our framework is

[1] Recent research highlights that major economic transitions can produce enduring effects on local labor markets and occupations, particularly when workers face barriers to adjustment (Bloom et al., 2024).

transparent, replicable, and easily extendable, while capturing granular heterogeneity in exposure. Compared to studies relying on online job postings (Saussay et al., 2022; Curtis and Marinescu, 2023; Bluedorn et al., 2023), our measures cover a broader segment of the workforce and reflect actual employment structures. Importantly, our scores allow researchers and policymakers to move beyond coarse, binary classifications and instead analyze a continuous distribution of occupational risk.

Using these scores, we document several new facts about occupational emissions exposure in the U.S. labor market between 2016 and 2022. First, emissions intensity is highly concentrated, with a small set of occupations and industries accounting for the majority of emissions. Second, occupational emissions intensity has declined over time. Third, we uncover substantial within-industry heterogeneity: even in high-emission industries, workers' emissions exposure varies significantly across occupations.

We then apply our measures in several ways. First, we examine demographic patterns, finding that higher-emission occupations are disproportionately held by older, male, native-born, and less-educated workers.Second, we study labor market outcomes, showing that higher-emission occupations tend to experience lower employment growth but higher hourly wages and vacancy growth. However, significant variation within emissions intensity quartiles suggests that emissions exposure is important but not the sole driver of labor market dynamics. Third, we construct commuting-zone level scores by aggregating occupational emissions, enabling a geographic analysis of exposure. Consistent with recent work on the regional effects of energy transformations (Leduc and Wilson, 2023), we find significant variation across regions.[2]

Finally, we use the occupational emissions scores to analyze the effects of coal mine closures between 2013 and 2020. Using detailed mine-level and commuting zone data, we show that closures lead to sharp declines in local employment, disproportionately affecting high-emission occupations. Regions also experience a measurable decline in average occupational emissions intensity following closures, validating the usefulness of our continuous scores in capturing adjustment dynamics. These findings complement recent work on the labor market impacts of coal decline (Colmer et al., 2024; Blonz et al., 2024; Du and Karolyi, 2023) and highlight the value of granular, occupation-based measures for analyzing structural economic adjustments.

This paper makes several contributions. First, we develop continuous, data-driven measures of occupational emissions exposure, providing a rich alternative to binary classifications. Second, we document novel facts about the distribution, evolution, and regional concentration of occupational emissions intensity. Third, we link occupational emissions exposure to key labor market outcomes, demographic differences, and geographic variation. Fourth, we illustrate the application of our measures by analyzing the labor market impacts of coal mine closures. Together, these

[2] Berlin et al. (2024) consider climate transition risk at the regional level with an application to community banks.

contributions provide a comprehensive framework for understanding labor market exposure to a major economic shift.

The rest of the paper proceeds as follows. Section 2 describes the construction of the occupational emissions scores. Section 3 details the data sources and mapping procedures. Section 4 presents the main results on the distribution, evolution, and heterogeneity of scores. Section 5 applies the measures to demographic, labor market, geographic, and event study analyses. Section 6 concludes.

2. Constructing and Extending Occupational Emissions Scores

To comprehensively assess the emissions intensity of occupations, we present a granular, data-driven approach for constructing an emissions score at the occupation level. This score captures the relationship between industry-level greenhouse gas emissions and occupational employment, providing a continuous measure of emissions exposure for each occupation.

The baseline measure offers an overall assessment of emissions intensity based on observed employment distributions across industries. We then extend this baseline measure by incorporating additional dimensions, such as within-industry concentration and wage differences, to deepen our understanding of occupational exposure to emissions-related risks. This section details the construction and interpretation of the baseline score and its extensions.

2.1. Baseline: Occupational Emissions Score (OES)

The Occupational Emissions Score (OES) is the baseline measure we construct to evaluate the emissions intensity of different occupations. This score provides an average emissions intensity for each occupation, reflecting its exposure based on the distribution of employment across industries with varying levels of greenhouse gas emissions.

The OES score for an occupation o at time t is defined as:

$$OES_{ot} = \frac{1}{Employment_{ot}} \times \left(\sum_{i} w_{iot}^{ind} \times Emissions_{it} \right) \tag{1}$$

where $w_{iot}^{ind} = \frac{Employment_{iot}}{Employment_{it}}$ represents the share of occupation o's employment within industry i in time t. Emissions$_{it}$ is the emissions for industry i in time t, and Employment$_{ot}$ is the total employment for occupation o in time t. This formula calculates the average emissions intensity for workers in a given occupation by weighting the emissions of each industry by the proportion of that occupation's employment within that industry. By dividing the weighted sum by the total employment for the occupation, we derive an average score that captures how exposed the occupation is to emissions-related risks.

In essence, the OES provides a clear metric for understanding how closely an occupation is tied to high-emission industries. When a substantial share of an occupation's employment is concentrated in sectors with high emissions, it suggests greater exposure to emissions-related economic risks. To illustrate, consider the example of "construction workers." Construction workers are employed across various industries, from residential building construction to oil and gas infrastructure. This heterogeneity in employment patterns is reflected in their OES score: if a significant share of the occupation is employed in high-emission sectors like oil and gas, the OES will be higher, indicating greater emissions intensity.

2.2. Extensions

2.2.1. Concentration-Adjusted Occupational Emissions Score (COES)

While the Occupational Emissions Score (OES) provides a broad measure of exposure by evaluating an occupation's average distribution across industries with varying emissions levels, it does not account for the concentration of that occupation within specific industries. To capture this additional dimension of risk, we introduce the Concentration-Adjusted Occupational Emissions Score (COES), which reflects how concentrated an occupation is within particular industries.

Basically, the COES score provides insights into the specific risks associated with an occupation being heavily tied to a few high-emission industries, making it a more nuanced measure of economic exposure. Such concentration may increase an occupation's exposure not only during shifts, but also in response to unexpected sector-specific shocks, such as commodity price fluctuations or regulatory changes. In these cases, industries with high emissions intensity may experience sudden declines or structural adjustments, magnifying the risk for occupations heavily concentrated within them. In this sense, the COES helps identify jobs that are not only broadly exposed to emissions-related risk, but also particularly sensitive to economic shocks due to their strong reliance on a narrower set of industries. In other words, by accounting for heterogeneity in employment concentration across industries, the COES allows us to distinguish between occupations that may have similar average exposure (OES) but differ meaningfully in their potential sensitivity to sector-specific changes.

We define the COES score for an occupation o at time $t$as:

$$COES_{ot} = \frac{1}{\text{Employment}_{ot}} \times \left(\sum_i w_{iot}^{ind} \times (1 + w_{iot}^{occ}) \times \text{Emissions}_{it} \right) \tag{2}$$

where $w_{iot}^{occ} = \frac{Employment_{iot}}{Employment_{ot}}$ measures the share of occupation o employed in industry i relative to the total employment of that occupation, reflecting the concentration of the occupation within that industry ($w_{iot}^{occ} < 1$).

The term $(1 + w_{iot}^{occ})$ is used to inflate the emissions score based on how concentrated an occupation is within a specific industry. Adding 1 ensures that all scores are at least as large as those computed by OES, while w_{iot}^{occ} acts as an adjustment factor to emphasize the impact of industry concentration. If an occupation is heavily concentrated in a specific industry (w_{iot}^{occ} is large), the COES score will be proportionately inflated, capturing the heightened risk due to the reliance on that particular industry. This adjustment also reflects the outside options available to workers: a higher concentration implies that workers may have fewer outside options and thus greater exposure to industry-specific risks. Conversely, a lower concentration suggests that workers likely to have more outside options, potentially reducing their exposure.

For example, consider "petroleum engineers." They are predominantly employed in the oil and gas extraction industry, a sector with high emissions. This concentration inflates their COES relative to their OES, highlighting the additional exposure that stems from their limited industry dispersion.

Overall, the COES provides a more refined measure of occupational emissions exposure by incorporating information about industry concentration. This refinement is particularly relevant for understanding labor market risks in the context of a shifting energy economy or other sector-specific risks.

2.2.2. Wage-Adjusted Occupation Emissions Score (WOES)

While the OES provides a broad measure of exposure by averaging emissions intensity across industries, it assumes that all occupations within an industry contribute equally to emissions. In practice, this is unlikely. Some occupations hold greater decision-making authority or influence over emissions-related practices, a dimension not captured by employment shares alone.

To address this, we construct the Wage-Adjusted Occupational Emissions Score (WOES), which adjusts for differences in average wages across occupations and industries. The underlying assumption is that higher-wage occupations are more likely to influence operational practices, technology adoption, or strategic decisions that can affect emissions intensity. For example, in the steel manufacturing industry, managers, who typically earn higher wages, are more likely than production workers to determine whether to implement energy efficiency upgrades. By incorporating wage information, the WOES provides a more nuanced perspective on an occupation's potential role in shaping industry practices.

The WOES for an occupation o at time t is defined as:

$$WOES_{ot} = \frac{1}{Employment_{ot}} \times \left(\sum_i w_{iot}^{ind_w} \times Emissions_{it} \right), \tag{3}$$

where

$$w_{iot}^{ind_w} = \frac{Employment_{iot}}{Employment_{it}} \times \frac{\overline{wage}_{iot}}{\overline{wage}_{it}}$$

with $\overline{wage}_{iot}$ representing the mean wage for workers in industry i, occupation o, at time t, and $\overline{wage}_{it}$ representing the mean wage for all workers in industry i at year t. This industry-wage weight reflects the importance of an occupation within an industry by accounting for both its employment share and its relative wage, effectively incorporating wage information into the emissions weighting.

By adjusting for relative wages, the WOES highlights two key distinctions. First, it differentiates between occupations based not just on their emissions exposure, but also on their potential to influence emissions outcomes. Second, it addresses an implicit assumption of the OES, that emissions are uniformly attributable across all workers in an industry, by acknowledging that higher-wage roles may bear more responsibility for (emissions-related) decisions.

The comparison between WOES and OES also provides valuable insights into the wage dynamics of an occupation relative to its industry. When the WOES exceeds the OES, it suggests that the occupation earns above-average wages relative to the industry and may have greater decision-making authority. Conversely, a WOES lower than the OES points to below-average wages, implying that while the occupation may be exposed to emissions risks, it likely has less control over work practices. These distinctions can have important implications for policies. Occupations in high-emission industries with below-average wages may face the brunt of emissions-related economic disruptions without the ability to shape outcomes. Support for these workers may require direct compensation, temporary assistance, or targeted upskilling. By contrast, high-wage occupations may be better positioned to adapt, and reskilling efforts may be more effective in those contexts.

Thus, the WOES offers a refined measure, capturing not only which occupations are exposed to emissions but also who may have the potential to shape industry practices and outcomes. When used alongside the OES and COES, it enriches our understanding of occupational dynamics in emissions-intensive sectors and provides a more comprehensive framework for analyzing labor market risks in the context of both economic shifts and structural changes.

Having introduced the Occupational Emissions Score (OES) and its two extensions, the Concentration-Adjusted Emissions Score (COES) and the Wage-Adjusted Emissions Score (WOES), we describe the data used to construct and analyze these measures in the next section.

3. Data

This section presents the process of gathering, cleaning, and combining multiple data sources to construct occupation-level emissions intensity scores.[3] The strength of our analysis lies in the integration of granular data on emissions and occupational characteristics, enabling a nuanced measurement of emissions intensity across job types. We collect data on greenhouse gas emissions, employment, wages, demographics, and job postings from various sources. Through a rigorous data cleaning and preparation process, we link these datasets to generate detailed emissions intensity scores, offering insights into labor market trends and the regional distribution of occupations by emissions intensity. Appendix B, Table B.1, lists our OES, WOES, and COES scores for all occupation codes, making them publicly available for researchers, analysts and policymakers.

3.1. Emissions

Emissions data is not available at the occupation level. Therefore, we rely on industry-level emissions data and allocate these emissions to occupations based on their employment within each industry. This approach allows us to approximate the linkage between emissions from industry activities and the occupations associated with those activities.

Our industry-level greenhouse gas (GHG) emissions data is sourced from the United States Environmental Protection Agency (EPA)'s Greenhouse Gas Reporting Program (GHGRP). The GHGRP requires approximately 8,000 large emission sources across various industries to report their annual CO2-equivalent emissions from key greenhouse gases—carbon dioxide, methane, nitrous oxide, and sulfur hexafluoride.

The GHGRP reports emissions from two primary sources: direct emissions (Scope 1) and indirect emissions related to the end-use of products (Scope 3). Scope 1 emissions are generated by activities directly controlled by an industry and are reported at the facility level. Scope 3 emissions, on the other hand, result from upstream suppliers and represent potential emissions that would be released if the products they produce, import, or export were consumed, combusted, or oxidized. For example, in petroleum refining, Scope 1 emissions arise from the combustion processes involved in transforming crude oil into gasoline, while Scope 3 emissions occur when gasoline is burned in cars or when jet fuel is used in airplanes.[4]

Our analysis focuses on the period from 2016 to 2021, incorporating both Scope 1 and Scope 3 emissions, which together account for up to 90% of U.S. greenhouse gas emissions. We selected

[3] Additional details on the data are provided in Appendix A.

[4] We also explored alternative data sources, such as Bloomberg's greenhouse gas emissions datasets, but could not obtain detailed scope data at the industry level for the United States. Therefore, we rely on the GHGRP.

this period for two reasons. First, Scope 3 emissions data were incomplete prior to 2016. Second, including Scope 3 emissions is important for understanding the full emissions footprint of industries, especially in sectors like fossil fuel production, where a significant portion of emissions arises from the end-use of their products.[5]

It is important to note the potential for *double-counting* between Scope 1 and Scope 3 emissions in emissions accounting. For example, if a steel plant (a Scope 1 emitter) buys coal from a supplier (who reports Scope 3 emissions), there can be overlap in reporting because the coal supplier's Scope 3 emissions eventually become the steel plant's Scope 1 emissions. Estimating the precise greenhouse gas emissions attributable to an industry is challenging due to this potential overlap between Scope 1 and Scope 3 emissions.[6]

To address this challenge, we apply two extreme approaches. First, we assume **no overlap** between the two types of emissions, treating the total emissions for an industry as the sum of its Scope 1 and Scope 3 emissions. This approach assumes that Scope 1 and Scope 3 emissions arise from entirely separate sources, providing an upper bound on emissions. Second, we assume **complete overlap**, where all Scope 1 emissions are fully accounted for by the Scope 3 emissions reported by upstream suppliers. Under this approach, an industry's total emissions are equal to the maximum of its Scope 1 and Scope 3 emissions, establishing a lower bound and ensuring no double-counting.[7]

The GHGRP reporting system, while comprehensive, has some limitations. First, it does not include direct emissions from agriculture or Scope 2 emissions which refer to indirect emissions from the generation of purchased electricity, steam, heating, or cooling consumed by an organization. Second, facilities with potential annual emissions below 25,000 metric tons of CO2-equivalent are exempt from reporting. To address these gaps, we assume industries not reporting Scope 1 or Scope 3 emissions have zero emissions.[8]

With these caveats in mind, we combine emissions data from the 2016-2021 GHGRP reports and aggregate facility-level data to the six-digit NAICS industry level. Approximately 250 six-digit NAICS industries report emissions annually in the GHGRP, out of a total of 1,271 detailed NAICS industries.[9] To align with Census data on employment, wages, and demographics, we constructed a crosswalk between NAICS and Census industry codes. As Census industry codes are less

[5]Although we could have extended the analysis back to 2010 by using only Scope 1 data, doing so would have provided an incomplete picture of the emissions intensity affecting workers in these industries.

[6]Graham and Knittel (2024) use elasticity-based methods to address such a potential overlap and highlight the complexities involved in accurately allocating emissions across scopes.

[7]Using both approaches, the results are similar, likely due to the concentration of emissions in a few key industries where Scope 1 emissions dominate.

[8]This assumption, while necessary for our analysis, is not particularly restrictive, as most non-reporting facilities are smaller emitters below the reporting threshold. Moreover, our analysis primarily aims to identify occupations that are associated with high levels of greenhouse gas emissions and are most exposed to the shift in the economy's energy mix.

[9]The 1,271 number refers to the total sum of NAICS codes under the 2007, 2012, and 2017 versions of the NAICS classification system.

detailed than six-digit NAICS codes, we aggregate the 1,271 six-digit NAICS codes into 245 Census industry codes. The resulting dataset provides annual CO2-equivalent emissions (Scope 1, Scope 3 maximum, and summed emissions) for each industry between 2016 and 2021.

Table 1: *Top 20 Industries with the Highest Reported Scope 1 and Scope 3 Emissions in 2022*

	2016			2022				
Industry Name	Scope 1 + 3	Scope 1	Scope 3	Scope 1 + 3	Scope 1	Scope 3	Share of Emissions in 2016 (%)	Share of Emissions in 2022 (%)
All Industries (Total)	7,079	2,987	4,091	7,181	2,689	4,492	100	100
Top 20 Industries in 2022:								
Petroleum refining	2,799	202	2,597	2,808	182	2,626	39.54	39.11
Fossil Fuel Electric Power Generation	1,841	1,841	0	1,553	1,553	0	26.01	21.63
Natural gas distribution	775	21	754	838	21	817	10.94	11.67
Oil and gas extraction	493	203	290	612	208	404	6.96	8.52
Petroleum and petroleum products merchant wholesalers	204	0	204	321	0	320	2.89	4.46
Industrial and miscellaneous chemicals	191	129	62	159	136	23	2.69	2.21
Pipeline transportation	84	46	38	145	65	80	1.19	2.02
Wholesale electronic markets, agents and brokers	49	0	49	100	0	100	0.69	1.40
Cement, concrete, lime, and gypsum products manufacturing	91	91	0	93	93	0	1.29	1.30
Waste management and remediation services	97	97	0	92	92	0	1.37	1.29
Services incidental to transportation	40	0	39	74	9	65	0.56	1.03
Iron and steel mills and steel products manufacturing	66	66	0	57	57	0	0.93	0.79
Agricultural chemicals	33	33	0	41	41	0	0.47	0.57
Pulp, paper, and paperboard mills	42	42	0	37	37	0	0.60	0.52
Coal mining	39	39	0	27	27	0	0.56	0.37
Resin, synthetic rubber, and fibers and filaments	27	27	0	25	25	0	0.39	0.34
Electric power generation, transmission and distribution	27	10	16	24	6	19	0.38	0.34
Other administrative, and other support services	25	2	22	23	2	21	0.35	0.32
Animal food, grain and oilseed milling	20	20	0	19	19	0	0.28	0.26
Aluminum production and processing	12	12	0	12	12	0	0.16	0.16
Average Industry	288	122	167	293	110	183	4.1	4.1

Notes: Emission values are reported in millions of metric tons of CO2e. The sample includes 245 industries, of which 125 report either Scope 1 or Scope 3 emissions. The remaining industries are assumed to have zero Scope 1 or Scope 3 emissions.

Table 1 presents the top 20 industries with the highest reported total Scope 1 and Scope 3 emissions in 2022, alongside their reported emissions in 2016 and their share of the overall emissions reported by the GHGRP. The top row summarizes data for all industries. In 2016, total reported emissions amounted to 7,079 million metric tons of CO2-equivalent, with Scope 1 emissions comprising 42% of this total and Scope 3 emissions accounting for the remaining 58%. By 2022, total reported emissions had increased slightly by about 1% to 7,181 million metric tons. Notably, while Scope 1 emissions decreased by around 10% during this period, Scope 3 emissions increased by about 10%, which may reflect changes in industry practices and consumer behavior.

The concentration of emissions becomes clear when examining the industry-level breakdown. Petroleum refining was the largest emitter in both 2016 and 2022, accounting for 39% of total reported emissions in 2022. Most of this industry's emissions are Scope 3, as its products—gasoline, diesel, and jet fuel—are combusted by end users. Similarly, fossil fuel electric power generation ranked second, contributing 21.6% of total emissions in 2022, with the majority stemming from Scope 1 activities. Together, the top five industries in 2022 accounted for over 85% of total reported emissions, highlighting the heavy concentration of emissions within a few sectors. This skewed distribution is further reflected in the average industry in our sample, which reported 293 million metric tons of emissions per year—just 4.1% of overall emissions.

3.2. Occupation Employment, Wages, and Demographics

We use data from the 2010-2022 Census American Community Survey (ACS) to link industry-level emissions to occupations. This data is sourced from the Integrated Public Use Microdata Samples (IPUMS) database (Ruggles et al., 2024). The primary advantage of this data source is its detailed information on respondents' occupations and industries, along with labor market demographics and geographic characteristics. Additional benefits include its large sample size and representativeness (1 percent of the U.S. population), as well as its annual frequency, which supports consistent and up-to-date analysis.[10]

Our sample comprises 447 distinct occupation codes. For each occupation-year pair, we construct variables for employment, mean annual wage, hourly wage, and demographic characteristics, including average age, gender composition, racial composition, and educational attainment. To construct our occupation emission scores, we use Census industry codes to link the GHGRP emissions data to ACS observations, thus connecting industries to occupations.

3.3. Job Openings

One application of our occupation-level emissions intensity scores is to analyze regional variations in occupational emissions intensity by comparing different geographic units. In addition to assessing the supply of workers in different occupations using employment data, we examine the demand for workers across geographic locations through job postings.

We use online job posting data collected by Lightcast, which aggregates job postings from more than 45,000 online job boards and company websites. This data provides near-complete coverage of jobs posted online, providing granular details on a job's occupation, industry, and location. Using commuting zones (based on the 1990 delineation) as our labor market units, we

[10]An alternative data source is the Bureau of Labor Statistics (BLS) Occupational Employment Statistics (OES), which provides aggregate employment and wage statistics by occupation and industry. However, the OES excludes many six-digit SOC by six-digit NAICS cells for confidentiality reasons. Moreover, it lacks some of the additional characteristics available in the ACS, such as demographic information, which allows for a more comprehensive analysis of occupations.

analyze the demand for workers in six-digit SOC occupations across various labor markets over time.

For each year from 2010 through 2022, we count the number of online job postings by Census occupation code within each commuting zone. We then calculate the share of job postings for a given occupation code out of the total number of job postings in the commuting zone for that year. By multiplying this share by the occupation's emissions score (developed earlier in this paper), we derive a commuting-zone-level occupational emissions score. This score reflects the local demand for occupations with varying emissions intensities and indicates whether a labor market is more emissions-intensive compared to others across the nation.

Additionally, we analyze changes in local demand for occupations over time to assess whether a given labor market is becoming more or less emissions-intensive on average. This temporal analysis provides important insights into how the demand for high- and low-emission occupations evolves across regions, offering useful context for policymakers seeking to understand changes in regional labor markets as the economy adapts to shifts in energy composition.

4. Results

4.1. Descriptive Statistics and Distributions

We begin by presenting descriptive statistics for the Occupation Emissions Score (OES), the Wage-Adjusted Occupation Emissions Score (WOES), and the Concentration-Adjusted Occupation Emissions Score (COES). Table 2 presents summary statistics for these three scores over the period 2016-2022. All three distributions are right-skewed, as indicated by the large discrepancies between their mean and median values. For instance, the mean OES is 83 metric tons of CO2e per worker per year, while the median is significantly lower at 14 metric tons of CO2e per worker per year. A similar pattern emerges for the WOES and COES, where most occupations exhibit relatively low emissions scores but a small number of occupations contribute disproportionately to the total.

Table 2: *Occupational Emissions Scores, Summary Statistics (2016-2022 Average)*

Summary Statistic	Score	Occupation Title
OES		
Mean	83	Sailors and marine oilers, and ship engineers
Standard Deviation	305	
Min	0.007	Special Education Teachers
5th Percentile	0.08	Food Preparation and Serving Related Workers, All Other
25th Percentile	1.01	Sewing Machine Operators
50th Percentile (Median)	14	Personal Financial Advisors
75th Percentile	512	Home Appliance Repairers
95th Percentile	233	Crushing, Grinding, Polishing, Mixing, and Blending Workers
Max	3,776	Chemical/Gas/Petroleum/Other Plant and System Operators
WOES		
Mean	80	Astronomers and Physicists
Standard Deviation	316	
Min	0.004	Barbers
5th Percentile	0.05	Phlebotmists
25th Percentile	0.68	Dental Hygienists
50th Percentile (Median)	10	First-Line Supervisors of farming, fishing, and forestry workers
75th Percentile	51	Other Financial Clerks
95th Percentile	225	Electrical and Electronics Engineers
Max	3,406	Chemical/Gas/Petroleum/Other Plant and System Operators
COES		
Mean	96	Training and Development Specialists
Standard Deviation	384	
Min	0.007	Special Education Teachers
5th Percentile	0.082	Dishwashers
25th Percentile	1.13	Personal Care and Service Workers, All Other
50th Percentile (Median)	14	Rail-Track Laying and Maintenance Equipment Operators
75th Percentile	52	Home Appliance Repairers
95th Percentile	240	Crushing, Grinding, Polishing, Mixing, and Blending Workers
Max	4,493	Chemical/Gas/Petroleum/Other Plant and System Operators
Number of Occupations	447	

Notes: All scores are reported in metric tons of CO2e. We use total emissions measured as the sum of Scope 1 and Scope 3 emissions. A small number of observations, with reported emissions below 0.001 tons, have been winsorized to 1.

This right-skewness is driven by a small group of occupations heavily concentrated in emissions-intensive industries. For example, Chemical/Gas/Petroleum/Other Plant Operators are consistently among the jobs with the highest emissions intensity across all three measures. Conversely, occupations like Special Education Teachers and Barbers rank among the lowest, with emissions scores close to zero. The large standard deviations—305 for OES, 384 for COES, and 316 for WOES—suggest substantial variation in emissions scores across occupations.

While the three scores share similar characteristics, important nuances emerge. COES amplifies the scores for occupations highly concentrated in a few high-emission industries, which explains its higher standard deviation. Although the concentration adjustment increases variability, it does not fundamentally change the overall distribution compared to OES. By contrast, WOES, which adjusts for wage differences, yields a smoother distribution with slightly lower mean and median values than OES and COES.

For instance, Chemical/Gas/Petroleum/Other Plant Operators have an OES score of 3,776, indicating that each worker in this occupation is associated with an average of 3,776 metric tons of CO2e emissions annually. Their COES rises to 4,493 metric tons of CO2e, reflecting their higher concentration within emissions-intensive industries and increasing their sensitivity to shifts in industry practices or policy changes. However, their WOES of 3,406 highlights that a significant share of these workers are lower-wage employees who may have less decision-making influence but remain exposed to industry changes.

Turning to the kernel density plot in Figure 1, we visualize the distributions of OES, WOES, and COES using logged values for better clarity. The plot shows that the OES and COES distributions are nearly identical, confirming that the concentration adjustment does not significantly alter the overall emissions profile. In contrast, the WOES curve, is more compressed and peaks at a lower value, reflecting the wage adjustment's role in moderating extreme values. While all three distributions remain skewed, WOES provides a slightly less skewed representation by accounting for wage differences.

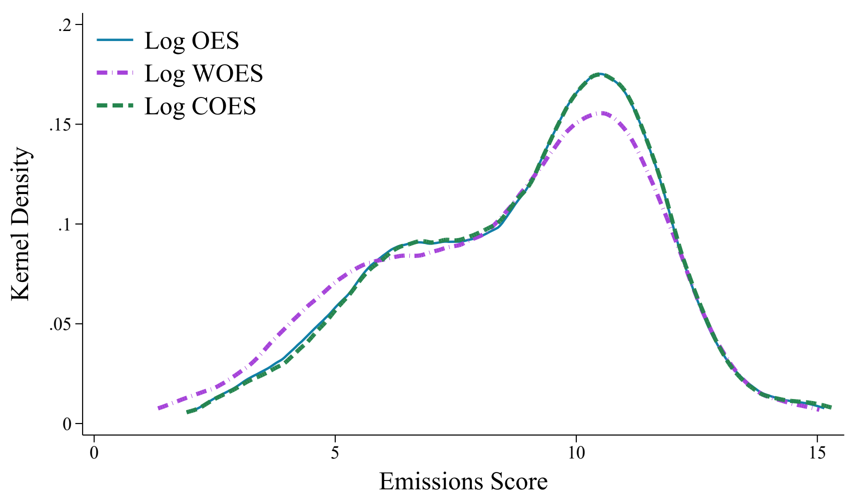


Figure 1: *Kernel Density Estimates of Occupational Emissions Scores (2016-2022 Average)*

Notes: The density estimates represent the distribution of average occupational emission scores from 2016 to 2022. Annual logged scores are collapsed into one average score for each of the 447 occupations in the sample.

Table 3: *Top and Bottom Occupations by Emissions Score (2016-2022 Average)*

	Rank	Occupation	Score
OES			
	Top 5 Scores	Chemical/Gas/Petroleum/Other Plant and System Operators	3,776
		Geological/Petroleum/Nuclear/Hydrologic/Other Science Technicians	2,481
		Petroleum, mining and geological engineers, including mining safety engineers	2,003
		Chemical Engineers	1,975
		Power Plant Operators, Distributors, and Dispatchers	1,923
	Bottom 5 Scores	Special Education Teachers	0.007
		Hairdressers, Hairstylists, and Cosmetologists	0.011
		Miscellaneous Personal Appearance Workers	0.012
		Preschool and Kindergarten Teachers	0.014
		Chiropractors	0.019
WOES			
	Top 5 Scores	Chemical/Gas/Petroleum/Other Plant and System Operators	3,406
		Petroleum, mining and geological engineers, including mining safety engineers	3,253
		Chemical Engineers	2,871
		Power Plant Operators, Distributors, and Dispatchers	2,075
		Geological/Petroleum/Nuclear/Hydrologic/Other Science Technicians	2,017
	Bottom 5 Scores	Barbers	0.004
		Preschool and Kindergarten Teachers	0.004
		Hairdressers, Hairstylists, and Cosmetologists	0.004
		Special Education Teachers	0.004
		Chiropractors	0.006
COES			
	Top 5 Scores	Chemical/Gas/Petroleum/Other Plant and System Operators	4,493
		Power Plant Operators, Distributors, and Dispatchers	3,345
		Geological/Petroleum/Nuclear/Hydrologic/Other Science Technicians	2,812
		Electrical Power-Line Installers and Repairers	2,769
		Petroleum, mining and geological engineers, including mining safety engineers	2,331
	Bottom 5 Scores	Special Education Teachers	0.007
		Hairdressers, Hairstylists, and Cosmetologists	0.011
		Miscellaneous Personal Appearance Workers	0.012
		Preschool and Kindergarten Teachers	0.014
		Chiropractors	0.019

Notes: This table lists the top and bottom five occupations based on their 2016-2022 OES, WOES, and COES scores. All scores are in metric tons of CO2e and use the sum of Scope 1 and Scope 3 emissions as the measure of total industry emissions.

Table 3 further highlights the distribution of emissions by listing occupations with the highest and lowest emissions intensities. As expected, occupations in energy production and distribution—such as Power Plant Operators and Petroleum Engineers—consistently rank at the top across all three measures. On the other hand, occupations in education and personal services, such as Special Education Teachers and Hairdressers, consistently rank at the bottom. Notably, there is strong consistency in the occupations appearing at the top and bottom of the rankings across the different scores, highlighting the robustness of our measures.

Table 4: *Top and Bottom Occupations by Change in Emissions Score (2016-2022 Change)*

Rank	Occupation	2016 Score	2022 Score	Change
OES				
Top 5 Scores	Derrick, rotary drill, and service unit operators, and roustabouts, oil, gas, and mining	439.213	1,083.820	644.607
	Petroleum, mining and geological engineers, including mining safety engineers	1,938.867	2,494.157	555.290
	Riggers	103.837	613.781	509.944
	Adhesive Bonding Machine Operators and Tenders	14.603	347.957	333.354
	Mining Machine Operators	262.597	575.653	313.056
Bottom 5 Scores	Boilermakers	1,815.979	1,004.211	-811.768
	Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders	828.549	76.481	-752.067
	Meter Readers, Utilities	1,770.535	1,243.495	-527.040
	Engine and Other Machine Assemblers	552.203	32.178	-520.025
	Power Plant Operators, Distributors, and Dispatchers	2,224.700	1,758.876	-465.823
WOES				
Top 5 Scores	Petroleum, mining and geological engineers, including mining safety engineers	3,384.638	4,135.459	750.821
	Riggers	72.898	492.646	419.748
	Chemical/Gas/Petroleum/Other Plant and System Operators	2,713.519	3,078.631	365.112
	Geological/Petroleum/Nuclear/Hydrologic/Other Science Technicians	2,049.320	2,365.579	316.259
	Chemists and Materials Scientists	290.320	562.054	271.735
Bottom 5 Scores	Power Plant Operators, Distributors, and Dispatchers	2,475.010	1,820.459	-654.551
	Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders	617.248	77.765	-539.483
	Boilermakers	1,102.197	715.499	-386.697
	Chemical Engineers	3,190.937	2,828.282	-362.654
	Control and Valve Installers and Repairers	1,229.418	871.343	-358.074
COES				
Top 5 Scores	Derrick, rotary drill, and service unit operators, and roustabouts, oil, gas, and mining	482.627	1,271.433	788.807
	Petroleum, mining and geological engineers, including mining safety engineers	2,267.017	2,893.606	626.588
	Riggers	105.651	634.914	529.262
	Mining Machine Operators	288.043	661.252	373.209
	Adhesive Bonding Machine Operators and Tenders	14.988	356.444	341.456
Bottom 5 Scores	Boilermakers	2,023.279	1,068.954	-954.325
	Power Plant Operators, Distributors, and Dispatchers	3,844.124	3,032.481	-811.643
	Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders	870.947	80.196	-790.751
	Meter Readers, Utilities	2,183.990	1,531.533	-652.457
	Control and Valve Installers and Repairers	1,870.068	1,323.879	-546.189

Notes: This table shows the top and bottom five occupations based on the change in their OES, WOES, and COES scores from 2016 to 2022. All scores are in metric tons of CO_2e, using the sum of Scope 1 and Scope 3 emissions as the measure of total industry emissions.

Table 4 expands on this analysis by presenting occupations that experienced the largest changes in emissions intensity between 2016 and 2022. Petroleum, Mining, and Geological Engineers and Rotary Drill Operators have shown significant increases in emissions scores, which may reflect growing activity in oil and gas extraction and expanded production. Meanwhile, occupations such as Boilermakers and Power Plant Operators have experienced declines in emissions scores. These changes may reflect technological advancements, shifts toward other energy sources, or regulatory changes that may have reduced their emissions intensity.

It is also important to assess the consistency and relationships across our three measures. For this purpose, figure 2 presents a correlation matrix that examines the relationships between OES, COES, and WOES. We construct two versions of each measure: a benchmark version that sums Scope 1 and Scope 3 emissions (assuming no overlap) and an alternative version that takes the maximum of Scope 1 and Scope 3 emissions (assuming complete overlap). The high correlations between the benchmark and alternative versions suggest that accounting for potential double-counting has minimal effect on measuring occupational emissions intensity. Moreover, the WOES is slightly less correlated with the OES and COES, likely due to the additional variability introduced by the wage adjustment. Overall, the strong correlations across all three measures highlight the robustness of our emissions intensity framework and validate the use of the OES as our baseline measure for the remainder of the analysis.

	OES_{Sum}	$WOES_{Sum}$	$COES_{Sum}$	OES_{Max}	$WOES_{Max}$
$WOES_{Sum}$	0.951				
$COES_{Sum}$	0.985	0.941			
OES_{Max}	0.997	0.941	0.989		
$WOES_{Max}$	0.960	0.996	0.956	0.956	
$COES_{Max}$	0.974	0.923	0.997	0.984	0.944

Figure 2: *Pairwise Correlation Matrix of Occupational Emissions Scores*

Notes: The matrix shows the pairwise correlation coefficients between the OES, WOES, and COES scores for occupation-year pairs. The sample consists of 447 occupations. Each score is calculated using two methods: one based on the sum of Scope 1 and Scope 3 emissions as total industry emissions, and the other based on the maximum of Scope 1 and Scope 3 emissions.

In summary, the descriptive statistics and distributions reveal significant skewness in occupational emissions intensity. A small number of occupations, concentrated in high-emission industries, dominate the emissions profile, while the majority of occupations contribute minimally. The additional insights provided by the WOES and COES scores highlight the importance of accounting for wage differences and industry concentration when evaluating occupational exposure to emissions-related risks.

4.2. Beyond Industries: The Importance of Occupational Heterogeneity

A potential critique of our approach is the focus on occupations rather than industries when analyzing emissions intensity. However, an industry-level analysis alone can overlook significant heterogeneity in workers' exposure to emissions-related risks. Many occupations are distributed across multiple industries with varying emissions profiles, and even within a single industry, workers in different occupations may face significantly different exposures. Moreover, recent research highlights the importance of occupations, rather than industries, in shaping worker outcomes amid economic transformations. For instance, Traiberman (2019) shows that in the context of exposure to import competition, most of the variation in worker outcomes is explained by occupations rather than industries. Similarly, Kambourov and Manovskii (2009) find that human capital is largely occupation-specific, and that occupational mobility is a key driver of wage dynamics and inequality. Building on these insights, our analysis focuses on occupational differences. This section shows that examining emissions intensity at the occupational level is important for understanding heterogeneity in exposure to adjustment risks, indicating significant variation even within the same industry.

Table 5 illustrates this heterogeneity by providing examples of occupations with varying emission intensities across industries. Panel I shows employment statistics for three occupations: petroleum engineers, secretaries and administrative assistants, and medical and health services managers, representing the top, middle, and bottom terciles of the 2022 OES distribution, respectively. For example, petroleum engineers are heavily concentrated in the high-emission petroleum refining industry, but are also employed in medium- and low-emission industries, such as construction, mining and oil field machinery, and gasoline stations. Secretaries and administrative assistants (medium OES) similarly span high- and low-emission industries, from petroleum refining to medical equipment and supplies. Medical and health services managers (low OES) are typically employed in low-emission sectors but are not completely insulated from emissions-intensive industries. These examples show that emissions exposure cannot be inferred solely from industry affiliation.

Table 5: Examples of Occupational Distribution across Industries with Varying Emission Levels

Industry		Occupation-Industry Pair		
Title	Emissions Ranking	Employment	% of Industry Employment	% of Occupation Employment
(1)	(2)	(3)	(4)	(5)
I. Occupations				
I.A. Petroleum Engineers (High Emissions Intensity)				
Petroleum Refining	High	2,457	1.2%	7.2%
Construction, mining, and oil field machinery	Medium	155	0.1%	0.5%
Gasoline Stations	Low	1,140	0.15%	3.4%
I.B. Secretaries and Administrative Assistants (Medium Emissions Intensity)				
Petroleum Refining	High	1,869	0.9%	0.1%
Structural metals, and tank and shipping container manufacturing	Medium	6,626	1.7%	0.2%
Medical equipment and supplies	Low	8,869	0.96%	0.3%
I.C. Medical and Health Services Managers (Low Emissions Intensity)				
Hospitals	High	344,132	4.0%	37.0%
Offices of physicians	Medium	78,696	3.5%	8.5%
Management, scientific and technical consulting services	Low	1,358	0.05%	0.1%
II. Industries				
II.A. Petroleum Refining (High Emissions Sector)				
Petroleum Engineers	High	2,457	1.2%	7.2%
Secretaries and Administrative Assistants	Medium	1,869	0.9%	0.1%
Food Service Managers	Low	120	0.06%	0.0%
II.B. Offices of Physicians (Medium Emissions Sector)				
General and Operations Managers	High	5,128	0.2%	0.4%
Secretaries and Administrative Assistants	Medium	102,809	4.6%	3.1%
Registered Nurses	Low	189,652	8.49%	4.6%
II.C. Advertising, public relations, and related services (Low Emissions Sector)				
Marketing and Sales Managers	High	49,817	7.1%	3.6%
Commercial And Industrial Designers	Medium	39,414	5.6%	3.4%
Advertising Sales Agents	Low	60,032	8.53%	44.5%

Notes: This table presents examples of occupations with different levels of emission intensity, based on the OES scores, and their distribution across industries with varying emission levels in 2022. High, medium, and low emission intensities are defined as the corresponding terciles of the (log) OES for occupations and total Scope 1 and Scope 3 emissions for industries. In Panel I, each sub-panel corresponds to a specific occupation, while in Panel II, each sub-panel corresponds to an industry. Employment figures are derived from the ACS for 2022.

Panel II of Table 5 shifts the perspective to industries—petroleum refining, offices of physicians, and advertising and public relations—which fall into the top, middle, and bottom terciles of industry emission levels in 2022. Each industry employs occupations from different parts of the OES distribution. For instance, in petroleum refining, petroleum engineers account for 1.2% of employment, while secretaries and administrative assistants for 0.9%, and food service managers for only 0.06%. These patterns show that even within industries classified by their emissions levels, workers face different exposures depending on their occupation. Petroleum engineers, for example, may face greater risk due to their involvement in emissions-heavy processes, while food service managers in the same industry are likely to be less affected.

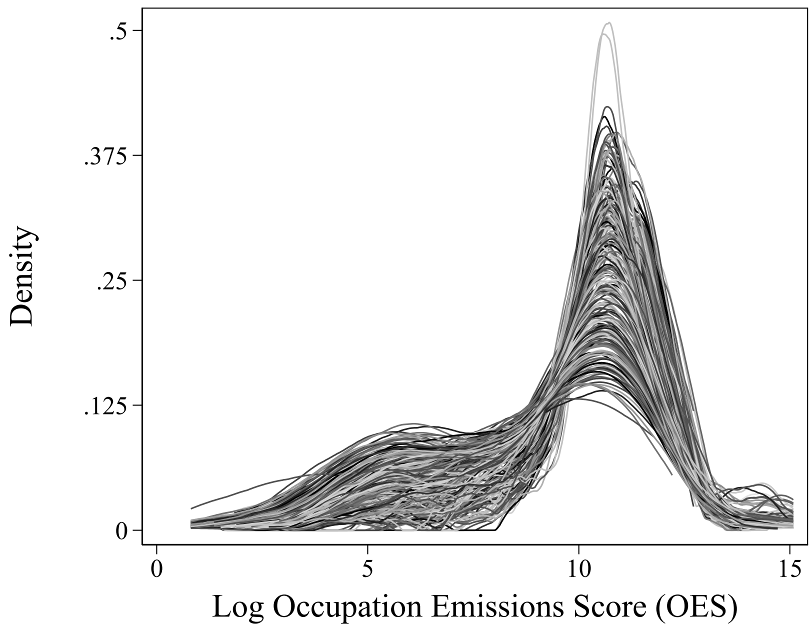


Figure 3: *Kernel Density Estimates of Occupational Emissions Scores across Industries (2022)*

Notes: Each line in the chart represents a kernel density estimate of the distribution of average occupational emissions scores (log annual scores for 2022) across the 245 industries in our sample.

Figure 3 further illustrates this point by presenting kernel density estimates of the (log) OES for all 245 industries in our sample. Within most industries, there is a wide spread of occupational emissions scores, spanning low, medium, and high values. This internal variation highlights that workers' emissions exposure depends not just on the industry they work in, but critically on their specific occupation.

In summary, relying solely on industry-level analysis alone would provide an and potentially misleading picture of labor market exposure to emissions-related risks. Occupations and industries are not interchangeable; both dimensions must be considered to accurately assess risks. The substantial heterogeneity within industries and the variation in exposure across occupations emphasize the need for granular, occupation-level analysis. Recognizing this heterogeneity is crucial for better mapping emissions risk across the workforce and informing analyses of labor market adjustment.

Having established the importance of occupational variation in emissions exposure, we now turn to the temporal evolution of occupational emissions scores. Analyzing changes over time offers insights into the dynamics of occupational exposure and the pace of the economy's diversification away from high-emissions activities.

4.3. Evolution of Scores Over Time

This section examines the evolution of our scores over time, offering insights into the dynamics of occupational emissions intensities. Figure 4 presents the average annual OES, WOES, and COES scores from 2016 to 2022. All three measures show a general decline in emissions intensity over this period, with COES consistently higher than OES, and WOES consistently lower. The levels differ due to the effects of concentration and wage adjustments, but the downward trends are broadly similar across all three scores.

The decreasing trend in average emissions scores suggests that some industries have reduced their emissions, particularly Scope 1 emissions, as documented earlier in Table 1. Additionally, shifts in employment concentration across occupations may have contributed to this decline. The sharp dip in 2020 aligns with the pandemic-driven contraction in economic activity, followed by a return to pre-pandemic trends in 2021.

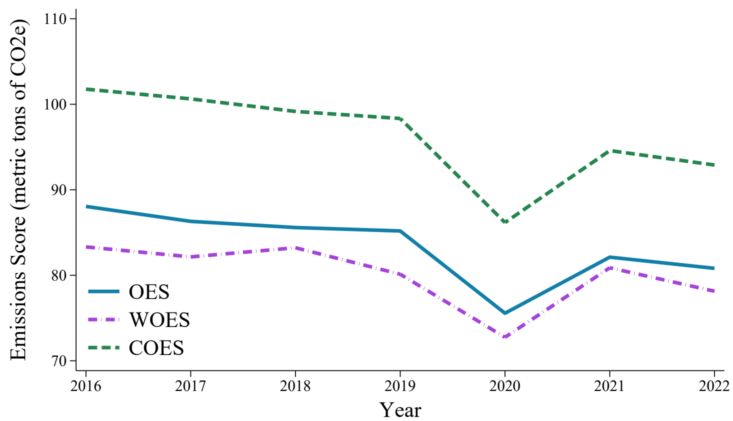


Figure 4: *Time Series of Average Emissions Scores*

Having discussed the overall trends in average scores, we next explore how the distribution of occupational emissions intensities has evolved over time. Figure 5 presents kernel density estimates of the (log) OES scores for 2016 and 2022. While the distribution remains right-skewed, there is a noticeable narrowing of the range by 2022, with fewer occupations at both the very high and very low ends of the emissions distribution. This suggests some convergence in emissions intensity across occupations, even though substantial skewness persists.

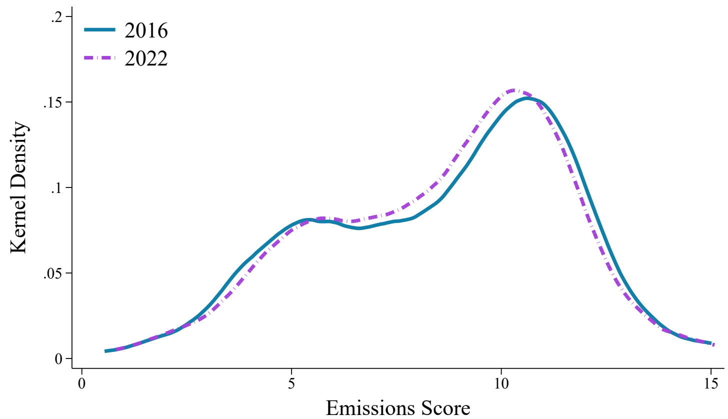


Figure 5: *Kernel Density Estimates of OES Scores (2016 vs. 2022)*

Notes: The density estimates show the distribution of logged OES scores in 2016 (solid blue line) and 2022 (dashed purple line) across the 447 occupations in our sample, highlighting changes in the distribution of emissions intensity over time.

Table 6: *Examples of Occupations: Percent Change in OES Scores (2016-2022) by Initial Tercile*

Tercile	Occupation	Percent Change
Largest Decrease		
Bottom Tercile	Automotive Glass Installers and Repairers	-52.23%
Middle Tercile	Dental Hygienists	-75.49%
Top Tercile	Biomedical and Agricultural Engineers	-43.96%
Insignificant Change		
Bottom Tercile	Nurse Anesthetists	-0.05%
Middle Tercile	Small Engine Mechanics	-0.17%
Top Tercil	Environmental Scientists and Geoscientists	-0.01%
Largest Increase		
Bottom Tercile	Actuaries	266.28%
Middle Tercile	Adhesive Bonding Machine Operators and Tenders	33.07%
Top Tercile	Riggers	15.38%

Notes: The table shows the percent change in logged OES scores between 2016 and 2022, grouped by their initial score tercile in 2016. Panel (a) lists occupations with the largest percent decreases in scores. Panel (b) presents examples of occupations with minimal changes in scores, and Panel (c) presents occupations that experienced the largest percent increases.

To further investigate these patterns, Table 6 presents changes in emissions scores by grouping occupations into terciles based on their initial 2016 OES levels. The goal is to assess whether declines in emissions intensity were broad-based or concentrated among particular types of occupations. Panel (a) lists occupations with the largest decreases in emissions intensity, such as automotive glass repairers and dental hygienists, with declines ranging from 44% to 75%. Panel (b) shows occupations with relatively stable emissions scores over time, while Panel (c) presents occupations with increases. For example, riggers experienced a modest 15% increase, and actuaries saw a larger percentage rise albeit from a low starting point. These patterns indicate that while most occupations experienced declines or stability in emissions intensity, some occupations—particularly in niche sectors—experienced increases, underscoring the uneven nature of the adjustment process.

Overall, the evolution of occupational emissions scores presents three key patterns: a general decline in average emissions intensity, a narrowing of the distribution over time, and uneven rates of change across occupations.

We next illustrate how our measures can be used to analyze economic conditions and differences. In Section 5.1, we analyze the relationship between emissions intensities and demographic characteristics. In Section 5.2, we explore how emissions intensity correlates with key labor market outcomes, including employment levels, wages, and job postings. In Section 5.3, we construct commuting-zone level scores using the OES to examine geographic variation. Finally, in Section 5.4, we present an event study using our measures to evaluate the effects of coal mine closures.

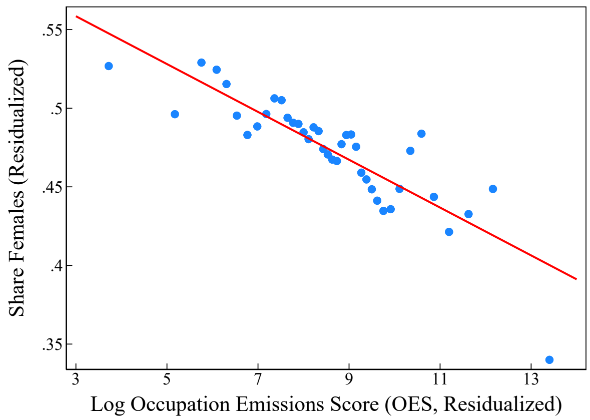
5. Applications

5.1. Demographic Differences

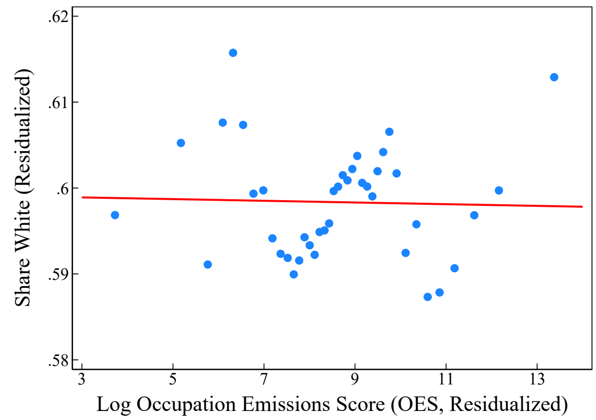
We begin the applications section by examining how demographic characteristics intersect with emissions intensity, highlighting potential discrepancies in the transformation. Using data from the 2016-2022 American Community Survey (ACS), we link key demographics—age, sex, race, and education—to occupation-level emissions scores.

Figure 6 presents residualized scatter plots, binned into 40 quantiles, to illustrate the relationship between demographic characteristics and occupational emissions intensity. The results show that higher-emission occupations are more likely to be held by older, native-born males.[11]

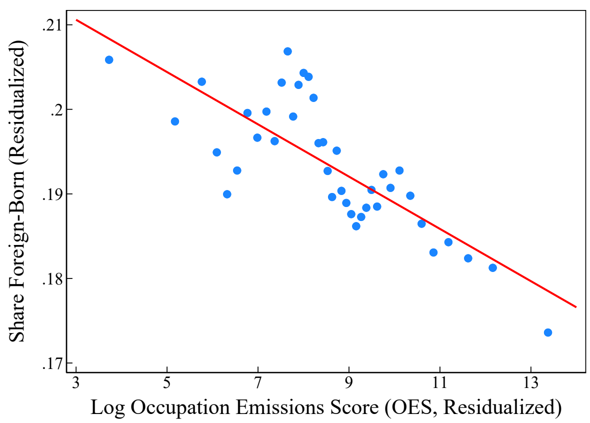
[11] Residual scatter plots control for industry and year fixed-effects, as well as all covariates except the characteristic of interest, to mitigate spurious correlations.



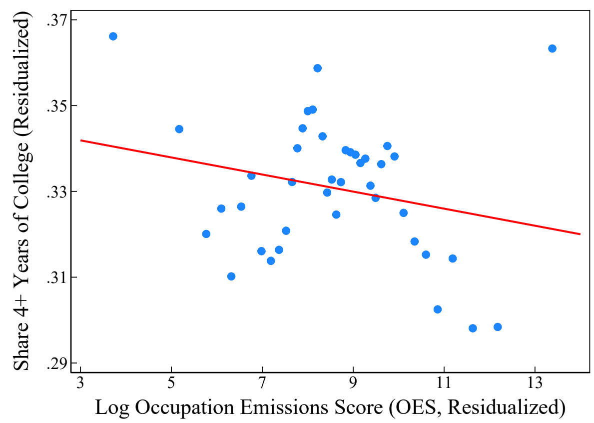
(a) *Share Females in Occupation*



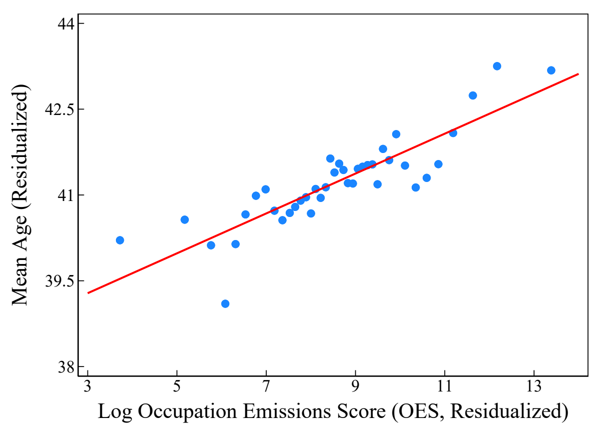
(b) *Share Non-Hispanic Whites in Occupation*



(c) *Share Foreign-Born in Occupation*



(d) *Share 4+ Years of College in Occupation*



(e) *Mean Age in Occupation*

Figure 6: *Residualized Binned Scatter Plots of OES and Demographic Characteristics*

Notes: The charts present residualized scatter plots of the relationship between the (log) occupational emissions score (OES) and key demographic characteristics: (a) share females, (b) share non-Hispanic whites, (c) share foreign born, (d) share individuals with 4+ years of college, and (e) mean age. Each dot represents an occupation score quantile (40 quantiles overall). Residuals are estimated with industry and year fixed effects, as well as the covariates listed in Table 7, using leave-one-out type estimation. Residuals are mean-standardized for ease of interpretation. Red lines are the fitted regression line for the relationship.

Table 7: *Relationship between OES Scores and Demographic Characteristics*

	Outcome: Log Occupation Emissions Score	
	(1)	(2)
Age	0.00811***	-0.0000145
	(0.000772)	(0.0000339)
Female	-0.283***	-0.00208**
	(0.0394)	(0.00102)
Foreign-Born	-0.106***	-0.00251***
	(0.0119)	(0.000835)
Race/Ethnicity (White Non-Hispanic Omitted)		
Black	-0.00933	0.00113
	(0.0207)	(0.00109)
Hispanic	0.00161	0.000599
	(0.0117)	(0.000819)
Other	0.0137	-0.000942
	(0.0104)	(0.000968)
Education (High Scool Omitted)		
Less Than High School	-0.159***	0.00251**
	(0.0256)	(0.00123)
2-Year College (associate degree)	0.000188	0.00117
	(0.0139)	(0.000880)
4-Year College (bachelor's degree)	0.0628	0.00153
	(0.0410)	(0.00117)
Graduate or Professional Degree	-0.296***	0.0002
	(0.0730)	(0.00185)
Log Occupation Emissions Score - Mean	8.64	
Log Occupation Emissions Score - SD	2.67	
Year Fixed Effects	X	X
Industry Fixed Effects	X	X
Occupation Fixed Effects		X
Observations	10,411,537	10,411,537
R-Squared	0.489	0.958

*Notes: The table reports coefficients from regressions where the dependent variable is the log occupation emissions score (OES) and the explanatory variables are demographic characteristics of individuals who report having that occupation in the American Community Survey (ACS). The data spans 2016-2022 and includes individuals aged 18-65 with at least one year of potential work experience. All regressions are weighted by ACS person weights, and standard errors clustered by occupation-year are shown in parentheses. **** $p < 0.01$; **** $p < 0.05$; *** $p < 0.1$.

Regression results in Table 7 further substantiate these findings. Estimates presented in column (1) suggest that older native-born white males are more likely to work in occupations with higher emissions intensity. The relationship with education is more nuanced: compared to high school graduates, individuals with less than a high school degree or a graduate degree are more likely to work in lower-emission occupations, while those with a bachelor's degree are more likely to work in higher-emission jobs.

When controlling for occupation fixed effects in column (2), the gender and nativity effects remain significant, while the statistical significance of age and race diminishes.[12] Interestingly, the

[12]The estimates in column (1) capture between-occupation variation in demographic characteristics of individuals relative to emissions intensity. However, they do not indicate how demographic characteristics change as an occupation becomes more or less emission-intensive. Column (2) addresses this by including occupation fixed effects, allowing the estimates to reflect within-occupation changes in demographic characteristics over time as emissions intensity varies.

coefficients on educational attainment change sign, suggesting that as workers in an occupation become more educated over time, the emissions intensity of the occupation tends to increase. Overall, these results highlight that higher-emission occupations are persistently associated with native-born males, underscoring the importance of targeted policies that help address demographic differences.

5.2. Occupational Emissions Intensity and Labor Market Outcomes

In this subsection, we explore how emissions intensity correlates with key labor market outcomes, including employment levels, wages, and job postings.

Figure 7 shows a positive relationship between emissions intensity and total employment levels, albeit with considerable variation. Regression results in Table 8 support this observation. Column (1) shows that higher-emission occupations are associated with higher employment levels. However, when controlling for occupation-specific factors in column (2), the positive relationship becomes statistically insignificant. In terms of labor force participation, the microdata estimate in column (2) of Table 8 suggests a negative relationship: a one standard deviation increase in an occupation's emission score (2.87) is associated with a 0.12% decline in the likelihood of participating in the labor force. A similar relationship is observed for being employed. These findings suggest that , within occupations, higher emissions scores are linked to lower labor force participation and employment levels.

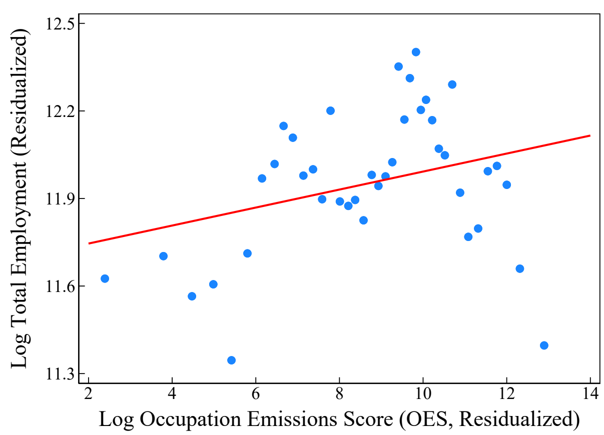


Figure 7: *Residualized Binned Scatter Plot of OES and Employment*

Notes: The chart shows the residualized scatter plot of the relationship between (log) total employment and (log) occupation emissions score (OES). Each dot corresponds to an occupation score quantile (40 quantiles overall). Residuals are estimated using year fixed effects and the covariates listed in Table 7, averaged at the occupation-year level. Residuals are mean-standardized for ease of interpretation. Red lines are the fitted regression line for the relationship.

Table 8: *Relationship between OES Scores and Labor Market Outcomes*

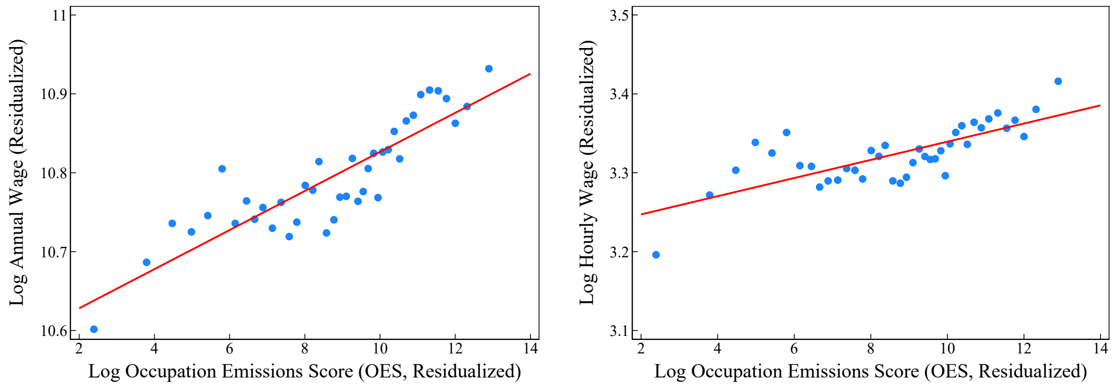
	Coefficient: Log Occupation Emissions Score (OES)	
	(1)	(2)
Log Total Employment	0.0311***	0.00210
	(0.00915)	(0.00380)
	[0.094]	[0.990]
	{3,129}	{3,129}
In labor force	0.00288***	-0.000443
	(0.000386)	(0.000436)
	[0.03]	[0.04]
	{10,411,537}	{10,411,537}
Employed	0.000733***	-0.000873**
	(0.000216)	(0.000430)
	[0.02]	[0.03]
	{9,064,142}	{9,064,142}
Log Nominal Annual Wage	0.0284***	-0.00194
	(0.00383)	(0.00146)
	[0.32]	[0.39]
	{8,914,317}	{8,914,317}
Log Nominal Hourly Wage	0.0136***	0.00174*
	(0.00208)	(0.00102)
	[0.33]	[0.40]
	{8,914,317}	{8,914,317}
Log Occupation Emissions Score -Mean	8.65	
Log Occupation Emissions Score -SD	2.87	
Year Fixed Effects	X	X
Industry Fixed Effects	X	X
Occupation Fixed Effects		X

*Notes: This table shows coefficients from OLS regressions where the dependent variables are labor market outcomes and the explanatory variable is the log occupational emissions score (OES). Standard errors clustered by occupation-year are reported in parentheses, R-squared values in squared brackets, and the number of observations in curly brackets. All regression models include the covariates listed in Table 7, span the years 2016-2022, and are weighted by ACS person weights. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.*

Figure 8 examines wage patterns, revealing positive relationships for annual and hourly wages. Occupations with higher emissions scores are associated with higher hourly and annual pay. However, as can be seen in Table 8, the relationship between emissions intensity and annual wages turns negative when controlling for occupation fixed effects. These findings highlight the complexity of wage dynamics in emissions-intensive roles, where workers may receive better hourly compensation but face greater economic uncertainty over a full year.

Figure 9 analyzes job postings data to assess the demand for workers. The results show a positive relationship between emissions intensity and the number of job postings, mirroring the patterns observed for total employment. This suggests that demand for higher-emission occupations remains strong.

While emission-intensive jobs often provide higher hourly wages and greater employment opportunities, they may also increase the exposure of certain demographic groups to structural adjustments.



***(a)** Log Mean Annual Wages*

***(b)** Log Mean Hourly Wages*

***Figure 8:** Residualized Binned Scatter Plots of OES and Wages*

Notes: The charts show the residualized binned scatter plot relationships between (log) mean annual wages (a) and (log) mean hourly wages (b) and the (log) occupational emissions score (OES). Each dot represents an occupation score quantile (40 quantiles overall). Residuals are estimated with industry and year fixed-effects, as well as the covariates listed in Table 7. Residuals are mean-standardized for ease of interpretation. Red lines represent the fitted regression line for the relationship.

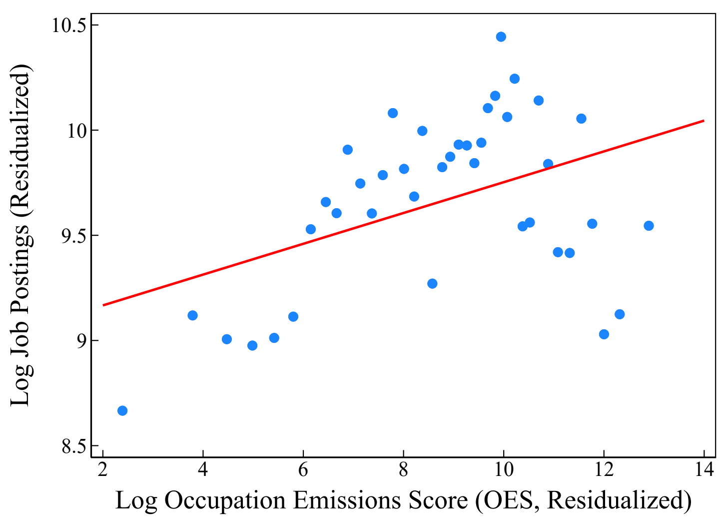


***Figure 9:** Residualized Binned Scatter Plot of OES and Online Job Postings*

Notes: The chart shows the residualized scatter plot relationship between (log) online job postings and the (log) occupational emissions score (OES). Each dot corresponds to an occupation score quantile (40 quantiles overall). Residuals are estimated using year fixed effects and the covariates listed in Table 7, averaged at the occupation-year level. Residuals are mean-standardized for ease of interpretation. Red lines are the fitted regression line for the relationship.

5.3. Identifying at-Risk Regions

5.3.1. Commuting-Zone Level Scores

Understanding the spatial distribution of occupational emissions intensity is important for analyzing local labor market conditions and shifts. Commuting zones, which group counties based on commuting patterns, offer a meaningful lens for studying the geography of emissions-related labor market risks and allow us to identify areas that are either leading or lagging in the transformation process.

To assess regional variation, we construct commuting-zone-level scores by aggregating occupational emissions intensity across local labor markets. Specifically, the commuting-zone score in year t is calculated as:

$$s_{zt} = \sum_{o} (w_{ozt}^{\text{occ}} \times OES_{ot}) \tag{4}$$

where w_{ozt} represents the share of occupation o's employment (or job openings) in commuting zone z relative to the total employment (or total job openings) in that zone at time t. This measure captures the average emissions intensity of the region's occupational structure.

To refine comparisons across regions, we also construct excess scores:

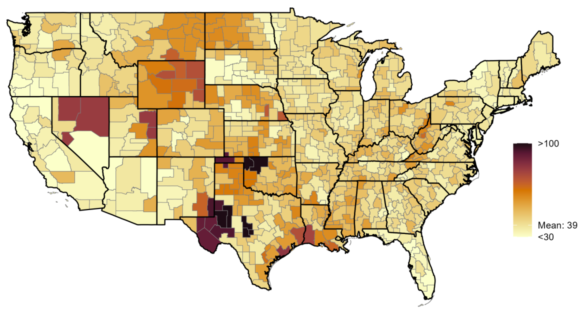
$$Excess_{zt} = s_{zt} - S_t. \tag{5}$$

where $S_t = \sum_z (s_{zt} \times w_{zt})$ is the national average of s_{zt}, w_{zt} is the share of employment (or job openings) in commuting zone z out of total employment (or job openings) in the nation. Positive excess scores indicate regions with relatively higher concentrations of emissions-intensive occupations compared to the national average, while negative excess scores reflect regions with relatively lower concentrations.

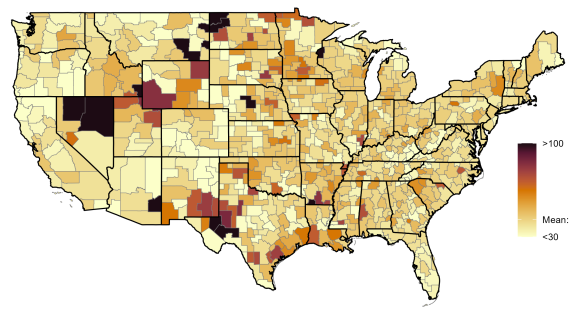
Mapping and analyzing these commuting-zone-level scores helps illustrate spatial patterns in occupational emissions exposure. Areas with higher excess scores may face greater adjustment pressures during the shift toward lower emissions intensity, while regions with lower scores may be better positioned for shifts in energy and industry composition.

5.3.2. Geographic Variation

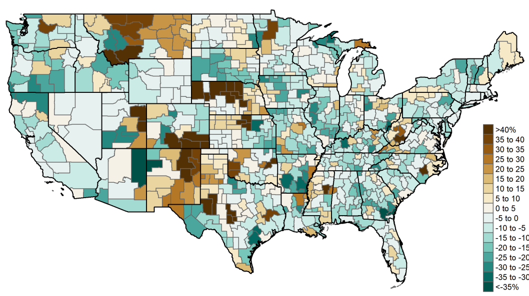
Geography-based emissions scores show notable regional variation in the exposure of local labor markets. Figure 10, Panel (a) shows the supply-based emissions scores for 2022, with higher values indicating that employment is more concentrated in high-emission occupations. Panel (b) presents a corresponding map based on online job postings, providing a forward-looking measure of emissions intensity by capturing demand for occupations in a given area. For example, if job postings in a region are associated with high emissions scores, this suggests a continued reliance on higher-emission occupations.



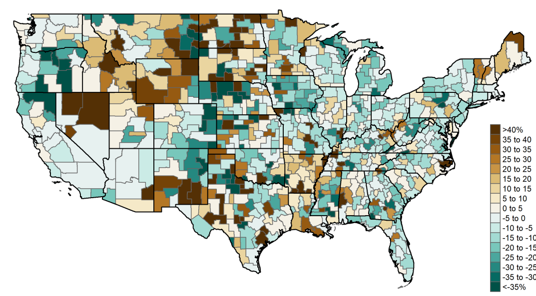
(a) *Employment-Based Emissions Scores (2022)*



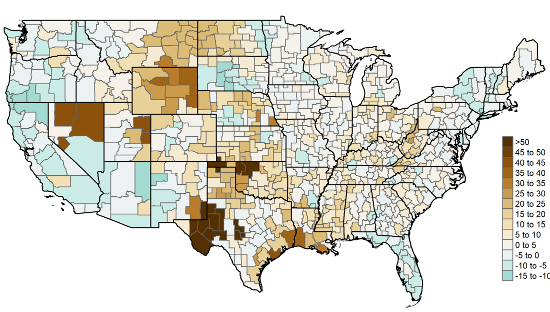
(b) *Job Postings-Based Emissions Scores (2022)*



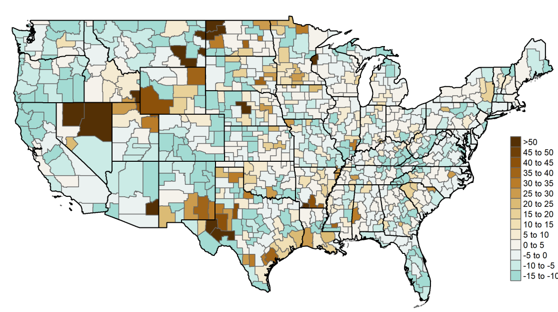
(c) *Change in Employment-Based Emissions Scores (2016-2022)*



(d) *Change in Job Postings-Based Emissions Scores (2016-2022)*



(e) *Employment-Based Excess Scores*



(f) *Job Postings-Based Excess Scores*

Figure 10: *Geography-Based OES Scores: Supply and Demand Perspective*

Panel (a) of Figure 10 shows that parts of the Midwest and Southwest exhibit higher emissions scores in 2022, while areas in the Northeast and West Coast have lower scores. This aligns with the presence of high-emission industries, such as oil and gas production in the Bakken region of North Dakota and western Texas, as well as metals and minerals mining in Nevada. In contrast, urban areas like New York City and San Francisco display lower emissions scores.

The forward-looking aspect of job postings provides additional insights. Panel (b) indicates that demand for high-emission jobs remains strong in certain areas. Notably, regions such as North Nevada exhibit demand for high-emission jobs outpacing supply, suggesting persistent reliance on these occupations.

Panels (c) and (d) present changes in commuting-zone scores from 2016 to 2022. The analysis suggests that many regions have become less emission-intensive over time, consistent with the overall decline in the OES score (Figure 4). However, some commuting zones in states like New Mexico, Montana, Nebraska, Nevada, and Wyoming have seen increased emissions intensity, suggesting that the adjustment is not uniform across regions.

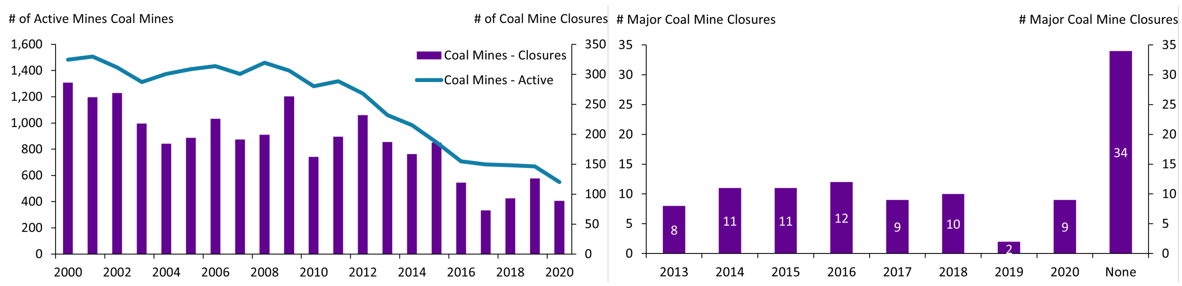
The relative exposure of regions compared to the national average is highlighted by excess scores, presented in Panels (e) and (f) of Figure 10. The results indicate that regions such as the Rocky Mountains, Southwest, and Midwest—particularly, Nevada, Wyoming, Texas, and North Dakota—are more reliant on high-emission jobs than the national average. Additionally, demand appears higher in these regions, making them especially at risk as the economy continues to diversify its energy mix.

5.4. Coal Mine Closures: An Event Study Application

5.4.1. Motivation, Data, and Methodology

The sharp contraction of the coal industry over the past two decades has had significant economic and social consequences for coal-dependent regions. Recent research documents declines in employment and earnings among coal workers, broader financial distress in affected communities, and limited recovery through mobility or reallocation (see, for example, Colmer et al. (2024), Blonz et al. (2024), Du and Karolyi (2023)). These studies emphasize the profound effects of concentrated shocks on regional economies.

Against this backdrop, we consider coal mine closures as a natural setting to illustrate how occupational emissions measures can be applied to analyze major economic changes. Coal mining is a high-emissions industry, and workers in mining-related occupations typically have high Occupational Emissions Scores (OES). We hypothesize that mine closures disproportionately reduce employment in high-emissions occupations, leading to a measurable decline in the emissions intensity of local employment as regions shift toward lower-emissions activities.



(a) *Active Coal Mines and Coal Mine Closures in the U.S., 2000–2020*

(b) *Number of Commuting Zones Experiencing Major Coal Mine Closures by Year*

Figure 11: *Coal Mines and Coal Mine Closures*

Notes: Panel (a): The blue line shows the number of active coal mines each year from 2000 to 2020, and the purple bars show the number of coal mine closures. Closures are defined as observing at least three consecutive years of zero production following the last year of positive production. Panel (b): Bars show the number of commuting zones experiencing major coal mine closures each year from 2013 to 2020. A major closure event is defined as the year with the largest number of coal mine closures in a commuting zone during this period. "NA" refers to commuting zones with at least one active coal mine from 2000 to 2024 that did not experience a closure between 2013 and 2020.

We draw on detailed mine-level data from the U.S. Mine Safety and Health Administration (MSHA), covering the universe of U.S. coal mines from 2000 to 2024. For each mine, we collect annual data on location, production, and employment. We define a closure as three consecutive years of zero reported hours worked, balancing the goal of capturing permanent shutdowns with minimizing misclassification of temporary idling.[13] We focus on "active" mines to ensure that identified closures represent meaningful employment disruptions. Figure 11 panel (a) shows the number of active coal mines and closures between 2000 and 2020. After relative stability in the early 2000s, the number of active mines declined significantly after 2008, with an acceleration following 2011. Annual closures fluctuated between about 50 and 250 per year.

To organize the event study, we aggregate mine closures to the commuting zone (CZ) level. We define each region's "major closure event" as the year between 2013 and 2020 with the largest number of closures. Figure 11 panel (b) presents the number of commuting zones experiencing major closures and those without closures. Overall, 72 commuting zones experienced major closure events, while 34 commuting zones with coal mines but no closures over this period serve as controls. Figure 12 maps the geographic distribution of treated and control regions, with treated regions concentrated along the Appalachian range, the Upper Midwest, and the Rockies.

[13] We define a mine as closed if it records three consecutive years of zero production following its last year of positive production. Results are robust to alternative thresholds (one to six years), available upon request.

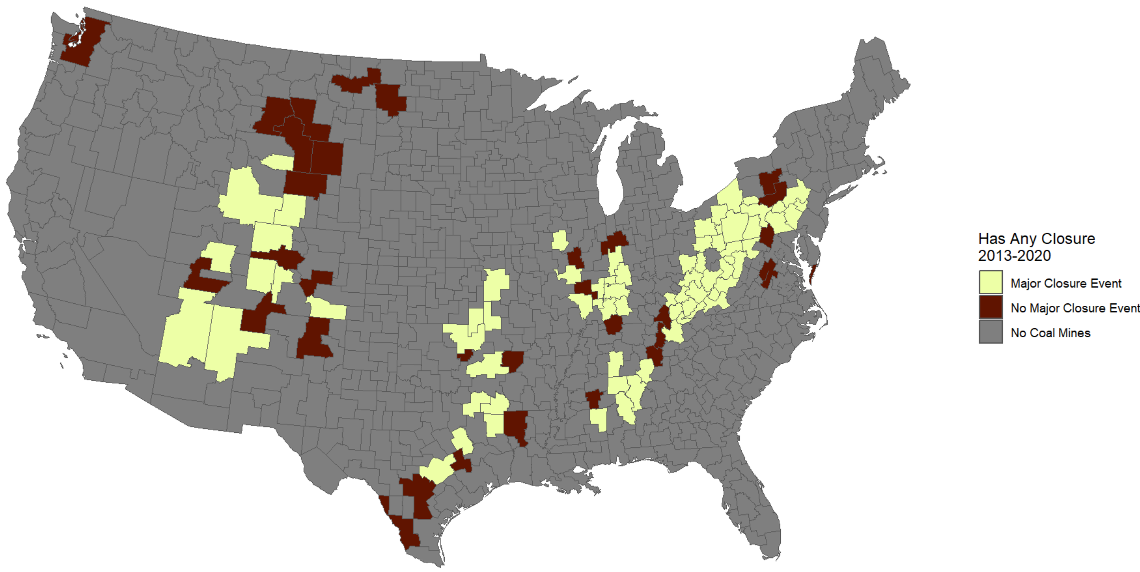


Figure 12: *Geographic Distribution of Commuting Zones by Major Closure Status*

Notes: The map shows commuting zones with at least one active coal mine from 2000 to 2024. Zones experiencing major closures during 2013–2020 are shown in yellow; zones without closures are shown in dark red.

To assess labor market effects, we use the U.S. Census Bureau's County Business Patterns (CBP) data to track the number of coal mining establishments, coal mining employment, and total employment at the county level. Although CBP data are subject to suppression in small cells, it remains the most comprehensive and consistent source for regional employment statistics.[14]

Our empirical strategy uses two complementary event study specifications. The first estimates:

$$y_{jt} = \sum_{k=-4}^{4} \beta_k \mathbb{1}[t - E_j = k] \times ln(OES_{j,2010}) + \alpha_j + \gamma_t + \varepsilon_{jt} \tag{6}$$

where y_{jt} is the outcome (e.g., coal mining employment, total employment, mean OES) in region j in year t; E_j is the major coal mine closure year of region j. $ln(OES_{j,2010})$ is the log of the region's 2010 Occupational Emissions Score. Region and year fixed effects, α_j and γ_t, control for time-invariant characteristics and common shocks. Coefficients are normalized relative to one year before closure ($\beta_{-1} = 0$). We bin years beyond ±4 into two categories to ensure balanced event windows.

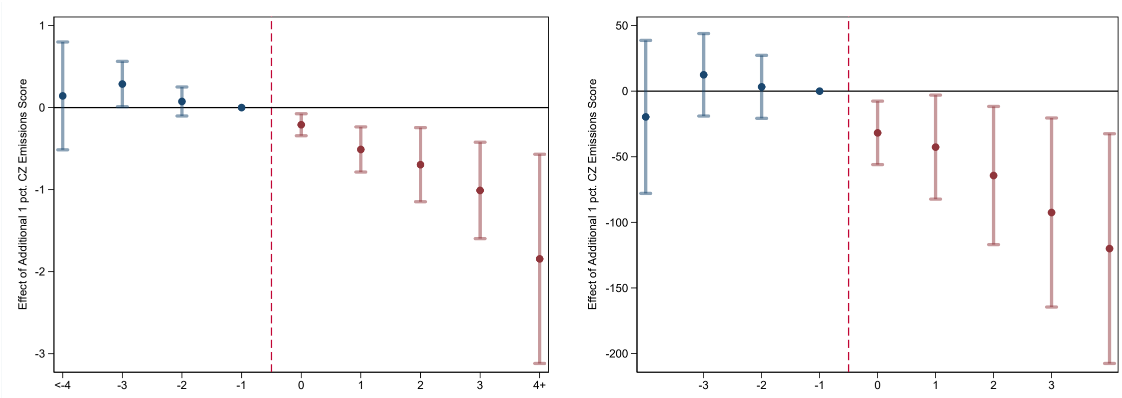
The second specification examines heterogeneity across occupations by interacting the closure event with occupation-level emissions intensity:

[14]Appendix A provides further details on CBP data processing and suppression handling.

$$y_{ojt} = \sum_{k=-4}^{4} \beta_k \mathbb{1}[t - E_j = k] \times ln(OES_{o,2010}) + \alpha_j + \gamma_t + \pi_o + \varepsilon_{jt} \tag{7}$$

where y_{ijt} is employment or job postings for occupation o in region j in year t, and π_o are occupation fixed effects.

Our identification relies on the assumption that absent closures, treated and control regions would have followed similar trends. We limit controls to regions with active coal mines but no closures between 2013–2020 to ensure a plausible counterfactual.



***(a)** Number of Coal Mining Establishments* ***(b)** Coal Mining Employment*

***Figure 13:** Event Study: Major Coal Mine Closures and Coal Mining Sector Outcomes*

Notes: Panel (a) shows event study coefficients for the number of coal mining establishments; panel (b) shows coal mining employment. Major closure events are defined as the year with the largest number of coal mine closures in each commuting zone between 2013 and 2020. 95% confidence intervals are shown, clustered at the commuting zone level.

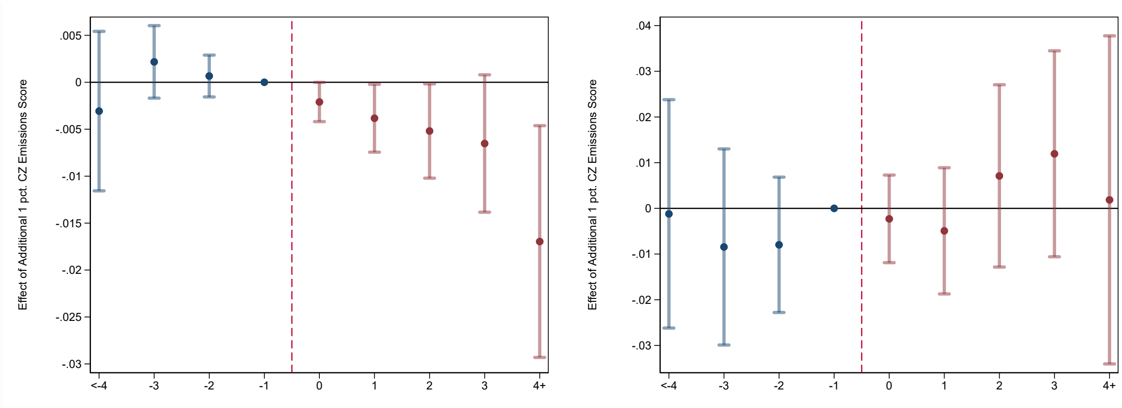
5.4.2. Results and Interpretation

Coal Mining Sector Effects

Figure 13 shows sharp, persistent declines in coal mining establishments (panel a) and coal mining employment (panel b) following closures. At the time of closure, a one percent higher initial emissions score is associated with 0.25 fewer mines and 50 fewer coal-mining jobs. Given a median emissions score of 3.3 (in logs), this implies approximately 0.85 fewer mines and 165 fewer jobs. These effects deepen over time, suggesting structural—not temporary—contractions. Relative to a baseline of 10 mines and 850 coal-mining jobs, these effects represent about a 20% decline.

Broader Labor Market Spillovers

Figure 14 (panel a) shows a 1.5% decline in total employment growth for every one percent increase in initial emissions score. Notably, the effect persists even when excluding coal mining employment, indicating broader local spillovers. Panel (b) examines online job postings. Despite the employment declines, postings do not decline significantly post-closure. This suggests that reductions are likely driven by fewer employers and establishments, rather than temporary labor shortages.



(a) *Log Total Employment* ***(b)*** *Log Total Job Postings*

Figure 14: *Event Study: Major Coal Mine Closures and Total Regional Employment and Job Postings*

Notes: Panel (a) shows event study coefficients for total commuting zone employment; panel (b) shows total commuting zone job postings. 95% confidence intervals are shown, clustered at the commuting zone level.

Occupational Emissions Score Effects

Figure 15 shows that commuting zones experience a statistically significant and persistent 5% decline in mean OES after closures. Pre-trends are mixed but generally downward, suggesting some anticipation effects. Results are robust to alternative emissions measures. These findings validate our OES framework: structural shocks lead to measurable shifts toward lower-emissions occupations.

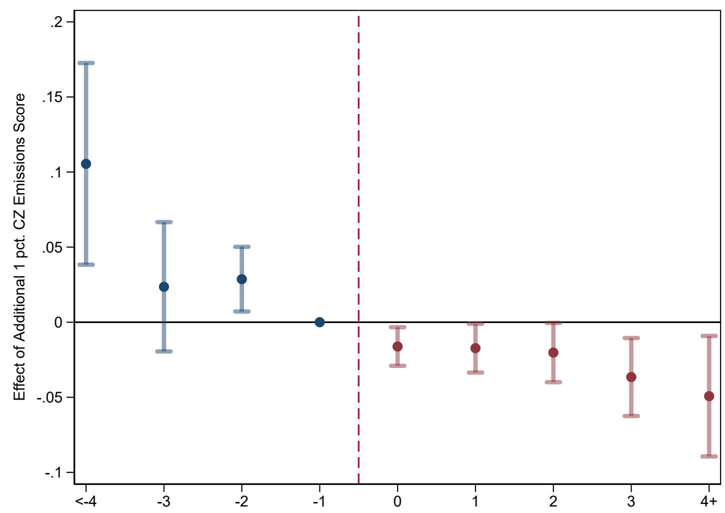
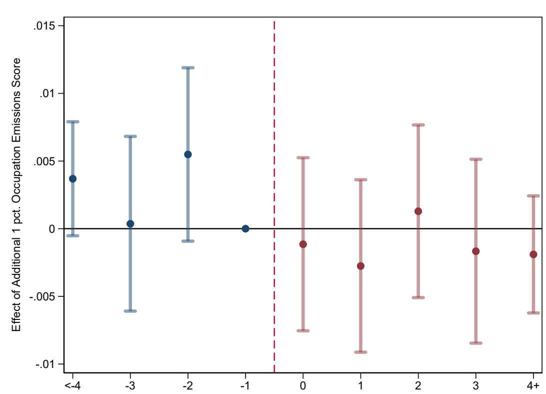


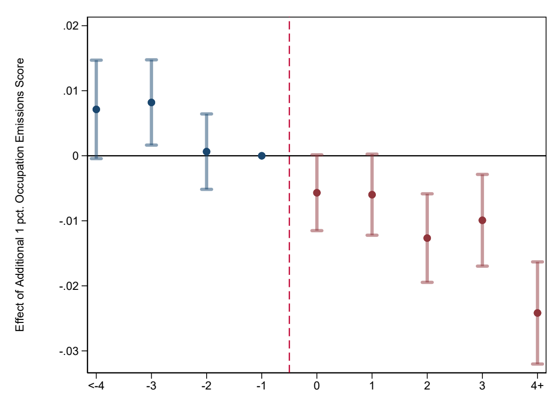
Figure 15: *Event Study: Major Coal Mine Closures and Commuting Zone Occupational Emissions Score (OES)*

Notes: The chart shows event study coefficients for the log Occupational Emissions Score (OES) at the commuting zone level. 95% confidence intervals are shown, clustered at the commuting zone level.

Occupation-Level Heterogeneity



(a) *Log Employment in Occupation-Region Level*



(b) *Log Job Postings in Occupation-Region Level*

Figure 16: *Event Study: Major Coal Mine Closures and Occupation-Level Employment and Job Postings*

Notes: Panel (a) shows event study coefficients for log occupation employment at the occupation-region-year level; panel (b) shows log occupation job postings. Estimates are based on the specification in Equation (7). 95% confidence intervals are shown, clustered at the occupation level.

Figure 16 shows occupation-level effects. Panel (a) documents that higher-emissions occupations experience larger employment declines post-closure, with the caveat that the estimates are noisy. Panel (b) shows that job postings for high-OES occupations decline more sharply, by

1–3% depending on the horizon. These patterns highlight the value of a continuous emissions score: they capture more nuanced differences in occupational exposure compared to binary classifications.

To summarize, our event study shows that coal mine closures lead to significant local employment declines, disproportionate losses among high-emissions occupations, and a shift toward lower-emissions employment. While regions become less emissions-intensive, these adjustments are accompanied by persistent employment contractions. These findings complement recent work (e.g. Colmer et al. (2024), Blonz et al. (2024), Du and Karolyi (2023)) documenting the costs of coal decline, and demonstrate that occupational emissions scores offer a granular and informative tool for analyzing labor market adjustments during economic adjustments.

6. Conclusion

We introduce new, data-driven measures of occupational emissions intensity that offer a granular perspective on labor market exposure to a major economic shift. By capturing multiple dimensions of emissions risk—overall exposure, industry concentration, and decision-making influence—our Occupational Emissions Score (OES) and its extensions reveal substantial heterogeneity across occupations and industries.

Applying these measures, we document several key patterns. Emissions intensity is highly concentrated in a small set of occupations, and even within industries, workers' exposure varies considerably by occupation. Emissions scores have declined modestly over time, but differences persist. Higher-emission occupations are disproportionately held by older, male, native-born, and less-educated workers, and are concentrated in particular regions. These occupations also experience slower employment growth but higher hourly wages and vacancy shares, indicating complex labor market dynamics.

Our event study of coal mine closures further shows the usefulness of continuous emissions scores: closures lead to sharp employment declines and a measurable shift toward lower-emissions occupations, illustrating how structural shocks can reshape workforce composition.

Taken together, these findings highlight the value of granular, occupation-level measures for understanding labor market adjustment during major economic developments. Our framework can support future research on occupational exposure, regional dynamics, and structural change, and can be readily adapted to different policy environments, time periods, or countries.

References

Autor, David H, David Dorn, and Gordon H Hanson, "The China syndrome: Local labor market effects of import competition in the United States," *American Economic Review*, 2013, *103* (6), 2121–2168.

_ , _ , and _ , "The China shock: Learning from labor-market adjustment to large changes in trade," *Annual Review of Economics*, 2016, *8* (1), 205–240.

Berlin, Mitchell, Sung Je Byun, Pablo D'Erasmo, and Edison Yu, "Measuring climate transition risk at the regional level with an application to community banks," *European Economic Review*, November 2024, *170.*

Blonz, Joshua, Brigitte Roth Tran, and Erin Troland, "The Canary in the Coal Decline: Appalachian Household Finance and the Transition from Fossil Fuels," Working Paper 2023-09, Federal Reserve Bank of San Francisco 2024.

Bloom, Nicholas, Kyle Handley, André Kurmann, and Philip A. Luck, "The China Shock Revisited: Job Reallocation and Industry Switching in U.S. Labor Markets," *NBER Working Paper*, 2024, (No. 33098).

Bluedorn, John, Niels-Jakob Hansen, Diaa Noureldin, Ippei Shibata, and Marina M Tavares, "Transitioning to a greener labor market: Cross-country evidence from microdata," *Energy Economics*, 2023, *126*, 106836.

Colmer, Jonathan, Eleanor Krause, Eva Lyubich, and John Voorheis, "Transitional Costs and the Decline of Coal: Worker-Level Evidence," *Manuscript*, 2024. University of Virginia and Harvard University.

Curtis, E. Mark and Ioana Marinescu, "Green Energy Jobs in the United States: What Are They, and Where Are They?," *Environmental and Energy Policy and the Economy*, 2023, *4*, 202–237.

Du, Ding and Stephen A. Karolyi, "Energy Transitions and Household Finance: Evidence from U.S. Coal Mining," *Review of Corporate Finance Studies*, 2023, *12* (4), 723–760.

Graham, Kailin and Christopher R Knittel, "Assessing the distribution of employment vulnerability to the energy transition using employment carbon footprints," *Proceedings of the National Academy of Sciences*, 2024, *121* (18), 1–8.

Hanson, Gordon, "The China Shock's Lessons for the Green Economy," *Foreign Affairs*, November 2021.

Hanson, Gordon H, "Local labor market impacts of the energy transition: prospects and policies," Technical Report, National Bureau of Economic Research 2023.

Kambourov, Gueorgui and Iourii Manovskii, "Occupational Mobility and Wage Inequality," *Review of Economic Studies*, 2009, *76* (2), 731–759.

Leduc, Sylvain and Daniel J. Wilson, "Climate Change and the Geography of the U.S. Economy," *Federal Reserve Bank of San Francisco Working Paper*, 2023, (2023-17).

Ruggles, Steven, Sarah Flood, Matthew Sobek, Daniel Backman, Annie Chen, Grace Cooper, Stephanie Richards, Renae Rodgers, and Megan Schouweiler, "IPUMS USA: Version 15.0 [dataset]," 2024.

Saussay, Aurélien, Misato Sato, Francesco Vona, and Layla O'Kane, "Who's fit for the low-carbon transition? Emerging skills and wage gaps in job ad data," 2022.

Traiberman, Sharon, "Occupations and Import Competition: Evidence from Denmark," *American Economic Review*, 2019, *109* (12), 4260–4301.

Vona, Francesco, Giovanni Marin, Davide Consoli, and David Popp, "Environmental regulation and green skills: an empirical exploration," *Journal of the Association of Environmental and Resource Economists*, 2018, *5* (4), 713–753.

Walker, W Reed, "The transitional costs of sectoral reallocation: Evidence from the clean air act and the workforce," *The Quarterly journal of economics*, 2013, *128* (4), 1787–1835.

Appendix

A. Data Appendix

This appendix provides further details about our data sources, cleaning and preparation processes.

A.1. Crosswalks

The GHGRP, OES, and ACS datasets use NAICS and SOC codes at varying levels of aggregation and across different releases. To achieve consistency, we created a crosswalk that harmonizes the codes across these datasets to a time-consistent format at the highest level of aggregation.

- NAICS Codes: We manually matched codes from the 2007, 2012, and 2017 NAICS releases, consolidating 1,271 6-digit codes into 255 time-consistent industries.

- SOC Codes: We crosswalked SOC codes from the 2010, 2013, and 2018 releases, consolidating 493, 480, and 531 6-digit codes, respectively, into 463 occupations consistent over 2010–2022.

Crosswalks are available upon request.

A.2. Emissions Data

Industry emissions data come from the Greenhouse Gas Reporting Program (GHGRP) provided by the EPA. We downloaded the 2022 Data Summary Spreadsheets (as of October 17, 2024), which include Scope 1 (direct emitters) and Scope 3 (suppliers) emissions.

1. Handling Missing NAICS Codes: Missing NAICS codes for 2022 facilities were filled if previously available. Facilities without NAICS codes were dropped.

Replaced Facility IDs:

Emitters: 1010040, 1005991, 1004045, 1009920, 1012548, 1013060, 1006829, 1002893, 1007994, 1005761, 1003320, 1013982, 1001687, 1000230, 1008387, 1005351, 1005734, 1013900, 1013016, 1014015, 1010106, 1010125, 1013071, 1004396, 1005704, 1013995, 1009821, 1011516, 1003607, 1005037, 1004500, 1003501, 1008757, 1006558, 1011192, 1006608, 1001684, 1002828, 1003506, 1007135, 1005998, 1000590, 1006975, 1011886, 1004317, 1004452, 1006324, 1009948, 1002887, 1006813, 1005341, 1008764, 1011503, 1006162, 1011909, 1001841, 1011124, 1007174, 1000377, 1006788, 1009877, 1007129, 1013481, 1003420, 1005297, 1000869, 1006061, 1006052, 1003449, 1014367, 1007472, 1010111, 1013994, 1006466, 1001644, 1010550, 1010309, 1008760, 1005808, 1000324, 1008761, 1010587, 1001762, 1009895, 1003327, 1006366, 1011240, 1003058, 1008766, 1000248, 1006367, 1006242, 1000593, 1002152, 1002674, 1002111, 1011471, 1010198, 1011220, 1011739, 1003488, 1004083, 1009342, 1003048, 1009600, 1002339, 1004949, 1003585, 1005040, 1009828, 1001682, 1003633, 1003490, 1006058, 1008288, 1004874, 1010057, 1013783, 1010328, 1010310, 1011237, 1005050

Suppliers: 1007994, 1003320, 1011320, 1012974, 1010355, 1010248, 1004874

Dropped Facilities:

Emitters: 1014471, 1008479

Suppliers: 1014447, 1010290, 1014500, 1014554

2. Scope-Specific Details:

Scope 1 (Direct Emitters): Combined across years.

2010

- Direct Emitters

2011-2015

- Direct Emitters, Onshore Oil & Gas Production, LDC Direct Emissions, and SF6 from Electrical Equipment

2016-2022

- Direct Emitters, Onshore Oil & Gas Production, LDC Direct Emissions, and SF6 from Electrical Equipment, Gathering & Boosting and Transmission Pipelines

Scope 3 (Suppliers): Observations marked "confidential" were treated as zero.

3. Aggregation

Emissions are aggregated at the 6-digit NAICS level. NAICS code 221112 (Fossil Fuel Power Generation) was manually split from its parent category 2211P. The processed data were saved as annual CSV files (2010–2022) for each scope.

A.3. OES Data

We used employment data from the Occupational Employment and Wage Statistics provided by the Bureau of Labor Statistics for 2015–2022. This was necessary to split employment for NAICS code 221112 (Fossil Fuel Power Generation) from 2211P.

Employment shares were calculated by:

1. Extracting 6-digit NAICS and SOC data from OES files (e.g., nat5d_6d_Myear_dl.xlsx).

2. Merging 4-digit NAICS data from corresponding files.

3. Aggregating SOC codes and crosswalking them to the modified occupation identifiers.

A.4. ACS Data

We retrieved the American Community Survey (ACS) data (2010–2022) from IPUMS, focusing on labor and geographic demographics at the occupation-industry-year level.

1. Data Harmonization:

- ACS data were crosswalked to our modified occupation and industry identifiers across three SOC cohorts: 2010–2012, 2013–2017, and 2018–2022.

- Observations with unemployed or unknown occupations were dropped.

2. Aggregation:

- Data were aggregated at the occupation-industry-year level using person weights for employment and wages.

- Observations from 8 highly aggregated 2-digit industries (e.g., NAICS 22, Utilities) were excluded for analytical precision.

The aggregated ACS data were then merged with the cleaned GHGRP data.

A.5. Emissions Scores

Using the merged ACS and GHGRP data, we constructed emissions scores following the methodology outlined in the paper:

1. Zero and Low Scores:

- Occupations with zero scores for any summed emissions measure (OES, COES, WOES) were dropped.

- Scores were winsorized to a minimum of 1 kg of CO (or 0.001 metric tons) to avoid extreme values.

2. Log Transformations: Logged scores were based on emissions measured in kg of CO to prevent negative values.

By the end of the process, we retained 447 occupations across 245 industries over 2010–2022, resulting in 5,118 occupation-year observations before narrowing the sample to 2016–2022.

A.6. Commuting Zones

We define commuting zones (CZs) using the 1990 definitions. Since ACS employment data are reported at the PUMA level:

1. We used David Dorn's crosswalk (2010 PUMAs to 1990 CZs) and an additional crosswalk (2010 to 2020 PUMAs) from IPUMS.

2. For 2020 PUMAs, we weighted observations by the proportion of the 2020 population mapped to 2010 PUMAs.

A.7. Jobs Postings Data

Job postings data were obtained from Lightcast, which aggregates postings from job boards and company websites.

1. Crosswalking Codes: SOC and NAICS codes in Lightcast were converted to our modified identifiers.

2. Geographic Mapping: Locations provided at the county level were crosswalked to commuting zones using USDA's "1980 and 1990 commuting zones" data.

3. Aggregation: Postings data were aggregated to the SOC-NAICS-county-year level before merging with emissions scores.

After crosswalking and cleaning, the sample was reduced to 423 occupations due to missing data in Lightcast.

A.8. Geographic Scores

The Lightcast data were merged with the combined ACS and GHGRP datasets (crosswalked to CZs). The geographic scores were then created following the methodology in the paper. The sample includes 423 occupations over 2016–2022, aligning with available and consistent emissions data.

B. Summary of Occupations

Table B.1 lists all occupations used in our analysis, including their titles, codes, and corresponding OES, WOES, and COES scores (in metric tons of CO). Occupations are organized by ascending occupational codes. Higher levels of aggregation are denoted with X's or Y's (e.g., 1721XX and 1721YY).

Table B.1: *List of Occupations with 2022 Emissions Scores*

Occupation Title	Occupation Code	OES Score	WOES Score	COES Score
General and Operations Managers	111021	91.49	117.17	91.82
Chief Executives and Legislators	1110XX	45.86	133.98	45.96
Advertising and Promotions Managers	112011	2.30	1.74	2.31
Marketing and Sales Managers	112020	37.95	44.52	38.01
Public Relations and Fundraising Managers	112030	33.48	35.90	33.55
Administrative Services Managers	113011	63.74	66.24	64.01
Computer and Information Systems Managers	113021	54.73	104.04	54.87
Financial Managers	113031	31.02	59.91	31.08
Industrial Production Managers	113051	107.75	154.44	108.59
Purchasing Managers	113061	100.59	125.79	101.19
Transportation, Storage, and Distribution Managers	113071	74.62	71.14	74.95
Compensation and Benefits Managers	113111	86.02	78.65	86.49
Human Resources Managers	113121	61.60	67.99	61.76
Training and Development Managers	113131	31.11	33.52	31.37
Farmers, Ranchers, and Other Agricultural Managers	119013	0.17	0.11	0.20
Constructions Managers	119021	11.69	11.26	11.71
Education And Childcare Administrators	119030	1.38	4.08	1.56
Architectural and Engineering Managers	119041	169.94	330.45	171.91
Food Service Managers	119051	1.42	0.81	1.42
Entertainment And Recreation Managers	119070	0.12	0.15	0.16
Lodging Managers	119081	0.16	0.24	0.23
Medical and Health Services Managers	119111	0.38	0.58	0.39
Natural Science Managers	119121	87.69	414.35	88.32
Property, Real Estate, and Community Association Managers	119141	24.13	16.53	24.29
Social and Community Service Managers	119151	2.28	2.62	2.28
Emergency Management Directors	119161	25.35	35.59	25.49
Other Managers	119XXX	80.37	117.02	80.71
Agents and Business Managers of Artists, Performers, and Athletes	131011	1.35	1.18	1.36
Buyers and Purchasing Agents, Farm Products	131021	7.64	7.84	7.76
Wholesale and Retail Buyers, Except Farm Products	131022	31.45	27.80	31.77
Purchasing Agents, Except Wholesale, Retail, and Farm Products	131023	81.06	60.84	81.45
Compliance Officers	131041	98.71	98.83	99.20
Cost Estimators	131051	50.12	31.76	50.26
Human Resources Workers	131070	32.29	29.01	32.34
Logisticians	131081	75.38	84.83	75.83
Management Analysts	131111	32.61	41.17	32.73
Meeting, Convention, and Event Planners	131121	26.70	28.77	28.05
Fundraisers	131131	0.53	0.77	0.59
Compensation, Benefits, and Job Analysis Specialists	131141	32.74	27.29	32.90
Training and Development Specialists	131151	60.89	53.04	61.19
Market Research Analysts and Marketing Specialists	131161	34.11	50.52	34.18
Business Operations Specialists, All Other	131199	66.49	91.34	66.71
Accountants and Auditors	132011	62.76	71.69	62.94
Appraisers and Assessors of Real Estate	132020	0.19	0.17	0.24
Budget Analysts	132031	41.60	21.53	41.87
Credit Analysts	132041	15.19	13.23	15.25
Financial and Investment Analysts	132051	66.91	63.74	67.54
Personal Financial Advisors	132052	7.95	11.26	10.22
Financial Examiners	132061	0.38	0.24	0.40
Credit Counselors and Loan Officers	132070	1.45	0.26	1.46

Table B.1: List of Occupations with 2022 Emissions Scores (continued)

Occupation Title	Occupation Code	OES Score	WOES Score	COES Score
Tax Examiners and Collectors, and Revenue Agents	132081	5.68	0.59	5.69
Tax Preparers	132082	3.98	5.10	3.98
Financial Specialists, All Other	132099	38.50	75.79	38.74
Computer And Information Research Scientists	151111	4.21	0.48	4.24
Computer Systems Analysts	151121	95.03	96.53	95.85
Information Security Analysts	151122	32.70	39.86	32.90
Computer Programmers	151131	27.34	35.17	27.40
Web And Digital Interface Designers	151134	3.37	2.96	3.38
Software Developers, Applications and Systems Software	15113X	20.14	26.47	20.18
Database Administrators And Architects	151141	47.31	48.08	47.54
Network and Computer Systems Administrators	151142	50.43	52.36	50.77
Computer Network Architects	151143	64.58	100.20	64.81
Computer Support Specialists	151150	32.70	30.42	32.79
Computer Occupations, All Other	151199	59.11	62.32	59.31
Actuaries	152011	21.62	21.86	21.70
Operations Research Analysts	152031	19.66	20.37	19.79
Other Mathematical Science Occupations	1520XX	44.97	49.05	45.16
Architects, Except Naval	171010	12.01	13.94	12.08
Surveyors, Cartographers, and Photogrammetrists	171020	34.85	24.89	35.17
Aerospace Engineers	172011	1.43	1.71	1.90
Chemical Engineers	172041	2100.71	2828.28	2402.39
Civil Engineers	172051	29.36	34.62	29.49
Computer Hardware Engineers	172061	23.02	32.73	23.06
Electrical and Electronics Engineers	172070	166.81	182.78	177.99
Environmental Engineers	172081	230.08	473.56	232.67
Biomedical and Agricultural Engineers	1720XX	0.41	1.08	0.43
Industrial Engineers, including Health and Safety	172110	165.45	205.09	166.76
Marine Engineers and Naval Architects	172121	4.73	5.96	5.00
Materials Engineers	172131	199.63	225.12	202.30
Mechanical Engineers	172141	68.09	93.00	68.59
Petroleum, mining and geological engineers, including mining safety engineers	1721XX	2494.16	4135.46	2893.61
Other Engineers	1721YY	193.82	231.61	200.64
Architectural and Civil Drafters	173010	100.10	64.72	100.76
Electrical and Electronic Engineering Technologists And Technicians	173020	169.21	152.06	171.08
Surveying and Mapping Technicians	173031	71.47	43.06	72.15
Agricultural and Food Scientists	191010	19.64	28.91	20.09
Biological Scientists	191020	1.05	1.07	1.11
Conservation Scientists and Foresters	191030	46.28	40.09	47.47
Other life scientists	1910XX	12.26	13.69	12.36
Astronomers and Physicists	192010	68.60	26.65	69.04
Atmospheric and Space Scientists	192021	28.64	43.02	29.13
Chemists and Materials Scientists	192030	432.85	562.05	447.68
Environmental Scientists and Geoscientists	192040	388.52	425.48	395.23
Physical Scientists, All Other	192099	29.55	29.34	29.84
Economists	193011	42.84	57.61	43.45
Psychologists	193030	0.36	0.38	0.36
Urban and Regional Planners	193051	7.81	9.78	7.92
Other Social Scientists	1930XX	41.98	39.20	42.24
Agricultural and Food Science Technicians	194010	20.83	9.57	21.04
Biological Technicians	194021	9.25	6.15	9.64
Chemical Technicians	194031	323.47	217.50	342.56
Geological/Petroleum/Nuclear/Hydrologic/Other Science Technicians	1940XX	2452.13	2365.58	2798.85
Forest/Conservation/Forensic/Other Life, Physical, and Social Science Technicians/Social Science Research Assistants	1940YY	51.27	51.85	51.59
Counselors	211010	0.27	0.24	0.30
Social Workers	211020	0.09	0.08	0.09
Probation Officers and Correctional Treatment Specialists	211092	0.10	0.01	0.11
Social and Human Service Assistants	211093	2.70	1.84	2.70
Other Community And Social Service Specialists	21109X	1.99	2.31	2.00
Clergy	212011	0.03	0.02	0.03
Directors, Religious Activities and Education	212021	0.01	0.00	0.01
Religious Workers, All Other	212099	0.02	0.01	0.02
Judicial Law Clerks	231012	0.02	0.04	0.02

Table B.1: *List of Occupations with 2022 Emissions Scores (continued)*

Occupation Title	Occupation Code	OES Score	WOES Score	COES Score
Lawyers, and judges, magistrates, and other judicial workers	2310XX	16.24	45.62	16.25
Paralegals and Legal Assistants	232011	5.17	2.70	5.18
Miscellaneous Legal Support Workers	232090	38.66	19.75	38.73
Postsecondary Teachers	251000	1.68	2.05	3.20
Preschool and Kindergarten Teachers	252010	0.01	0.00	0.01
Special Education Teachers	252050	0.00	0.00	0.00
Other Teachers and Instructors	253000	13.97	14.21	14.00
Archivists, Curators, and Museum Technicians	254010	0.22	0.15	0.23
Librarians And Media Collections Specialists	254021	0.40	0.37	0.48
Library Technicians	254031	0.27	0.10	0.31
Teacher Assistants	259040	0.19	0.07	0.21
Other educational instruction and library workers	2590XX	11.61	30.38	11.73
Artists and Related Workers	271010	0.52	0.35	0.53
Commercial And Industrial Designers	271020	21.49	18.70	21.53
Actors	272011	0.35	0.03	0.36
Producers and Directors	272012	1.73	2.05	1.74
Athletes, Coaches, Umpires, and Related Workers	272020	1.18	0.95	1.22
Dancers and Choreographers	272030	0.01	0.01	0.02
Musicians, Singers, and Related Workers	272040	0.13	0.03	0.13
Entertainers and Performers, Sports and Related Workers, All Other	272099	0.21	0.14	0.21
Broadcast Announcers And Radio Disc Jockeys	273010	0.09	0.04	0.09
News Analysts, Reporters, And Journalists	273020	0.13	0.11	0.13
Public Relations Specialists	273031	68.83	92.78	69.12
Editors	273041	2.69	2.58	2.70
Technical Writers	273042	30.58	28.86	30.66
Writers and Authors	273043	2.63	2.57	2.64
Miscellaneous Media and Communication Workers	273090	11.98	4.18	12.00
Photographers	274021	3.75	2.06	3.77
Television, Video, and Motion Picture Camera Operators and Editors	274030	0.23	0.20	0.24
Other Media And Communication Equipment Workers	2740XX	10.14	9.77	10.21
Chiropractors	291011	0.00	0.00	0.00
Dentists	291020	0.05	0.17	0.05
Dieticians and Nutritionists	291031	0.64	1.45	0.66
Optometrists	291041	0.03	0.07	0.04
Pharmacists	291051	0.10	0.19	0.11
Physicians and Surgeons	291060	0.22	0.72	0.25
Physician Assistants	291071	0.18	0.37	0.20
Podiatrists	291081	0.23	0.06	0.24
Occupational Therapists	291122	0.05	0.04	0.05
Physical Therapists	291123	0.06	0.06	0.07
Radiation Therapists	291124	4.43	0.78	4.49
Recreational Therapists	291125	0.27	0.33	0.28
Respiratory Therapists	291126	0.11	0.10	0.18
Speech-Language Pathologists	291127	0.04	0.04	0.04
Other Therapists	29112X	0.04	0.02	0.04
Veterinarians	291131	0.11	0.22	0.16
Registered Nurses	291141	0.96	0.87	1.00
Nurse Anesthetists	291151	0.10	0.24	0.13
Audiologists	291181	0.11	0.18	0.13
Nurse Practitioners and Nurse Midwives	2911XX	0.09	0.15	0.11
Healthcare Diagnosing Or Treating Practitioners, All Other	291299	0.03	0.05	0.03
Clinical Laboratory Technologists and Technicians	292010	0.87	0.51	0.90
Dental Hygienists	292021	0.01	0.01	0.01
Diagnostic Related Technologists and Technicians	292030	1.15	1.32	1.20
Emergency Medical Technicians and Paramedics	292041	1.43	2.01	1.43
Health Practitioner Support Technologists and Technicians	292050	1.04	1.87	1.05
Licensed Practical and Licensed Vocational Nurses	292061	0.15	0.10	0.16
Medical Records and Health Information Technicians	292071	0.92	0.59	0.96
Opticians, Dispensing	292081	0.01	0.01	0.01

Table B.1: *List of Occupations with 2022 Emissions Scores (continued)*

Occupation Title	Occupation Code	OES Score	WOES Score	COES Score
Miscellaneous Health Technologists and Technicians	292090	1.44	1.38	1.45
Other Healthcare Practitioners and Technical Occupations	299000	0.37	0.22	0.39
Nursing, Psychiatric, and Home Health Aides	311010	0.11	0.05	0.11
Occupational Therapy Assistants and Aides	312010	0.18	0.02	0.19
Massage Therapists	319011	0.06	0.06	0.06
Dental Assistants	319091	0.01	0.01	0.01
Medical Assistants	319092	0.14	0.07	0.16
Medical Transcriptionists	319094	0.32	0.07	0.33
Pharmacy Aides	319095	0.04	0.02	0.04
Veterinary Assistants and Laboratory Animal Caretakers	319096	0.09	0.04	0.13
Phlebotmists	319097	0.31	0.05	0.33
Other Healthcare Support Workers	31909X	10.85	10.34	10.87
First-Line Supervisors of Correctional Officers	331011	0.26	0.32	0.27
First-Line Supervisors of Police and Detectives	331012	0.23	0.19	0.24
First-Line Supervisors of Fire Fighting and Prevention Workers	331021	13.27	16.49	13.34
Miscellaneous First-Line Supervisors, Protective Service Workers	331090	21.85	22.77	21.92
Firefighters	332011	2.50	2.43	2.51
Fire Inspectors	332020	6.94	6.30	6.98
Bailiffs, Correctional Officers, and Jailers	333010	0.10	0.12	0.11
Detectives and Criminal Investigators	333021	1.07	0.49	1.09
Police Officers	333050	0.82	0.79	0.83
Miscellaneous law enforcement workers	3330XX	0.70	0.64	0.73
Animal Control Workers	339011	0.02	0.01	0.02
Private Detectives and Investigators	339021	18.79	12.34	18.89
Security Guards and Gaming Surveillance Officers	339030	22.17	17.03	22.33
Crossing Guards And Flaggers	339091	9.86	4.68	10.29
Transportation Security Screeners	339093	10.20	8.29	11.95
Other Protective Service Workers	33909X	3.00	1.38	3.03
Chefs and Head Cooks	351011	0.19	0.15	0.19
First-Line Supervisors of Food Preparation and Serving Workers	351012	0.31	0.18	0.31
Cooks	352010	0.53	0.12	0.53
Food Preparation Workers	352021	0.53	0.03	0.53
Bartenders	353011	0.29	0.16	0.30
Combined Food Preparation and Serving Workers, Including Fast Food	353023	0.01	0.00	0.01
Waiters and Waitresses	353031	0.03	0.02	0.03
Food Servers, Nonrestaurant	353041	0.51	0.10	0.51
Dishwashers	359021	0.08	0.02	0.08
Host and Hostesses, Restaurant, Lounge, and Coffee Shop	359031	0.06	0.01	0.06
Food Preparation and Serving Related Workers, All Other	3590XX	0.09	0.02	0.09
First-Line Supervisors of Housekeeping and Janitorial Workers	371011	3.98	5.64	3.98
First-Line Supervisors of Landscaping, Lawn Service, and Groundskeeping Workers	371012	4.98	5.30	4.98
Maids and Housekeeping Cleaners	372012	0.73	0.21	0.74
Janitors and Building Cleaners	37201X	15.61	7.42	15.63
Pest Control Workers	372021	0.70	0.36	0.70
Other Grounds Maintenance Workers	373010	3.82	1.52	3.83
Supervisors of Personal Care And Service Workers	391000	2.17	2.18	2.20
Animal Trainers	392011	0.14	0.08	0.17
Animal Caretakers	392021	0.12	0.06	0.13
Gaming Services Workers	393010	0.09	0.13	0.14
Ushers, Lobby Attendants, and Ticket Takers	393031	0.57	0.06	0.58
Other Entertainment Attendants And Related Workers	393090	0.17	0.04	0.21
Barbers	395011	0.02	0.00	0.02
Hairdressers, Hairstylists, and Cosmetologists	395012	0.00	0.00	0.00
Miscellaneous Personal Appearance Workers	395090	0.02	0.03	0.02
Baggage Porters, Bellhops, and Concierges	396010	3.70	2.09	3.88
Tour and Travel Guides	397010	1.86	0.90	1.93
Childcare Workers	399011	0.12	0.22	0.12
Recreation and Fitness Workers	399030	0.29	0.40	0.31

Table B.1: *List of Occupations with 2022 Emissions Scores (continued)*

Occupation Title	Occupation Code	OES Score	WOES Score	COES Score
Residential Advisors	399041	1.01	0.16	1.62
Personal Care and Service Workers, All Other	399099	0.66	0.56	0.67
First-Line Supervisors of Retail Sales Workers	411011	1.75	1.51	1.75
First-Line Supervisors of Non-Retail Sales	411012	55.24	62.77	55.61
Cashiers	412010	2.23	0.62	2.23
Counter and Rental Clerks	412021	10.05	3.70	10.22
Parts Salespersons	412022	0.30	0.15	0.30
Retail Salespersons	412031	0.10	0.09	0.10
Advertising Sales Agents	413011	0.14	0.28	0.14
Travel Agents	413041	0.58	0.43	0.58
Sales Representatives, Services, All Other	413099	51.64	51.47	51.95
Sales Representatives, Wholesale and Manufacturing	414010	80.54	87.21	81.16
Models, Demonstrators, and Product Promoters	419010	20.60	1.42	20.89
Real Estate Brokers and Sales Agents	419020	5.89	7.19	6.03
Sales Engineers	419031	61.27	71.39	61.56
Telemarketers	419041	4.93	2.30	4.94
Door-to-Door Sales Workers, News and Street Vendors, and Related Workers	419091	0.93	0.20	0.93
Sales and Related Workers, All Other	419099	5.18	3.11	5.19
First-Line Supervisors of Office and Administrative Support Workers	431011	27.90	22.98	27.94
Switchboard Operators, Including Answering Service	432011	23.43	0.98	23.53
Telephone Operators	432021	15.19	16.69	15.29
Communications Equipment Operators, All Other	432099	1.91	1.72	2.11
Bill and Account Collectors	433011	46.47	29.99	46.79
Billing and Posting Clerks	433021	38.10	19.86	38.35
Bookkeeping, Accounting, and Auditing Clerks	433031	46.35	23.46	46.44
Payroll and Timekeeping Clerks	433051	24.51	19.21	24.57
Procurement Clerks	433061	99.85	98.93	100.79
Other Financial Clerks	433099	22.76	31.98	22.83
Court, Municipal, and License Clerks	434031	0.67	0.30	0.69
Credit Authorizers, Checkers, and Clerks	434041	1.75	0.99	1.75
Customer Service Representatives	434051	36.43	22.10	36.58
Eligibility Interviewers, Government Programs	434061	0.16	0.13	0.21
File Clerks	434071	34.45	14.78	34.64
Hotel, Motel, and Resort Desk Clerks	434081	0.14	0.09	0.26
Interviewers, Except Eligibility and Loan	434111	7.53	2.32	7.58
Library Assistants, Clerical	434121	1.13	0.11	1.21
Loan Interviewers and Clerks	434131	0.10	0.06	0.10
Human Resources Assistants, Except Payroll and Timekeeping	434161	119.10	55.41	119.75
Receptionists and Information Clerks	434171	12.07	7.88	12.09
Reservation and Transportation Ticket Agents and Travel Clerks	434181	3.79	2.12	4.01
Correspondent clerks and order clerks	434XXX	39.19	16.75	39.28
Other Information And Records Clerks	434YYY	2.03	0.75	2.09
Cargo and Freight Agents	435011	26.15	38.12	34.41
Couriers and Messengers	435021	3.29	1.38	3.29
Dispatchers	435030	39.07	27.59	39.53
Meter Readers, Utilities	435041	1243.49	702.64	1531.53
Production, Planning, and Expediting Clerks	435061	183.14	196.75	184.75
Shipping, Receiving, and Traffic Clerks	435071	42.59	26.20	42.74
Stock Clerks and Order Fillers	435081	6.60	4.92	6.61
Weighers, Measurers, Checkers, and Samplers, Recordkeeping	435111	182.79	124.43	185.01
Secretaries and Administrative Assistants	436010	30.21	17.51	30.26
Data Entry Keyers	439021	31.53	19.04	31.60
Word Processors and Typists	439022	4.44	2.71	4.46
Mail Clerks and Mail Machine Operators, Except Postal Service	439051	8.78	12.37	8.84
Office Clerks, General	439061	30.35	15.40	30.43
Office Machine Operators, Except Computer	439071	2.02	0.69	2.07
Proofreaders and Copy Markers	439081	3.58	2.38	3.64
Statistical Assistants	439111	51.61	32.98	51.88
Other Office And Administrative Support Workers	439XXX	33.53	21.96	33.63
First-Line Supervisors of farming, fishing, and forestry workers	451011	64.78	52.38	65.11
Agricultural Inspectors	452011	38.73	24.40	39.13

Table B.1: *List of Occupations with 2022 Emissions Scores (continued)*

Occupation Title	Occupation Code	OES Score	WOES Score	COES Score
Graders and Sorters, Agricultural Products	452041	2.01	1.03	2.06
Other Agricultural Workers	4520XX	0.62	0.43	0.65
Fishing And Hunting Workers	453000	3.33	3.96	3.33
Forest and Conservation Workers	454011	13.21	2.57	13.30
Logging Workers	454020	13.36	26.19	13.39
First-Line Supervisors of Construction Trades and Extraction Workers	471011	85.23	83.81	85.78
Boilermakers	472011	1004.21	715.50	1068.95
Carpenters	472031	14.16	6.22	14.18
Carpet, Floor, and Tile Installers and Finishers	472040	0.07	0.02	0.08
Cement Masons, Concrete Finishers, and Terrazzo Workers	472050	21.60	14.21	22.36
Construction Laborers	472061	16.06	9.73	16.08
Construction Equipment Operators	47207X	58.58	54.83	58.93
Drywall Installers, Ceiling Tile Installers, and Tapers	472080	0.02	0.01	0.03
Electricians	472111	115.56	93.40	118.28
Glaziers	472121	3.40	3.76	3.70
Insulation Workers	472130	286.45	153.90	292.17
Painters, Construction and Maintenance	472140	14.26	12.33	14.27
Pipelayers, Plumbers, Pipefitters, and Steamfitters	472150	191.64	144.79	193.94
Plasterers and Stucco Masons	472161	2.94	1.44	2.96
Roofers	472181	0.09	0.09	0.09
Sheet Metal Workers	472211	25.89	24.68	26.04
Structural Iron and Steel Workers	472221	13.01	12.51	13.13
Brickmasons, Blockmasons, Stonemasons, and Reinforcing Iron and Rebar Workers	472XXX	15.76	8.26	15.80
Helpers, Construction Trades	473010	13.80	2.83	13.90
Construction and Building Inspectors	474011	11.95	16.39	12.02
Elevator Installers and Repairers	474021	10.52	2.60	10.54
Fence Erectors	474031	1.16	0.77	1.18
Hazardous Materials Removal Workers	474041	197.71	210.54	209.93
Highway Maintenance Workers	474051	8.56	4.91	8.88
Rail-Track Laying and Maintenance Equipment Operators	474061	3.78	2.78	3.87
Miscellaneous construction workers including solar Photovoltaic Installers, and septic tank servicers and sewer pipe cleaners	4740XX	20.90	20.21	22.49
Surface Mining Machine Operators And Earth Drillers	475020	131.01	34.22	134.74
Explosives Workers, Ordnance Handling Experts, and Blasters	475031	132.69	91.49	135.51
Mining Machine Operators	475040	575.65	510.07	661.25
Miscellaneous extraction workers including roof bolters and helpers	4750XX	362.08	174.64	385.48
Derrick, rotary drill, and service unit operators, and roustabouts, oil, gas, and mining	4750YY	1083.82	675.03	1271.43
First-Line Supervisors of Mechanics, Installers, and Repairers	491011	171.28	182.46	173.57
Computer, Automated Teller, and Office Machine Repairers	492011	23.84	14.23	23.90
Radio and Telecommunications Equipment Installers and Repairers	492020	54.50	48.45	54.71
Avionics Technicians	492091	4.91	3.99	5.30
Electric Motor, Power Tool, and Related Repairers	492092	89.56	83.11	92.32
Electronic Home Entertainment Equipment Installers and Repairers	492097	0.39	0.16	0.39
Security and Fire Alarm Systems Installers	492098	19.21	12.65	19.40
Electrical and electronics repairers, transportation equipment, and industrial and utility	49209X	481.75	552.85	575.83
Aircraft Mechanics and Service Technicians	493011	15.27	14.06	17.67
Automotive Body and Related Repairers	493021	0.50	0.33	0.50
Automotive Glass Installers and Repairers	493022	0.01	0.01	0.01
Automotive Service Technicians and Mechanics	493023	7.05	6.24	7.06
Bus and Truck Mechanics and Diesel Engine Specialists	493031	61.11	36.00	61.42
Heavy Vehicle and Mobile Equipment Service Technicians and Mechanics	493040	108.47	86.10	109.09

Table B.1: *List of Occupations with 2022 Emissions Scores (continued)*

Occupation Title	Occupation Code	OES Score	WOES Score	COES Score
Small Engine Mechanics	493050	26.65	28.28	26.69
Miscellaneous Vehicle and Mobile Equipment Mechanics, Installers, and Repairers	493090	1.90	1.76	1.92
Control and Valve Installers and Repairers	499010	1168.00	871.34	1323.88
Heating, Air Conditioning, and Refrigeration Mechanics and Installers	499021	11.31	8.46	11.33
Home Appliance Repairers	499031	25.82	25.44	25.98
Maintenance Workers, Machinery	499043	73.45	46.02	73.90
Millwrights	499044	217.71	165.71	222.25
Industrial and Refractory Machinery Mechanic	49904X	146.99	94.01	147.94
Electrical Power-Line Installers and Repairers	499051	1450.54	1426.74	2581.65
Telecommunications Line Installers and Repairers	499052	29.82	31.07	30.15
Precision Instrument and Equipment Repairers	499060	201.65	217.22	204.70
Maintenance and Repair Workers, General	499071	141.57	106.83	142.33
Coin, Vending, and Amusement Machine Servicers and Repairers	499091	0.21	0.19	0.22
Locksmiths and Safe Repairers	499094	7.88	6.81	7.93
Riggers	499096	613.78	492.65	634.91
Helpers–Installation, Maintenance, and Repair Workers	499098	10.03	2.65	10.05
First-Line Supervisors of Production and Operating Workers	511011	333.45	314.58	340.10
Electrical, Electronics, and Electromechanical Assemblers	512020	51.81	60.87	52.16
Engine and Other Machine Assemblers	512031	32.18	15.59	33.24
Structural Metal Fabricators and Fitters	512041	54.08	47.14	70.63
Miscellaneous Assemblers and Fabricators	5120XX	14.87	8.02	15.00
Bakers	513011	0.32	0.15	0.32
Butchers and Other Meat, Poultry, and Fish Processing Workers	513020	7.85	5.43	8.62
Food and Tobacco Roasting, Baking, and Drying Machine Operators and Tenders	513091	14.36	6.05	15.05
Food Batchmakers	513092	8.51	3.66	8.84
Food Cooking Machine Operators and Tenders	513093	5.38	3.24	5.61
Food Processing Workers, All Other	513099	17.16	12.75	18.85
Computer Numerically Controlled Tool Operators And Programmers	514010	19.98	17.87	20.11
Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic	514020	26.81	20.48	28.59
Machine Tool Cutting setters, Operators, and Tenders, Metal and Plastic	514030	23.63	16.98	24.45
Machinists	514041	125.72	127.65	126.55
Metal Furnace Operators, Tenders, Pourers, and Casters	514050	54.10	62.80	62.67
Model Makers, Patternmakers, and Molding Machine Setters, Metal and Plastic	5140XX	17.85	21.10	18.76
Tool and Die Makers	514111	7.38	5.66	7.46
Welding, Soldering, and Brazing Workers	514120	121.09	72.43	121.79
Other Metal Workers And Plastic Workers	514XXX	21.01	17.93	21.63
Prepress Technicians and Workers	515111	6.87	3.10	6.96
Printing Press Operators	515112	3.10	1.46	3.16
Print Binding and Finishing Workers	515113	3.02	1.26	3.14
Laundry and Dry-Cleaning Workers	516011	0.25	0.13	0.26
Pressers, Textile, Garment, and Related Materials	516021	18.07	6.33	18.12
Sewing Machine Operators	516031	0.46	0.35	0.48
Shoe and Leather Workers and Repairers	516040	0.07	0.09	0.07
Tailors, Dressmakers, and Sewers	516050	0.19	0.04	0.19
Textile Machine Setters, Operators, And Tenders	516060	6.53	2.27	6.98
Upholsterers	516093	0.28	0.07	0.29
Miscellaneous textile, apparel, and furnishings workers except upholsterers	51609X	3.60	5.34	3.83
Cabinetmakers and Bench Carpenters	517011	0.07	0.11	0.07
Furniture Finishers	517021	0.05	0.02	0.06
Sawing Machine Setters, Operators, and Tenders, Wood	517041	3.00	2.18	3.40
Woodworking Machine Setters, Operators, and Tenders, Except Sawing	517042	4.02	1.97	4.31
Other Woodworkers	5170XX	0.63	0.28	0.66
Power Plant Operators, Distributors, and Dispatchers	518010	1758.88	1820.46	3032.48

Table B.1: *List of Occupations with 2022 Emissions Scores (continued)*

Occupation Title	Occupation Code	OES Score	WOES Score	COES Score
Stationary Engineers and Boiler Operators	518021	134.10	126.64	135.17
Water and Wastewater Treatment Plant and System Operators	518031	99.85	24.53	104.94
Chemical/Gas/Petroleum/Other Plant and System Operators	518090	3551.74	3078.63	4115.13
Chemical Processing Machine Setters, Operators, and Tenders	519010	194.70	170.33	211.95
Crushing, Grinding, Polishing, Mixing, and Blending Workers	519020	199.86	175.56	208.21
Cutting Workers	519030	24.88	12.84	25.66
Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders	519041	83.45	52.83	88.02
Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders	519051	76.48	77.77	80.20
Inspectors, Testers, Sorters, Samplers, and Weighers	519061	130.44	108.75	131.09
Jewelers and Precious Stone and Metal Workers	519071	0.57	0.32	0.59
Medical, Dental, and Ophthalmic Laboratory Technicians	519080	0.21	0.11	0.21
Packaging and Filling Machine Operators and Tenders	519111	24.65	11.21	25.47
Painting Workers	519120	68.59	12.70	68.92
Photographic Process Workers and Processing Machine Operators	519151	2.72	2.72	2.74
Adhesive Bonding Machine Operators and Tenders	519191	347.96	142.38	356.44
Etchers and Engravers	519194	6.18	41.94	6.37
Molders, Shapers, and Casters, Except Metal and Plastic	519195	31.61	19.61	33.67
Paper Goods Machine Setters, Operators, and Tenders	519196	58.61	53.08	78.20
Tire Builders	519197	6.47	5.48	11.89
Helpers–Production Workers	519198	183.05	48.56	184.86
Miscellaneous Production Workers, Including Equipment Operators and Tenders	5191XX	185.89	164.71	187.66
Supervisors of Transportation and Material Moving Workers	531000	55.17	51.53	56.27
Aircraft Pilots and Flight Engineers	532010	7.51	6.54	7.60
Air Traffic Controllers and Airfield Operations Specialists	532020	33.09	61.48	48.34
Flight Attendants	532031	0.51	0.31	0.61
Ambulance Drivers and Attendants, Except Emergency Medical Technicians	533011	2.66	0.65	2.76
Bus Drivers	533020	5.47	1.91	5.49
Driver/Sales Workers and Truck Drivers	533030	45.76	32.28	46.11
Taxi Drivers and Chauffeurs	533041	2.83	1.34	2.86
Motor Vehicle Operators, All Other	533099	11.51	2.87	11.81
Locomotive Engineers and Operators	534010	19.10	10.89	19.17
Railroad Conductors and Yardmasters	534031	3.24	3.26	3.26
Other Rail Transportation Workers	5340XX	1.45	1.30	1.46
Ship and Boat Captains and Operators	535020	42.40	59.50	45.03
Sailors and marine oilers, and ship engineers	5350XX	64.76	57.76	66.82
Parking Lot Attendants	536021	0.67	0.17	0.68
Automotive and Watercraft Service Attendants	536030	54.96	16.03	55.32
Transportation Inspectors	536051	77.37	90.98	79.10
Passenger Attendants	536061	8.77	3.44	9.84
Miscellaneous transportation workers including bridge and lock tenders and traffic technicians	5360XX	57.09	36.36	59.87
Crane and Tower Operators	537021	194.56	137.39	198.84
Industrial Truck and Tractor Operators	537051	50.87	22.91	51.07
Cleaners of Vehicles and Equipment	537061	10.33	5.76	10.38
Laborers and Freight, Stock, and Material Movers, Hand	537062	40.59	24.07	40.70
Machine Feeders and Offbearers	537063	77.26	39.41	77.90
Packers and Packagers, Hand	537064	11.55	4.71	11.61
Pumping Station Operators	537070	1052.89	714.53	1115.39
Refuse and Recyclable Material Collectors	537081	95.61	67.94	155.54
Conveyor, Dredge, And Hoist And Winch Operators	5370XX	9.73	5.94	9.84
Other Material Moving Workers	5371XX	247.18	128.48	250.59

__Table B.1:__ List of Occupations with 2022 Emissions Scores (continued)

Occupation Title	Occupation Code	OES Score	WOES Score	COES Score
Military Officer Special and Tactical Operations Leaders	551010	0.92	1.14	1.83
First-Line Enlisted Military Supervisors	552010	0.92	0.96	1.83
Military Enlisted Tactical Operations and Air/Weapons Specialists and Crew Members	553010	0.92	0.52	1.83
Military, Rank Not Specified	559830	0.92	0.77	1.83

Notes: All scores are reported in metric tons of CO2eq and are based on 2022 emissions.

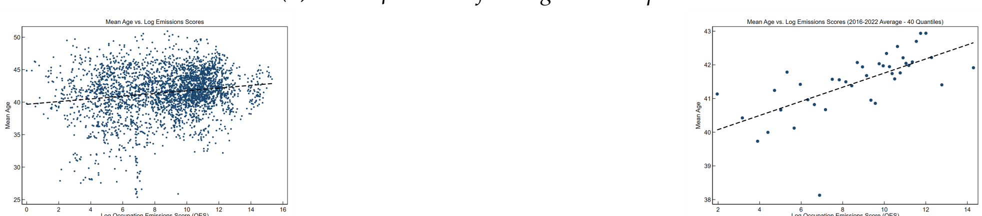
C. Additional Results

***(a)** Share Females in Occupation*

***(b)** Share Non-Hispanic Whites in Occupation*

***(c)** Share Foreign-Born in Occupation*

***(d)** Share 4+ Years of College in Occupation*



***(e)** Mean Age in Occupation*

***Figure C.1:** Scatter Plots of OES and Demographic Characteristics (Left: Occupation-Year Level, Right: OES Quantile Level)*

Notes: The charts show the relationship between demographic characteristics and the log OES. Charts on the left column present scatterplots where each dot represents an occupation-year pair (447 occupations, 2016-2022). Charts on the right column display scatterplots where each dot corresponds to an OES quantile (based on the 2016-2022 average score; 40 quantiles total). The demographic characteristics include: (a) share females, (b) share non-Hispanic whites, (c) share foreign born, (d) share individuals with 4+ years of college, and (e) mean age. Dashed lines are the fitted regression line for each relationship.