Carbon Taxes in Spatial Equilibrium

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Abstract

Residential, industrial, and commercial carbon dioxide emissions vary substantially across cities and sectors; this variation has led to concerns about the distributional consequences of carbon pricing policies. I develop and estimate a spatial equilibrium model to quantify the incidence from a stylized carbon tax across cities, sectors, and education groups in the U.S. The model features heterogeneous households, firms in multiple locations, sectors that use energy and labor as imperfect substitutes, and region-specific carbon emissions rates due to differences in the fuel mix used to generate electricity. A uniform carbon tax has substantial distributional effects, with non-college-educated manufacturing workers living in the Midwest and South bearing the greatest burden. Cities with mild climates, carbon-efficient power plants, and services-oriented economies experience modest population increases as households move in response to the carbon tax. The share of the total tax burden attributable to coal-fired electricity varies significantly across regions. Additionally, I use the model to demonstrate that progressive compensation leads to a decline in aggregate carbon emissions due to a reallocation of workers into cities and less carbon-intensive sectors.

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1 Introduction

Carbon emissions create well-recognized negative externalities. The Intergovernmental Panel on Climate Change (IPCC) inventories rising sea levels, temperatures, and changes in the pattern, frequency, and intensity of extreme weather events (storms, heat waves, and droughts) as a few of the likely consequences of climate change. Among professional economists, carbon taxes receive widespread support as a tool for reducing emissions due to the economic efficiency offered by the tax (Climate Leadership Council, 2021). Despite this support from economists, global policy efforts to implement carbon prices have been fairly limited.[1] Sallee (2019) argues that the distributional concerns arising from carbon pricing—and more specifically, the ability to precisely predict lump-sum transfers for those who bear the greatest burden of the tax—account for disparities between the policy preferences of economists and voters.

Several factors lead to heterogeneity across households in the burden of carbon taxes. Carbon is a byproduct of energy production, so differences in the carbon intensities of power plants across regions will lead to spatial differences in the effect of a carbon tax on electricity prices. These increases in electricity prices (and other fuel prices)—and their differences across space—create heterogeneous initial impacts on households through two distinct channels: labor demand and household energy expenditures. On the labor-demand side, a carbon tax will reduce output from emissions-intensive industries and lead to a reallocation of input demand away from energy use towards other inputs. Furthermore, industries tend to cluster in particular cities; this clustering implies that a carbon tax will have differential impacts on labor demand (and hence wages) across both cities and sectors. On the energy expenditure side, household demand for energy (derived from demand for heating and cooling) varies across space, primarily due to differences in climate.[2] Thus, a nationally uniform carbon price creates heterogeneous impacts on households stemming from differences across cities in the resulting energy price increases and the disutility delivered by these price increases. The labor demand channel and the household energy expenditure channels imply that the burden from a carbon tax is a function of the joint spatial distributions of sectors (and their respective production technologies), households, and the mix of fuels used regionally to generate electricity. This paper contributes to the carbon-pricing policy debate by estimating the spatial and sectoral distribution of incidence across education groups from a carbon tax in the United States.

To measure the burden from a carbon tax, I develop and estimate a quantitative spatial equilibrium model. At the core of the model is a discrete choice problem for households who must select both a sector and a location. Wages are endogenous, and production is a city- and sector-specific function of imperfectly substitutable labor and energy inputs. Locations vary in

[1] As of 2020, some 40 countries had enacted some form of carbon pricing (World Bank, 2020).

[2] Lyubich (2021) demonstrates that location explains over half of the variation in household carbon emissions—15-25% of the overall variation in carbon emissions.

terms of their amenities, their housing supply curves, the emissions intensity of their electricity generation and power-plant technologies, and their input-use intensities in producing goods and services. Output markets are assumed to be perfectly competitive.

Within the model, the welfare effects of a national carbon tax will vary geographically *and* sectorally for four reasons. First, locations vary in terms of the marginal benefit of energy consumption and the carbon content of the fuel mix used by local power plants (Glaeser and Kahn, 2010). Cities with warmer climates, such as Houston, tend to have a higher marginal benefit of electricity consumption due to greater demand for air-conditioning, resulting in higher household energy demand and thus greater carbon emissions. Second, within the U.S., the carbon intensity of power plants varies significantly across regions; some areas such as the Midwest and South are much more dependent on coal-fired electricity than other areas such as the West.[3] Third, sectors vary in the amount of energy used for production processes and the degree to which labor and energy are technologically substitutable. For example, the manufacturing sector is significantly more energy-intensive than the services sector, so a carbon tax will have a considerably larger effect on manufacturing wages and employment than services. Lastly, in the context of the model, cities vary in their industrial employment composition. Due to the differences in the fuel mix used by regional power plants, a carbon tax will differentially impact energy prices across cities, which in turn will have heterogeneous impacts on worker's wages. In response to the energy price and wage changes, workers can relocate across cities and sectors as the relative attractiveness of each city-sector changes. This re-sorting of workers across space and sectors results in equilibrium adjustments in rental markets that further affect utility. Therefore, accurately recovering the overall tax incidence across different types of households necessitates a general equilibrium analysis that permits households and firms to respond to the variety of changes that a carbon tax induces.

I discipline the model's structural parameters using a variety of publicly available data. I use data from the American Community Survey (ACS) and Census to estimate household preference parameters and household carbon emissions. More specifically, I estimate the model's labor supply parameters using a two-step procedure involving maximum likelihood and instrumental variables, similar to the approach taken by Berry, Levinsohn, and Pakes (2004). I use a combination of calibration and estimation to obtain production functions that are both city-specific and sector-specific.

To monetize the incidence of a carbon tax, I calculate the average compensating variation, which is the average dollar amount required for a household in each city-sector to be indifferent to the carbon tax. I find significant unequal distributional consequences across cities and sectors from a uniform carbon tax. I find that a carbon tax of $31 per ton would result in a mean decrease of 926 vs. 1,417 utility-equivalent dollars per year for college vs. non-college

[3] Figure 8 in Section A.5 provides a map of US regional emissions rates from electricity.

households, respectively – with significant heterogeneity across cities and sectors. Furthermore, I find that this carbon tax would reduce emissions by 19.8% and lead to a reallocation of workers away from manufacturing (by 11.1%) and into less-carbon intensive jobs in the services sector. Due to differences in wages across cities, compensating variation (monetized incidence) masks important underlying heterogeneity in tax burden. Thus, I separately examine compensating variation in *percentage* terms rather than dollars— which I refer to simply as "incidence," (as opposed to *monetized* incidence or compensating variation). I find that cities on the West Coast and New England experience lower incidence than cities elsewhere due to their relatively carbon-efficient power plants and services-oriented economies.

The model predicts migration patterns across cities consistent with the spatial variation in tax incidence. Generally, cities in the Western and New England Census Divisions experience population increases, while cities in the South and Midwest experience population decreases. For example, California experiences an overall population increase of roughly 2%. Cities in California have mild climates, source their electricity from carbon-efficient power plants, and have services-oriented economies. Thus, a carbon tax induces migration to California, as households benefit from California's relatively climate-policy resilient economy. Despite being less mobile, non-college-educated households move in greater rates in response to the carbon tax—underscoring the more significant tax burden that these households bear.

Motivated by the remarkable decline in the share of electricity generated from coal over the last 15 years, I use the the model to decompose the carbon tax incidence into two distinct components: coal and non-coal.[4] I re-calculate regional emissions rates from electricity generation in the absence of coal and re-simulate the $31 carbon tax in the context of this alternative and cleaner grid.[5] I find that the compensating variation falls by nearly 40%, and this decline exhibits regional heterogeneity. Coal-generated electricity is highly carbon-intensive and thus is responsible for a larger share of the total incidence in coal-dependent regions. This finding suggests that as the electricity grid decarbonizes, the payment required to compensate households for a carbon tax will decline by a significant amount.

I use the model to simulate a carbon tax with various compensation schemes. Due to the regressive nature of carbon taxes, some proposed carbon pricing legislation includes progressive transfer payments.[6] In simulations with carbon taxes and transfers, I focus on varying the progressivity of the payments to households. The simulations reveal a novel relationship

[4] This decline is well documented— for example, see Mendelevitch, Hauenstein, and Holz (2019). I demonstrate the national and regional decline in the share of coal-generated electricity in figure 3.

[5] To be clear, this exercise is purely decompositional. Carbon pricing policies impact the rate of adoption for carbon-efficient electricity generation since coal is carbon-intensive. For an example, see Scott (2018).

[6] For example, the recently introduced Stemming Warming and Augmenting Pay (SWAP) act specifically calls for "...20% (of revenues) to establish a carbon trust fund for block grants to offset higher energy costs for low-income households, climate adaptation, energy efficiency, carbon sequestration, and research and development programs" (U.S. House of Representatives, 2019).

between the progressivity of transfers and *aggregate* carbon emissions: aggregate emissions are lower with progressive transfers than with lump-sum transfers. The mechanism behind this relationship is straightforward. Wages exhibit spatial and sectoral correlation, so progressive transfers are also correlated across space and sectors. In an equilibrium with progressive transfers, lower-wage cities receive larger transfers and thus attract more workers (relative to a policy with lump-sum transfers), all else equal. The progressivity of the transfers will impact aggregate carbon emissions if wages are correlated with carbon emissions (at the city-sector level) due to the reallocation of workers into areas with higher transfers.

Indeed, there is a positive correlation between wages and emissions in the data – and the model predicts a larger share of workers shifting away from jobs with high wages in emissions-intensive sectors, thus causing aggregate emissions to fall. My results suggest that using carbon tax revenue for income redistribution may have the unappreciated unintended benefit of reducing aggregate emissions—and therefore, has the potential to enhance the effectiveness of the policy in meeting emissions targets.

Literature. I am not the first to recognize—or model— the distributional impacts of carbon taxation. For example, Rausch, Metcalf, and Reilly (2011) (RMR) use a calibrated version of MIT's US Regional Energy Policy model and a sample of roughly 15,000 households to demonstrate considerable heterogeneity across demographic groups in the incidence of a carbon tax.[7,8] Hafstead and Williams (2018) use a two-sector general equilibrium model and conclude that the unemployment effects of a carbon tax will be negligible due to growth in clean industries. Using a macroeconomic lifecycle model, Fried, Novan, and Peterman (2021) (FNP) find that in the welfare-maximizing allocation of carbon tax revenue, two-thirds goes to a reduction in capital-income taxes and one third towards increasing the progressivity of the income tax. My results are complementary to those of FNP. While I abstract from dynamics, my model's geographic and sectoral heterogeneity allows me to capture the relationship between income redistribution and aggregate emissions. In a recent working paper, Castellanos and Heutel (2019) (CH) conclude that alternative assumptions about worker mobility potentially play a significant role in the aggregate employment effects from carbon pricing. RMR and CH make different assumptions about labor mobility; in RMR, workers are mobile across sectors but not locations. CH examines edge cases with perfect mobility and perfect immobility. My work explicitly models (and then estimates) the process by which households make city-sector choices —including moving costs. Even if employment remains constant, my work considers that relocating to new jobs and locations is costly.

An extensive empirical literature has demonstrated that environmental regulation has het-

[7] Other examples of research that looks at the distributional consequences from carbon pricing includes Goulder et al. (2019), Williams III et al. (2015), and Beck et al. (2015). To my knowledge, I am the first to estimate the heterogeneous welfare effects from a carbon tax in a locational discrete-choice setting.

[8] For details on the Regional Energy Policy model, see Yuan et al. (2019).

erogeneous impacts across sectors. Recent work by Yamazaki (2017) finds that energy-intensive sectors saw larger relative losses in wages from the carbon tax in British Columbia, Canada. In British Columbia, overall unemployment decreased due to a shift in demand towards less energy-intensive sectors due to the revenue recycling decisions (i.e., transfers that households received from the tax).[9] In complementary work, Yip (2018) finds that the British Columbia carbon tax was implemented mainly at the expense of individuals without a college degree, as these workers are generally in more energy-intensive sectors with fewer outside options.[10] Other research has demonstrated broader distributional effects from environmental regulation. For example, Walker (2013) examines the labor-market impacts of the 1990 amendments to the Clean Air Act (CAA). These amendments involved command-and-control regulations that established thresholds for the maximum allowable ambient concentrations of pollutants. Using a triple-difference approach, Walker finds significant reductions in employment in manufacturing (and other energy-intensive sectors) due to these regulations. Curtis (2014) examines the labor market impacts of the EPA's NO_x budget trading program—which was a type of cap and trade program enacted in 2003—and reaches conclusions similar to Walker (2013). Specifically, sectors that are more energy-intensive experience larger losses in unemployment.

Methodologically, the present paper is closely related to Diamond (2016), Piyapromdee (2021), Colas and Hutchinson (2021), and Colas and Morehouse (2021) (CM). These papers estimate general equilibrium models of location choice in which wages and rents respond endogenously to agents' location choices. The model in CM is designed to measure changes in *residential* carbon emissions from relaxing stringent land-use regulations. This paper departs from the model in CM along three significant dimensions. First, I model energy as a production input for firms. This allows for endogenous wage changes in response to energy price changes that ensue from a carbon tax. Second, firms vary across cities and sectors — with different factor intensities and productivities. The sectoral composition of industries at a given location will impact the welfare of local workers (for reasons described above) and thus will have first-order consequences for household sorting. Lastly, households make a *joint* choice concerning both their city and their sector. To assess the welfare effects of a carbon tax, my model combines empirical insights from a large literature on the distributional consequences of carbon pricing and extends the modeling strategy used in Colas and Morehouse (2021). I build a unified framework that simultaneously analyzes the variation in labor-market responses to carbon taxes across cities and sectors.

Overall, my objective in this paper is to improve policy-makers' understanding of the

[9] The tax was supposed to be revenue-neutral. In practice, it did not turn out this way. Yamazaki (2017) notes "tax credits have been exceeding tax revenues since its implementation."

[10] Other recent empirical work has examined the effects of carbon taxes implemented in different countries, such as Martin, De Preux, and Wagner (2014). The authors find minimal adverse unemployment impacts from the UK's carbon tax.

distributional consequences of carbon taxes. The empirical structural model I develop allows me to obtain quantitative estimates of the varying incidence levels across cities and sectors. The rest of this paper proceeds as follows. Section 3 provides an overview of the data, Section 2 details the structural model, Section 4 discusses the estimation procedure and how key parameters are identified, Section 5 discusses the parameter estimates, section 6 examines selected counterfactuals, and Section 7 concludes.

2 Model

This section describes a general equilibrium model where households make a joint, discrete choice over location and sector. Conditional on location and sector, households consume a numeraire good, housing, and energy services. These different decisions, and the linkages between these related markets, are crucial for determining the net welfare effects of a carbon tax. Labor demand arises from perfectly competitive firms that differ across locations and sectors. Housing demand follows from the location choices of agents, and housing supply is increasing in the price of housing.

More specifically, a household has an exogenously given education level and birthplace. Locations vary in terms of the location-specific consumption goods (amenities) they provide, wages, rents, the marginal utility of energy consumption, and the carbon intensity of the local power plants. Sectors vary in input use intensity and unobservable sectoral amenities (e.g., employment benefits). Firms with nested CES technologies combine college-educated and non-college-educated labor with electricity and gas in production within each sector at each location. Each location functions as a small open economy, so wider national and international markets always satisfy any excess demand.

To capture the labor-market effects of a carbon tax, I introduce heterogeneity across locations and sectors of production for the output good. Across locations and sectors, firms vary by all input-use intensities (a set of parameters). Variation in production parameters reflects differences across locations in available labor supply and variation in regional energy prices. Furthermore, across sectors (but not locations), firms vary by their elasticities of substitution across energy inputs and the mix of energy and labor. Some sectors, such as agriculture, can substitute relatively easily between labor and energy. Other sectors, such as construction, cannot.

In my model, a uniform national carbon tax will have location-and sector-specific welfare effects for several reasons. First, locations vary in their marginal utilities of energy consumption (*e.g.* they have different climates), and their power plants have different degrees of carbon intensities. Consequently, the consumption of the same amount of electricity will imply different levels of emissions across locations. Second, a carbon tax will have varying effects on wages.

Consumption of energy in production leads to emissions. The specific amount of energy used and carbon emitted depends on the firm's sector and location. After the carbon tax, wages will change through two particular channels. First, as a direct result of the carbon tax, the relative price of energy inputs will increase, so the firm will substitute other inputs and reduce output. Second, there will be adjustments to equilibrium wages to the extent that there are differential impacts on labor demand across locations and sectors. Thus, workers in regions/sectors with higher carbon emissions will see a relatively large decrease in wages and will sort towards sectors and locations with lower carbon intensities.

2.1 Households

A household consists of one or more individuals. If a household contains more than one working-aged individual, the "agent" refers to the putative household head. Agents are endowed with an education level and native birth state. They receive utility from the consumption of a numeraire good, housing, energy services, and amenities. Each agent makes a one-time decision over locations and employment sectors. Let $j \in J$ index cities, $n \in N$ index sectors, and $e \in \{l, c\}$ index education groups (where l indicates that the household has "less than a college degree" and c indicates that the agent has a 'college degree or greater"). Agent i's utility from living in city j and working in sector n is characterized as:

$$u_i(c, h, x_m | e, j, n) = \alpha_e^c \log c + \alpha_e^H \log h + \sum_m \alpha_{ejn}^m \log x_m + \lambda_{ijn}, \tag{1}$$

where c is consumption of the numeraire good, h is consumption of housing, x_m is consumption of fuel type $m \in \{\text{elec}, \text{gas}, \text{oil}\}$ and λ_{ijn} is amenities. I parameterize amenities as

$$\lambda_{ijn} = f(j, \mathcal{B}_i) + \xi_{ejn} + \sigma_e \epsilon_{ijn}, \tag{2}$$

where the function $f(j, \mathcal{B}_i)$ is a function of the agent's birth location, $\mathcal{B}_i$, and location j, ξ_{ejn} is an unobserved component of amenities that all workers share within an education group-city-sector. The term ϵ_{ijn} is an idiosyncratic preference shock drawn from a Type I Extreme Value distribution (EV1) with mean zero and shape parameter σ_e. Variation in ξ_{ejn} captures differences in amenities across locations and sectors. Heterogeneity in ξ_{ejn} across cities (but within the same sector) are driven by heterogeneity in location-specific market or non-market consumption goods such as air quality, crime, schools, or the number of restaurants in the city. Variation in ξ_{ejn} within the same city but across sectors is due to variation in the availability of non-pecuniary benefits across sectors. I parameterize f as:

$$f(j, \mathcal{B}_i) = \gamma_e^{div} \mathbb{I}\left(j \in \mathcal{B}_i^{div}\right) + \gamma_e^{\text{dist}} \phi\left(j, \mathcal{B}_i^{st}\right) + \gamma_e^{\text{dist2}} \phi^2\left(j, \mathcal{B}_i^{st}\right), \tag{3}$$

where $\mathbb{I}\left(j \in \mathcal{B}^{div}\right)$ is an indicator for j being in worker i's birth division, $\phi(j, \mathcal{B}_i^{st})$ is the Euclidean distance between location j and the agent's birth state $\mathcal{B}_i^{st}$, and $\phi^2(j, \mathcal{B}_i^{st})$ is the squared Euclidean distance between j and $\mathcal{B}_i^{st}$.[11] As noted by Bayer, Keohane, and Timmins (2009), individuals tend to have a preference for locations with greater accessibility to their birth state, where I model accessibility simply as distance.

Agents face the following budget constraint

$$w_{ejn} = c + R_j H + \sum_m P_j^m x_m, \tag{4}$$

where w_{ejn} is the wage level for an agent of education level e in city j and sector n. R_j and P_j^m represent the rental and energy prices (of each type m) in city j, which are constant across sectors and demographic groups.

Maximizing the utility described by equation (1) subject to the budget constraint represented by equation (4) yields constant shares of income devoted to housing and fuel consumption:

$$\begin{aligned} H_{ejn}^{\star} &= \frac{\alpha_e^H w_{ejn}}{\boldsymbol{\alpha}_{ejn} R_j} \\ x_{ejn}^{m\star} &= \frac{\alpha_{ejn}^m w_{ejn}}{\boldsymbol{\alpha}_{ejn} P_j^m} \qquad \forall m \in \{\text{elec}, \text{gas}, \text{oil}\}, \end{aligned}$$

where to simplify the notation in what follows, I define the parameter $\boldsymbol{\alpha}_{ejn}$ as:

$$\boldsymbol{\alpha}_{ejn} = \alpha_e^c + \alpha_e^H + \sum_m \alpha_{ejn}^m.$$

I then solve for the agent's constrained utility maximization problem to yield the corresponding indirect utility function associated with location j and sector n

$$v_{ijn} = \left(\boldsymbol{\alpha}_{ejn}\right) \log(w_{ejn}) - \alpha_e^H \log R_j - \sum_m \alpha_{ejn}^m \log P_j^m + f(j, \mathcal{B}_i) + \hat{\lambda}_{ijn}, \tag{5}$$

[11] This specification is slightly unusual in that I use an indicator for birth *division* and not state. Since the model only includes 70 CBSAs (plus 9 census divisions as outside options), not every state is represented – but all census divisions are.

where I again simplify the notation by defining:

$$\hat{\lambda}_{ijn} = \lambda_{ijn} + \sum_m \alpha_{ejn}^m \log\left(\alpha_{ejn}^m\right).$$

Given the EV1 assumption on the idiosyncratic preference shock (ϵ_{ijn}) the probability agent i with education level e chooses option jn is given by the familiar logit form:

$$P_{ijn}^e = \frac{\exp(\frac{\bar{v}_{ijn}}{\sigma_e})}{\sum_{j'}\sum_{n'}\exp(\frac{\bar{v}_{ij'n'}}{\sigma_e})}, \tag{6}$$

where $\bar{v}_{ijn} = v_{ijn} - \sigma_e \epsilon_{ijn}$.

2.2 Firms & Housing Supply

Firms. Firms competing in perfectly competitive factor markets combine both labor and energy inputs to produce a sector-specific, tradeable good. I model each location as a small, open economy, so firms treat their output price (denoted by P_n) as exogenous. Firms in city j and sector n produce according to:[12]

$$Y_{jn} = A_{jn} K_{jn}^{\eta} \mathcal{I}_{jn}^{1-\eta},$$

where $\mathcal{I}_{jn}$ is a conventional CES aggregator for energy and labor inputs also specific to that sector and location:

$$\mathcal{I}_{jn} = \left(\alpha_{jn}\mathcal{E}_{jn}^{\rho_{el}^n} + (1-\alpha_{jn})\mathcal{L}_{jn}^{\rho_{el}^n}\right)^{\frac{1}{\rho_{el}^n}}.$$

Furthermore, the CES aggregator is applied to two-component CES aggregators. $\mathcal{E}_{jn}$ aggregates the use of electricity (denoted by E_{jn}) and natural gas (denoted by G_{jn}) by firms. $\mathcal{L}_{jn}$ aggregates the use of workers with a college degree or more education (denoted by C_{jn}) and workers without a college degree or less education (denoted by L_{jn}) by firms. Specifically, these component aggregators are parameterized as:

$$\mathcal{E}_{jn} = \left(\zeta_{jn} E_{jn}^{\rho_e^n} + (1-\zeta_{jn}) G_{jn}^{\rho_e^n}\right)^{\frac{1}{\rho_e^n}}$$
$$\mathcal{L}_{jn} = \left(\theta_{jn} C_{jn}^{\rho_l} + (1-\theta_{jn}) L_{jn}^{\rho_l}\right)^{\frac{1}{\rho_l}}.$$

[12] The recent applied general equilibrium literature has utilized nested CES production functions with various functional forms. See Brockway et al. (2017) for a discussion.

Firm electricity demand generates emissions indirectly (at the regional power plants), so these emissions are sensitive to both use *and* the carbon efficiency of local power plants. Natural gas consumption leads to direct emissions but does not vary by location because I assume the carbon emissions rate of natural gas is the same everywhere.

Given that I assume factor markets are perfectly competitive, input prices are equal to their marginal products. I assume the supply of capital is perfectly elastic with rental rate $\bar{r}$. The firm chooses its level of capital such that the price of capital is equal to its marginal product.[13] Specifically, the first-order condition for capital utilization yields:

$$K_{jn} = \left(\frac{P_n A_{jn} \eta \mathcal{I}_{jn}^{1-\eta}}{\bar{r}} \right)^{\frac{1}{1-\eta}}. \tag{7}$$

Using equation (7), I can write the system of first-order conditions to derive the inverse energy and labor demand curves:

$$\begin{aligned} P_{jn}^E &= \mathcal{A}_{jn} \mathcal{I}_{jn}^{1-\rho_{el}^n} \mathcal{E}_{jn}^{(\rho_{el}^n - \rho_e^n)} \alpha_{jn} \zeta_n E_{jn}^{\rho_e^n - 1} \\ P_{jn}^G &= \mathcal{A}_{jn} \mathcal{I}_{jn}^{1-\rho_{el}^n} \mathcal{E}_{jn}^{(\rho_{el}^n - \rho_e^n)} \alpha_{jn} (1 - \zeta_n) G_{jn}^{\rho_e^n - 1} \\ W_{jn}^C &= \mathcal{A}_{jn} \mathcal{I}_{jn}^{1-\rho_{el}^n} \mathcal{L}_{jn}^{(\rho_{el}^n - \rho_l)} (1 - \alpha_{jn})(\theta_{jn}) C_{jn}^{\rho_l - 1} \\ W_{jn}^L &= \mathcal{A}_{jn} \mathcal{I}_{jn}^{1-\rho_{el}^n} \mathcal{L}_{jn}^{(\rho_{el}^n - \rho_l)} (1 - \alpha_{jn})(1 - \theta_{jn}) L_{jn}^{\rho_l - 1}, \end{aligned} \tag{8}$$

where

$$\mathcal{A}_{jn} = P_n A_{jn} \left(\frac{A_{jn} \eta}{\bar{r}} \right)^{\frac{\eta}{1-\eta}} (1 - \eta).$$

Rents. The housing supply curve is upward sloping with city-specific elasticities and intercepts. Specifically, I parameterize the housing supply curve as:

$$R_j = \bar{K}_j H_j^{\beta_j}. \tag{9}$$

Differences in $\bar{K}_j$ across cities reflect differences in local construction costs. The amount of land available for production and the tightness of local land-use restrictions drives variation in β_j (Saiz, 2010). For example, consider a city with less available land for development. All else equal, the marginal cost of developing land that is relatively more scarce will be greater, which

[13] In Appendix A.1.1 I provide more details for the first order condition derivations.

will lead to a higher value of β_j. Taking logs of equation (9) yields:

$$\log(R_j) = \log(\bar{K}_j) + \beta_j \log(H_j). \tag{10}$$

The log-log form in equation (10) highlights the constant elasticities of the housing supply curves used in the model.

2.3 Energy Supply

There are three energy markets in the model: electricity, natural gas, and oil. For each market, demand is endogenous and downward sloping. I assume that natural gas and fuel oil are traded on international markets, and their supply is perfectly elastic. Due to high transmission costs, I assume electricity is traded within NERC regions but not across them. Furthermore, I segment electricity supply into two separate markets: residential and industrial. Electricity supply varies across the type of consumer k due to differences in transmission costs for households compared to firms. Conditional on consumer type, electricity supply varies across local labor markets j due to differences in transmission costs within a NERC region $\mathcal{R}$. I parameterize the inverse supply curve for electricity as:

$$P^{\text{elec}}_{kj} = a_{kj} Q^{\mu}_{\mathcal{R}(j)}, \tag{11}$$

where $k \in \{\text{Residential}, \text{Industrial}\}$ indexes the consumer "type", a_{kj} is the consumer-city intercept, $Q_{\mathcal{R}(j)}$ is the electricity supply in NERC region $\mathcal{R}$ (where $R(j)$ maps cities to their corresponding NERC region), and μ is the inverse electricity supply elasticity.

To be clear, the model developed in this paper says nothing about dynamics, and any identified equilibrium is considered a "long-run" equilibrium. Typically in the short run, electricity markets models use "constant-order dispatch curves." In the long run, however, electricity suppliers can respond to changes in demand by opening new power plants or switching fuel types.[14]

2.4 Emissions

In the context of the model, carbon emissions arise from the consumption of energy inputs by agents and firms. Agents consume natural gas, fuel oil, and electricity, whereas firms consume natural gas and electricity. I assume a constant carbon emissions factor of 117 lbs per thousand cubic feet for natural gas and 17 lbs per gallon for fuel oil.[15] Emissions from

[14] Scott (2021) shows that the EPA's Mecury and Toxic Air standards induced many power plants to convert their coal generators to natural gas.

[15] https://www.eia.gov/tools/faqs/faq.php?id=73t=11

electricity generation vary across NERC regions, denoted by $\delta_{\mathcal{R}}^{elec}$. I assume that total regional carbon emissions from electricity in a NERC region equals the output-weighted average carbon-emission factors for individual electricity generating units (EGUs). The emissions factor in NERC region $\mathcal{R}$ is therefore given by:

$$\delta_{\mathcal{R}}^{elec} = \sum_{g \in \mathcal{R}} \frac{\text{elec}_g}{\text{elec}_{\mathcal{R}}} \times \frac{\text{CO}_{2,g}}{\text{elec}_g},$$

where elec_g is the amount of electricity produced by a generator g, $\text{elec}_{\mathcal{R}}$ is the total amount of electricity produced in NERC region $\mathcal{R}$ and $\text{CO}_{2,g}$ is the total (yearly) amount of carbon dioxide emitted by generator g. More generally, I write the emissions factor for fuel-type m in city j as:

$$\delta_j^m = \begin{cases} \delta_{\mathcal{R}(j)}^{elec} & \text{if } \ m \in \{\text{elec}\} \\ \delta_m & \text{if } \ m \in \{\text{gas}, \text{oil}\} \end{cases}$$

To obtain aggregate emissions, I multiply the energy consumption in city j and sector n by the respective conversion factors for agents and firms and then sum these. Concretely, this is given by:

$$\texttt{Emis} = \sum_j \sum_n \delta_j^m \hat{f}_{jn},$$

where $\hat{f}_{jn} = \sum_m \sum_e N_{ejn} x_{ejn}^m + E_{jn} + G_{jn}$ is the sum of city-sector agent fuel consumption ($N_{ejn} x_{ejn}^m$) and firm fuel consumption.

2.5 Equilibrium

Equilibrium in the model is achieved when agents and firms make optimal choices and all markets clear. Specifically, an equilibrium requires:

(1) **Utility Maximization.** Each agent must be in a sector and at a location that yields maximal utility, given their constraints. The equilibrium population for each education group-city-sector, $N_{ejn}^{\star}$, can thus be determined by: $N_{ejn}^{\star} = N \times s_{ejn}$, where $s_{ejn} = \frac{1}{N} \sum_i P_{ijn}^e$ are the shares computed from the choice probabilities in equation (6).

The population distribution determines each city's housing and energy demand. Housing demand in city j is given by the sum of all individual agents' demands. I write total equilibrium housing and energy demand in city j as

$$\begin{aligned} H_j^{\mathcal{D}} &= \sum_{e\in E}\sum_{n\in N} N_{ejn}^{\star} \times \frac{\alpha_e^H w_{ejn}}{\boldsymbol{\alpha}_{ejn} R_j} \\ x_j^{\mathcal{D}} &= \sum_{e\in E}\sum_{n\in N} N_{ejn}^{\star} \times \frac{\alpha_{ejn}^m w_{ejn}}{\boldsymbol{\alpha}_{ejn} P_j^m} \qquad \forall m \in \{\text{elec, gas, oil.}\} \end{aligned} \tag{12}$$

Aggregate labor supply is given by the number of efficiency units of labor supplied by each worker:[16]

$$\mathcal{L}_{ejn}^{S} = N_{ejn} \times \ell^e. \tag{13}$$

(2) **Profit Maximization.** Firms maximize profits. This implies that the first-order conditions given by equation (8) must be satisfied.

(3) **Market Clearing.** All markets in the model need to clear. Namely, supply and demand must be balanced in the labor market, in the housing market, and in all energy markets.

3 Data

I combine data from multiple sources. I obtain individual-level data from the ACS and Census. Energy prices and sectoral energy use data come from the Energy Information Association (EIA). I employ data from the Environmental Protection Agency (EPA) to calculate power-plant carbon emissions.

3.1 Sources

Household Data. The time-aggregated 5-year ACS (Ruggles et al., 2010) has detailed individual-level information for more than 5 million individuals in the US from 2012-2016. Crucially, the ACS has both where the individual currently resides (down to the MSA level) and their current sector. Furthermore, the ACS provides information on the individual's monthly rent payments, pre-tax and after-tax wages, and energy expenditures for various fuel types. In estimation, I use repeated cross-sections of 5% samples of 1990, 2000, and 2010 censuses. I stratify households into one of two education levels: having a college degree (or more) or having less than a college degree. In selecting my sample, I closely follow the strategies used by other researchers and thus relegate the details of the process to Appendix A.7.

CBSA Data and Sectoral Data. My measure of a "city" (or location, in the model) is a Core Based Statistical Area (CBSA). CBSAs correspond to distinct (and relatively closed) labor

[16] Estimation of efficiency units of labor is relatively standard and thus the details can be found in Section A.1.2

markets and are the Office of Management and Budgets' official definition of a metropolitan area. I restrict the choice set to the 70 largest CBSAs by 1980 population, plus nine additional "outside options" — one for each census division. I categorize workers in one of five sectors: services, construction, agriculture, manufacturing, and an outside option sector. These five sectors account for roughly 90% of total 2016 employment.[17] My selection of cities and sectors results in a choice set containing 395 elements, where each choice is a city-sector pair. I focus on household consumption of three energy types: electricity, natural gas, and fuel oil. The ACS and census contain information on household expenditures of each of these energy types. I combine household energy expenditure data with state-level energy price data from the EIA to calculate household energy consumption. The methods by which I construct wage, rent, and household energy consumption series in Appendices A.1.2, A.1.3, and A.2 respectively.

Energy and Emissions Data. I use sector-level aggregated energy consumption data from the EIA. The EIA's Manufacturing Energy Consumption Survey (MECS) provides information on aggregate manufacturing energy consumption, while EIA's Annual Energy outlook provides aggregate energy consumption data for construction, agriculture, and other sectors. I also collect data on aggregate electricity and natural gas consumption for the services sector from the EIA. For privacy (and security) reasons, none of my data contain information about sectoral energy demand at the city level. I impute city-sector energy consumption as that city's share of employment (for that sector) multiplied by total sectoral energy consumption. In other words, energy consumption for a city-sector is proportional to the city's level of employment for that sector.[18]

I assume a constant carbon emissions rate for natural gas (117 lbs per thousand cubic feet) and for fuel oil (17 lbs per gallon), respectively. Carbon emissions from electricity, however, vary with the fuel used to generate that electricity. I use power-plant level data from the EPA's Emissions Generation Resource Integrated Database (eGRID). Local power plants often trade with each other to meet demand, so I use nine North American Electric Reliability Council (NERC) regions to calculate carbon emissions factors for electricity. While power plants occasionally trade across the borders of these NERC regions, the NERC regions are, for the most part, effectively closed markets Holland and Mansur (2008). I calculate the emissions factor as the weighted average CO_2 emissions per megawatt-hour of electricity of all plants in a given NERC region. A map of these regions and their respective emissions factors is provided in section A.5.

[17] I drop some sectors such as military and other public services from the sample. For more details, see Appendix A.7.

[18] For more details, see Appendix A.7.2. This assumption implies that energy-labor ratios will be constant across cities (but not necessarily industries).

4 Estimation

In taking my model to the data, I use a combination of calibration and estimation. I focus on the exposition of the labor supply parameters. The labor demand and rent parameters are fairly standard, and are described in sections A.1.2 and A.1.3, respectively. Appendix Table 7 provides a full summary of the model's estimation and calibration.

4.1 Labor Supply

To estimate the preference parameters of the agent's utility function, I use a two-step estimation procedure that combines maximum likelihood and an instrumental variables approach. The estimation procedure exploits repeated cross-sections of household microdata. Specifically, I use repeated cross-sections of 5% samples of the U.S. Census for 1990, 2000, and 2010 and the 2017 five-year American Community Survey. Let $t \in \{1990, 2000, 2010, 2017\}$ denote the sample year. In what follows, I provide details for each step of the estimation routine.

Step one: Maximum Likelihood. I normalize indirect utility by the standard deviation of the preference shock. More specifically, I divide equation 5 by σ_e to yield:

$$
\begin{aligned}
v_{ijnt} = {} & \Theta_e^w \log(w_{ejnt}) - \Theta_e^r \log(R_{jt}) - \sum_m \Theta_{ejnt}^m \log P_{jt}^m + \\
& \Theta_{et}^{div} \mathbb{I}\left(j \in \mathcal{B}_i^{div}\right) + \Theta_{et}^{\text{dist}} \phi\left(j, \mathcal{B}_i^{st}\right) + \Theta_{et}^{\text{dist2}} \phi^2\left(j, \mathcal{B}_i^{st}\right) + \\
& \xi_{ejnt} + \epsilon_{ijnt},
\end{aligned}
$$

where the new notation for the preference parameters (Θ) indicates the original parameter multiplied by $\frac{1}{\sigma_e}$. I write the shared (conditional on education group) component of utility associated with each city-sector as:

$$
\delta_{ejnt} = \underbrace{\Theta_e^w \log(w_{ejnt}) - \Theta_e^r \log(R_{jt}) - \sum_m \Theta_{ejnt}^m \log P_{jt}^m}_{\text{observed}} + \overbrace{\xi_{ejnt}}^{\text{not observed}} . \tag{14}
$$

I will refer to the δ_{ejnt} values as the "mean utilities" associated with each choice. I emphasize the separability between the observable and unobservable components to the mean utilities because this structure is crucial for matching the model's choice shares to the choice shares observed in the data. Given equation (14), I can re-write the probability that agent i chooses city-sector jn as:

$$P_i(\delta_{ejnt}, \mathbf{\Theta}_{et}) = \frac{\exp\left(\delta_{ejnt} + \Theta_{et}^{div}\mathbb{I}\left(j \in \mathcal{B}_i^{div}\right) + \Theta_{et}^{\text{dist}}\phi\left(j, \mathcal{B}_i^{st}\right) + \Theta_{et}^{\text{dist2}}\phi^2\left(j, \mathcal{B}_i^{st}\right)\right)}{\sum\limits_{j' \in J}\sum\limits_{n' \in N}\exp\left(\delta_{ej'n't} + \Theta_{et}^{div}\mathbb{I}\left(j' \in \mathcal{B}_i^{div}\right) + \Theta_{et}^{\text{dist}}\phi\left(j', \mathcal{B}_i^{st}\right) + \Theta_{et}^{\text{dist2}}\phi^2\left(j', \mathcal{B}_i^{st}\right)\right)}. \tag{15}$$

Then, using these choice probabilities, the log-likelihood function is given by:

$$\mathbf{L}(\mathbf{\Theta}_{et}) = \sum_{i=1}^{N^e}\sum_{n \in N}\sum_{j \in J}\mathbb{I}_{ijn}\log(P_i(\delta_{ejnt}, \mathbf{\Theta}_{et})), \tag{16}$$

where $\mathbb{I}_{ijn}$ is an indicator equal to one if agent i chooses to live in city j and work in sector n and N^e is the total number of workers of education group e. I jointly estimate the mean utilities δ_{ejnt} and the parameter vector $\mathbf{\Theta}_{et}$ with a nested fixed-point algorithm, proposed in Berry (1994).[19] For details of the implementation of this algorithm, see appendix A.6.1.

Step two: Decomposition. In the second step, I decompose the mean utilities to estimate the parameter vector (Θ_e^w, Θ_e^r). To limit the dimensionality of the parameter space, I elect not to estimate the parameters Θ_{ejnt}^m. Instead, I follow Colas and Morehouse (2021), and define $\tilde{\alpha}_{ejnt}^m = \frac{\alpha_{ejnt}^m}{\alpha_{ejt}}$. Given the Cobb-Douglas utility function, the expenditure share of fuel type m is given by $\frac{x_{ejnt}^m \times P_{jt}^m}{w_{ejnt}^m} = \tilde{\alpha}_{ejnt}^m$. I choose values for the $\tilde{\alpha}_{ejnt}^m$ to match the estimated expenditure shares.[20] Next, I rewrite the mean utility as:

$$\delta_{ejnt} = \Theta_e^w \log(\tilde{w}_{ejnt}^{EA}) + \Theta_e^r \log(R_{jt}) + \xi_{ejnt}, \tag{17}$$

where $\tilde{w}_{ejnt}^{EA} = \dfrac{\log(w_{ejnt}) - \sum_m\left(\tilde{\alpha}_{ejnt}^m \log(P_{jt})\right)}{1 - \sum_m \tilde{\alpha}_{ejnt}^m}$ is income adjusted for the energy budget.[21] Taking first differences of equation (17) yields my estimating equation:

$$\Delta\delta_{ejn} = \Theta_e^w \Delta\log(\tilde{w}_{ejn}^{EA}) + \Theta_e^r \Delta\log(R_j) + \Delta\xi_{ejn}, \tag{18}$$

where $\Delta\xi_{ejn}$ is the change in the shared unobservable component of amenities. Changes in unobservable amenities at the city or sector level (such as construction of a new park) *mechanically* confound OLS estimates of Θ_e^w and Θ_e^r. For example, consider a city-wide school

[19] I implement this algorithm with the Nevo (2000) strategy to speedup the contraction mapping proposed in Berry (1994). With a slight abuse of notation, this is given by $\exp(\delta_{\tau+1}) = \exp(\delta_\tau) \times \frac{s_{jn}^{\text{data}}}{s_{jn}^{\text{model}}(\delta_\tau)}$ where τ denotes iteration number and $s_{jn}^{\text{model}}(\delta_\tau)$ are the predicted choice shares—which are a function of the mean utilities.
[20] For details on how I impute baseline energy use by city and demographic group, see Appendix A.2.
[21] For details of this transformation, see Appendix A.3.

improvement program.[22] This will induce migration towards this city (due to an increase in the value of choosing this location). Equilibrium wages and rents adjust to the new population level (governed by the equations described in Section 2), further affecting utility. Thus, even after taking first differences, Θ_e^w cannot be consistently estimated via pooled OLS.

I use an instrumental variables strategy that exploits exogenous local labor demand shocks. More specifically, I employ an instrument first introduced by Katz and Murphy (1992). The instrument uses historical industry concentration patterns at the city level and interacts them with changes in hours worked across each industry.[23] Specifically, I can write the Katz-Murphy (KM) index for city j between any two sample periods as:

$$\Delta Z_{ejnt} = \sum_{\iota \in n} \omega_{ej\iota}^{1990} \times \left(\Delta \text{Hours}_{e,-j,\iota}\right),$$

where $\omega_{ej\iota}^{1990}$ is the 1990 share of total hours worked by industry ι in city j by education group e as a fraction of the total hours worked in all industries in city j by education group e in 1990. $\Delta\text{Hours}_{e,-j,\iota}$ is the change in national hours worked in all cities other than city j. I construct the differences in national hours (omitting city j), $\Delta\text{Hours}_{e,-j,\iota}$, as decadal differences between each of my sample years.[24]

Finally, to instrument for Θ_e^r, I follow Diamond (2016) and interact the Katz-Murphy index with the elasticity of the housing supply curve. Note that I construct my current instrument such that it generates exogenous labor demand shocks at the *city-sector* level. Rents are assumed to vary only across cities (and not sectors), so I use a slightly different version of the instrument in which I sum over all industries and sectors within a city. Concretely, I write the "city-level" KM index as: $\Delta\tilde{Z}_{ejt} = \sum_n \omega_{ejn}^{1990} \times \left(\Delta\text{Hours}_{e,-j,n}\right)$. Differences in the responsiveness of housing prices to population changes generate the variation used to identify Θ_e^r. For example, suppose we have two cities that experience identical labor demand shocks. The city with the less-elastic housing supply curve will see rents bid up faster. This variation in rents is assumed to be exogenous to changes in unobservable amenities. After estimating the agent's preference parameters and the mean utilities, I calculate the unobservable component of amenities as the residuals from equation (17).

[22] Diamond (2016) considers the case where residential amenities are endogenous to individual location choices.
[23] For a discussion of shift-share instruments see Goldsmith-Pinkham, Sorkin, and Swift (2020).
[24] Given that I am estimating the model's labor supply parameters using pooled first differences, I need to estimate mean utilities (and hence individual moving-cost parameters) for each of my cross-sections. Each cross-section has a likelihood function constructed from millions of observations and 395 choices. Even with cloud computing, it is not computationally feasible to estimate the individual choice parameters on the entire sample. As a consequence, I make various sample restrictions to limit the number of observations. I describe these in detail in Section A.7.

4.2 Other Parameters

Electricity Supply The reduced-form equilibrium expression for residential electricity prices is given by:

$$\log(P^{\text{elec}}_{kj}) = a_{kj} + \mu \times \log(x^{elec,\mathcal{D}}_{j}),$$

where $x^{\text{elec},\mathcal{D}}_{j} = \sum_{e\in E}\sum_{n\in N} N_{ejn} \times \frac{\alpha^{m}_{ejn} w_{ejn}}{\alpha_{ej} P^{m}_{j}}$ is electricity demand in city j. I calibrate the electricity supply curve using $\kappa = \frac{1}{2.7}$ following Dahl and Duggan (1996). Simplifying this expression yields an analogous expression to equation 37:[25]

$$\log(P^{elec}_{kj}) = \frac{\mu}{1+\mu} \log\left(\sum_{e}\sum_{n} N_{ejn} \frac{\left(\alpha^{\text{elec}}_{ejn} \times w_{ejn})\right)}{\alpha_{ejn}}\right) + a_{kj} \quad \text{for} \quad k = \text{residential}, \tag{19}$$

I choose the $a_{kj}s$ to match the data. When k = industrial, the I set $a_{kj} = \log(P^{\text{elec}}_{kj}) - \mu \times \log(E_j)$, where $E_j = \sum_n E_{jn}$ is firm energy consumption in city j (aggregated over sectors).

Firms and Rents As does Card (2009), I calibrate the elasticity of substitution between college and non-college workers to 2.5. I set my baseline calibration of energy-labor substitution elasticities to those in Koesler and Schymura (2012).[26] Inter-Fuel-substitution elasticities come from Serletis, Timilsina, and Vasetsky (2010).

I solve for input use intensities and total factor productivity (TFP) using relatively standard algebra and thus relegate the details to Appendix A.1.2. I calibrate housing supply elasticities to those estimated in Saiz (2010). The reduced-form rental supply can be found in Appendix A.1.3.

5 Parameter Estimates

Table 1 displays the preference parameters estimates.

[25] I abuse notation here slightly. Technically, the intercept term in equation 19 is $\frac{a_j}{1+\kappa}$.

[26] Fried (2018) calibrates a similar parameter, the elasticity of substitution between energy and non-energy inputs, to be close to zero. This requires energy and non-energy inputs to be used in fixed proportions.

Year	No College Θ^{div}_{lt}	Θ^{dist}_{lt}	Θ^{dist2}_{lt}	College Θ^{div}_{ct}	Θ^{dist}_{ct}	Θ^{dist2}_{ct}
1990	1.696	-3.4318	0.741	1.418	-2.649	0.628
	(0.004)	(0.002)	(0.001)	(0.063)	(0.033)	(0.016)
2000	1.677	-3.438	0.806	1.412	-2.618	0.644
	(0.011)	(0.005)	(0.003)	(0.036)	(0.010)	(0.004)
2010	1.702	-3.226	0.711	1.474	-2.523	0.601
	(0.003)	(0.003)	(0.002)	(0.011)	(0.006)	(0.003)
2017	1.698	-3.218	0.696	1.489	-2.609	0.644
	(0.004)	(0.005)	(0.004)	(0.012)	(0.006)	(0.003)
Income and Rents		No College			College	
Θ^{w}_{e}		3.558^{***}			7.0362^{***}	
		(0.591)			(0.815)	
Θ^{r}_{e}		-2.160^{***}			-3.731^{***}	
		(0.372)			(0.348)	
Cragg-Donald F-Stat: 14.63						

Table 1: Standard errors are in parentheses. Maximum likelihood standard errors are estimated with numerical derivatives. Stars indicate statistical significance: *p<0.05; **p<0.01; ***p<0.001.

All of the parameter estimates have signs that are consistent with the extant literature. For each education group and year, $\Theta^{div}_{et} > 0$ and thus agents receive a utility premium for locating within their birth division. Furthermore, all agents receive disutility for locating farther away from their birth state ($\Theta^{dist}_{et} < 0$). However, the marginal disutility of an additional mile on utility declines with distance (Θ^{dist2}_{et}). The birth-division premium and marginal disutility of each mile are also larger in absolute magnitude for college than non-college-educated agents. These estimates suggest that household heads with a college degree are more mobile than those without a college degree.

To my knowledge, none of the existing literature uses the exact functional form I have chosen for individual moving costs. However, Diamond (2016) estimates a birth-division indicator (Θ^{div}_{et}) for colleged and non-college-educated workers while Colas and Hutchinson (2021) estimate the distance and distance squared parameter (Θ^{dist}_{et} and Θ^{dist2}_{et}). My estimates for Θ^{dist2}_{et} are very stable across years for both education groups, with the premium being roughly 20% higher for agents without a college degree. This is consistent with Diamond (2016) – who estimates the parameter to be consistently around 1.2 for college-educated and non-college-educated workers. My parameter estimates for Θ^{dist}_{et} and Θ^{dist2}_{et} are in a range similar to what is estimated Colas and Morehouse (2021) (CM). However, CM estimates the parameters for different demographic groups, so a direct comparison is inappropriate.

It is even more difficult to compare my estimates of Θ_e^w and Θ_e^r to the literature, given that I am the first to estimate these parameters for city-sector pairs. My estimates are slightly smaller in magnitude than those of Colas and Hutchinson (2021) and in a similar range to those of Diamond (2016). As do both of these papers, I find $\Theta_c^w > \Theta_l^w$, which indicates that workers with a college degree (or more) are more responsive to changes in wages. I also find that $|\Theta_l^r| > |\Theta_c^r|$, which is different from Colas and Hutchinson (2021) but consistent with some specifications of Diamond (2016).

Model Fit. I use the fully estimated model to simulate the baseline equilibrium.[27] In Figure 1, I compare the model's predicted city-sector choice shares by education group to the data:

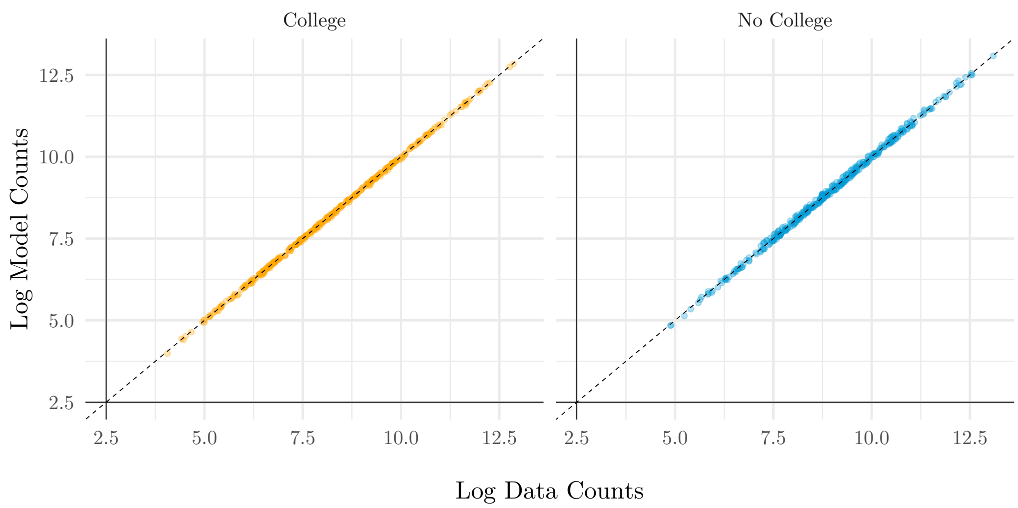

Figure 1: For college and non-college-educated workers, these two graphs plot the model's predicted log city-sector shares on the vertical against the corresponding log city-sector shares in the data. The black dashed line is the 45-degree line.

Appendix A.2.4 provides analogous scatterplots for household energy consumption. The model appears to fit the data well.

6 Counterfactuals

Recently, there has been an increasing legislative effort in the US to pass a carbon tax. In late July of 2019, three carbon tax bills were introduced to Congress: the Climate Action Rebate Act of 2019 (CAR act), the Stemming Warming and Augmenting Pay Act (SWAP Act), and the Raise

[27] Details of how I solve for the equilibrium of the model can be found in Section A.6.2.

Wages, Cut Carbon Act of 2019 (RWCC Act). Fundamentally, all three bills are examples of Pigouvian taxes; however, their implementations vary. One of the primary differences between the bills is the use of government revenue. For example, the CAR act proposes distributing 70% of the tax revenue to low-income and middle-income households in the form of lump-sum payments. In contrast, the SWAP and RWCC acts propose using revenues to reduce payroll taxes.[28] Motivated by these recent examples of proposed legislation, I use my model to assess carbon pricing in conjunction with various transfer schemes.

A carbon tax will affect the price of energy differently for each fuel type. Recall that I assumed the supply curves for fuel oil and natural gas are perfectly elastic, and the emissions rate for each of these fuel types is constant across locations and given by δ^m. With the introduction of a carbon tax, the price of natural gas and fuel oil in city j is given by:

$$\tilde{P}_j^m = P_j^m + \tau\delta^m.$$

For electricity, I construct city-level supply curves as in Equation (11). With the carbon tax, the supply curve is given by:

$$P_{kj}^{\text{elec}}(\tau, \delta_{\mathcal{R}(j)}) = a_{kj} Q_{\mathcal{R}(j)}^{\mu} + (\tau \times \delta_{\mathcal{R}(j)}^{\text{elec}}),$$

where I write the electricity supply curve, $P_{kj}^{\text{elec}}(\tau, \delta_{\mathcal{R}(j)})$, as a function of the tax level τ, and the emissions rates $\delta_{\mathcal{R}(j)}$.

6.1 The Welfare Effects of Carbon Taxes

In this section, I simulate a carbon tax of \$31 dollars per ton—the Social Cost of Carbon (SCC) as estimated by Nordhaus (2017). I calculate the compensating variation (CV) for agent i as:

$$CV_i = \mathbb{E}[V(\tau > 0)] - \mathbb{E}[V(\tau = 0)] \times \frac{w_{ejn}}{\Theta_e^w}, \tag{20}$$

where $V(\tau) = v_{ijn}(\tau, j^\star, n^\star)$ is the indirect utility, given tax level τ, evaluated at equilibrium choices $j^\star$ and $n^\star$ and the expectation $\mathbb{E}$ is taken over the idiosyncratic preference shocks. Note that because v_{ijn} is measured in log-utility units, $\mathbb{E}[V(\tau > 0)] - \mathbb{E}[V(\tau = 0)]$ is approximately equivalent to percentage change in utility. Multiplying by $\frac{w_{ejn}}{\Theta_e^w}$ converts this to a dollar amount.

[28] For more details of these bills, see https://taxfoundation.org/carbon-tax-bills-introduced-congress/.

Agent i's expected utility is given by:

$$\mathbb{E}[V(\tau)] = \bar{\gamma} + \log\left(\sum_{j'\in J}\sum_{n'\in N}\exp\left(\Theta_e^w \log(w_{ej'n'}) - \Theta_e^r \log(R_{j'}) - \sum_m \Theta_{ej'n'}^m \log P_{j'}^m + \xi_{ej'n'} + f(j, \mathcal{B}_i; \hat{\theta}_e)\right)\right),$$

where $\bar{\gamma}$ is Euler's constant and $f(j, \mathcal{B}_i; \hat{\theta}_e)$ is the distance function (equation 3) evaluated at the estimated parameter vector $\hat{\theta}_e$. The distribution of CV across cities and sectors is displayed in Figure 2.

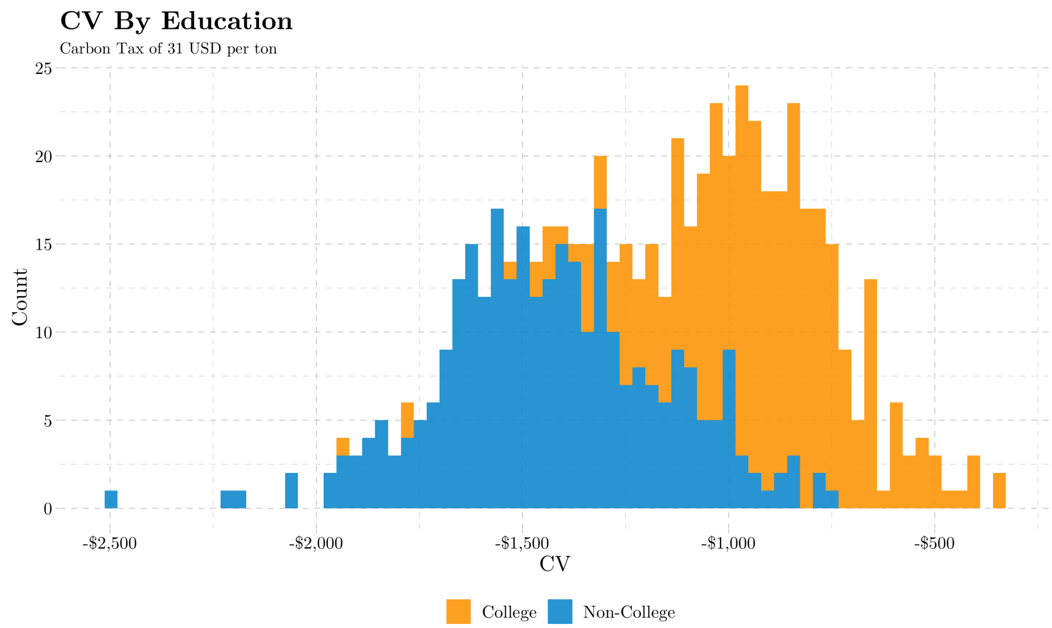

Figure 2: The distribution of compensating variation from a carbon tax of $31 per ton in the absence of coal-fueled electricity.

Figure 2 demonstrates considerable individual heterogeneity in the burden of a carbon tax. The model predicts that carbon prices are regressive; the mean college educated agent faces a tax burden of $926 while the mean non-college-educated agent faces a burden of $1,417.[29] The tax regressivity is consistent with a large literature that observes that lower-income households spend larger portions of their budget constraints on energy and work in more energy-intensive sectors. Indeed, this is reflected in my estimates of $\tilde{\alpha}_{ejn}^m$ (energy type m's budget share).[30] Additionally, the model predicts a significant decline in manufacturing employment. Manufacturing, which is relatively carbon-intensive, experiences an 11.1% decrease in employment with a 12.7% reduction in college workers and a 10.4% reduction in college workers. The services sector—which is relatively green—experiences an increase in employment. There is a 2.01%

[29] I did not impose the tax regressivity on the model's structure in any way.
[30] Summary statistics for these estimates can be found in Table 6.

increase in aggregate services employment, with a 1.78% increase for college workers and a 2.34% for non-college workers.

Figures 10 and 15 in Appendix A.5.2 disaggregate Figure 2 by industry and Census Region. Manufacturing has a substantially higher tax burden than other sectors for both college-educated and non-college-educated workers. Cities and sectors in the Midwest and West have marginally higher average compensating variation from the tax than other regions. Table 2 summarizes the key results from the carbon tax.

τ = \$31/ton:	%Δ Emissions: −19.8			
No Transfers	Mean CV (\$)	Mean/st.dev CV	%Δ Man. Emp	%Δ Ser. Emp
Total	−1,221	−3.14	−11.1	2.01
College	−926	−3.55	−12.7	1.78
Non-College	−1,417	−4.16	−10.4	2.34

Table 2: Counterfactual Results from a \$31 per ton carbon tax. Mean CV is calculated using equation (20). Percent changes in emissions and employment are relative to baseline levels.

Non-Monetized Incidence. While my primary welfare metric is compensating variation, I also examine tax incidence defined as the *percent change* in wages needed to compensate households for the carbon tax.[31] Compensating variation may mask substantial underlying heterogeneity in tax burden due to differences in wages across cities. For example, San Francisco may experience a small degree tax burden as a percentage of wages. San Francisco has a services-based economy with a mild climate and carbon-efficient power plants. However, San Francisco has high average wages. Thus, the average household in San Francisco may require a large *dollar* transfer in response to the carbon tax. Conversely, Detroit may experience a large loss in utility due to its manufacturing-oriented economy, less mild climate, and relatively dirtier power plants. Detroit also has relatively low wages, which lowers the dollar amount needed to compensate households in Detroit for the carbon tax, all else equal. Despite the potentially larger loss in utility in Detroit, the compensating variation in San Francisco could be higher due to differences in wages across the two cities.

Indeed, I find compensating variation is higher (in magnitude) in cities that deliver high wages, such as those on the West Coast and New England. In Figure 11, I replicate figure 10, except I compare non-monetized tax incidence rather than changes in compensating variation. I aggregate these changes to the state level and map them in Figures 12 and 13. These figures reveal that households in the Midwest and South generally experience larger percent decreases in utility from the carbon tax, despite having similar if not lower compensating variation.

[31] Compensating variation is in levels; this metric is a percent change. I calculate percent change in utility as $CV \times \frac{1}{w_{ejn}}$, or just $(\mathbb{E}[V(\tau > 0)] - \mathbb{E}[V(\tau = 0)]) \times \frac{1}{\Theta_e^w}$.

Migration. Next, I examine how the spatial distribution of households shifts with the carbon tax. More specifically, I calculate the percent change in aggregate population and by education group for each city, aggregated across all sectors. I display the results in Appendix A.5.3 at the state level, both aggregated and disaggregated by education level.

In general, the model predicts that cities with more mild climates and less-emissions intensive power plants will experience population increases. For example, the carbon tax induces an inflow of households to Seattle, Washington, increasing the city's population by 1.5%. Washington is part of the WECC NERC region (see Figure 8) and has relatively carbon efficient power plants, so electricity prices do not increase as much in Seattle as in other cities. Additionally, Seattle's economy is more services-oriented than many other cities. On the other hand, cities such as Cincinnati experience population decreases. Relative to Seattle, Cincinnati's climate requires more household energy, and the electricity in Cincinnati is less carbon-efficient than in Seattle. Additionally, Cincinnati has a lower share of workers in relatively carbon-efficient services-based jobs than Seattle. Overall, the model predicts that the carbon tax will reduce Cincinnati's population by 2.29%.

Despite being less mobile than college-educated households, the model predicts larger changes in shares of non-college-educated households in most cities. In Figures 18 and 17, I show that the average city experiences a 0.1% decrease in its share of non-college-educated households, and only a .03 % decrease in it's share of educated college households. College-educated workers are more responsive to changes in prices (as estimated in section 4), so the relatively larger migration flows of non-college workers demonstrate the larger degree of tax burden that these households bear.

Tax Incidence and Elections. Next, I examine how changes in utility from the carbon tax correlate with political preferences. I focus my analysis on the share of cities voting for Donald Trump during the 2016 presidential election. Donald Trump's voting base was less educated and concentrated in less populated areas (Doherty, Kiley, and Johnson, 2018)—features that are correlated with higher tax incidence.[32]

I combine my tax-incidence estimates with publicly available, county-level presidential election voting data from the MIT Election Data and Science Lab (MIT, 2018). For each CBSA in my sample, I compute the average (across counties within the CBSA) share of the vote going to Donald Trump in the 2016 primary presidential election, weighted by total votes in each county. In Figure 19, I plot the tax incidence (again, defined as the percent change in wages needed to compensate households for the carbon tax) against Trump's vote shares. Additionally,

[32] Donald Trump has been consistently skeptical of climate change and policy. On December 6th, 2013, in a tweet that was deleted with his account, Donald Trump stated "Ice storm rolls from Texas to Tennessee - I'm in Los Angeles and it's freezing. Global warming is a total, and very expensive, hoax!"

I plot compensating variation against share of household voting for Trump in Figure 20.

As expected, counties with a larger share of Trump voters experience larger changes decreases in utility, on average.[33] The counties with a higher percentage of Trump voters (and thus larger tax incidence) are arguably those least likely to vote in favor of a carbon tax. Further complicating the political feasibility of the tax is that areas with a *lower* share of Trump voters have a *higher* (in magnitude) compensating variation, on average. This difference between tax incidence and monetized tax incidence (compensating variation) is again driven by differences in wages across cities; cities such as San Francisco have a low share of Trump voters, relatively low tax incidence, but relatively high compensating variation due to the high baseline wages in San Francisco. Overall, these results highlight a particular challenges with the political feasibility carbon-pricing legislation.

6.2 The Effects of Coal-Fired Electricity

In large part due to significant decreases in natural gas prices with the advent of fracking technologies, the share of electricity generated by coal in the United States has dropped precipitously since the mid-2000s. In the early 2000s, coal generated over 70% of power nationally. By 2015 coal's share had diminished to under 40% of generation.[34] Coal emits a considerable amount of carbon compared to natural gas, so the declining share of coal will have first-order consequences for the welfare effects of pricing carbon. As coal's share of electricity generation continues to decline, the revenue needed to compensate households for carbon pricing will also fall. I illustrate the decline in coal nationally and across NERC regions in figure 3.

[33] Note that I did not target political preferences in the estimation, so this result strengthens the validity of the model's parameter estimates.

[34] This is for many reasons in addition to the decline of natural gas prices, but this is not the point of this paper. See Arias, Reinbold, and Restrepo-Echavarria (2017) for a brief discussion.

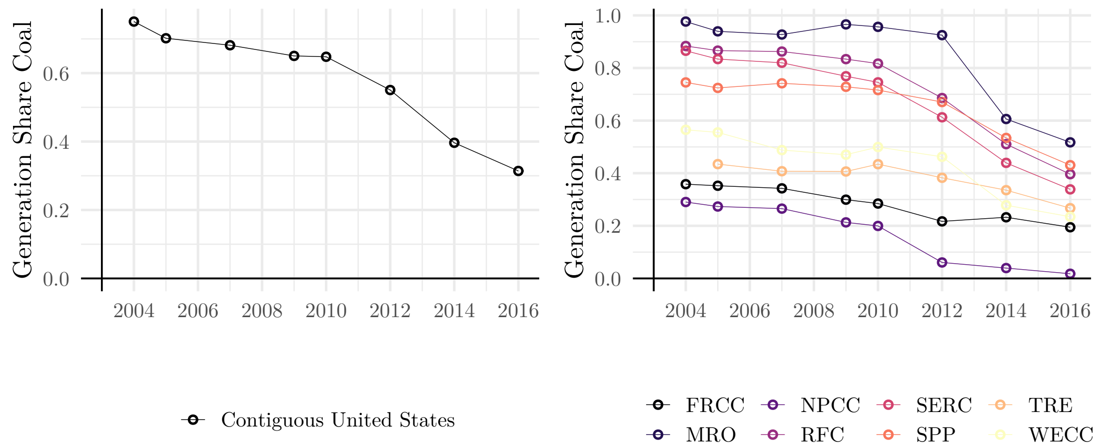

Figure 3: Share of electricity generated by coal nationally and across NERC regions between 2004 and 2016. Shares are computed using annual plant-level generation data from eGRID.

No Coal. Motivated by the remarkable decline in the share of the electricity generated by coal, I use the model to decompose the tax incidence into two components: coal and non-coal. More specifically, I estimate the proportion of the total compensating variation that is attributable to coal-fired electricity. I recalculate emissions factors for each region in the absence of coal. Without coal, there are considerably lower emissions rates across the US. A map of the changes in emissions factors from dropping coal is in Section A.5. With the new, absent-of-coal emissions factors in hand, I resimulate the $31 per ton carbon tax under a "no-coal" economy. I display the distribution of CV, split by education level in figure 4.

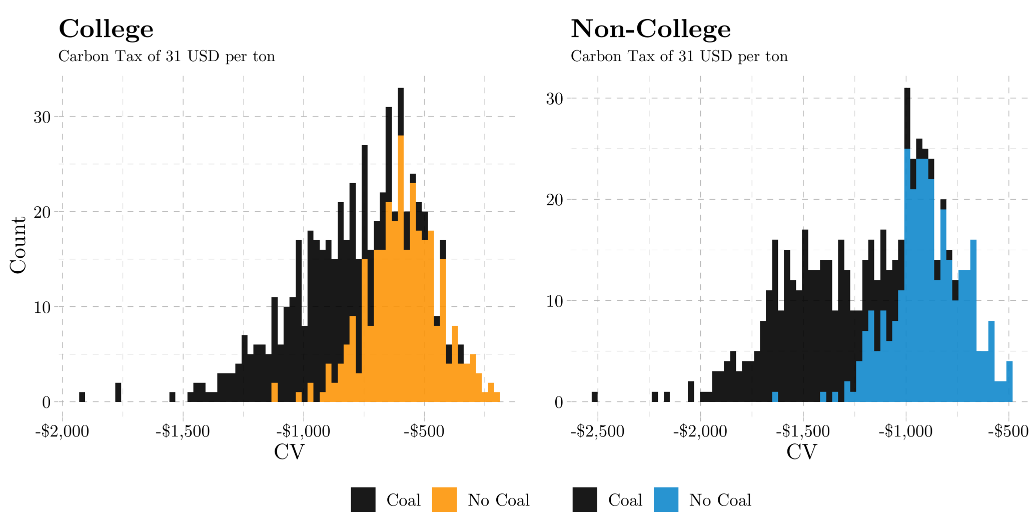

Figure 4: The distribution of compensating variation from a carbon tax of $31 per ton in the absence of coal.

Without coal, the mean college and non-college agents experience a \$352 and \$543 dollar decline in their tax incidence. Percentage-wise, the change is marginally larger for non-college workers as they are generally more energy-intensive cities and sectors.

Furthermore, the distribution of incidence compresses without coal-fired electricity. The distributions of tax incidence are tighter due to the geographic distribution of coal; many coal plants are in the Midwest and South. In Appendix A.5.2 figure 10 I show that for non-college workers, the change in tax incidence is greatest in the midwest. In contrast, for college workers, the change in incidence is remarkably stable across regions. I display the main results for the "no-coal" scenario in table 3 below.

τ = \$31/ton: **No Coal**	Mean CV (\$)	Mean/st.dev CV	%Δ Man. Emp	%Δ Ser. Emp
Total	−757	−3.11	−8.15	1.51
College	−594	−3.33	−9.56	1.31
Non-College	−874	−4.06	−7.51	1.68

Table 3: Counterfactual Results from a \$31 per ton carbon tax in the absence of coal. Mean CV is calculated using equation (20). Percent changes in emissions and employment are relative to baseline levels.

To be clear, this is purely a decompositional and bounding exercise of the tax incidence for what the distribution of incidence *could* look like without coal. A carbon price will impact the rate at which coal shuts down. In reality, the supply curves of electricity are determined by a "constant dispatch order." The plant uses the lowest marginal cost fuel-type generator until a fuel-specific capacity constraint. The plant switches on the next lowest (fuel-specific) marginal cost generators upon hitting the fuel constraint. As coal has a low marginal operating cost, removing coal would likely significantly impact the supply curve slope, further changing the impact of a carbon tax on electricity prices and tax incidence. I leave it to future work to recover the incidence of carbon pricing with dynamic coal shares and a micro-founded electricity supply curve.

This counterfactual is highly policy-relevant as coal's decline continues. My decomposition demonstrates that a significant proportion of the total compensating variation (roughly 40%) from carbon pricing is attributable to coal-fired electricity. These simulations suggest policy-makers may compensate households significantly less to remain indifferent between a carbon tax and no tax in a low coal future.

6.3 Equity and Emissions

Next, I examine the relationship between progressive transfers and aggregate emissions. I provide a motivating example from the data and then extend the baseline model to include government payments.

Wages and Emissions. Variation in household carbon emissions across cities and sectors is well documented. This variation is largely driven by 1) differences in climate across cities, 2) differences in emissions intensities from regional power plants, 3) differences in preferences for energy consumption, and 4) differences in income levels across households. Cities also host different industries which vary in their energy use, and hence emissions intensities. Thus, any policy that affects the spatial and sectoral population distribution will also impact aggregate emissions.

If lower-wage city-sectors have, on average, higher emissions, then progressive redistribution may *increase* aggregate emissions. This relationship arises because the more carbon-intensive city-sector combinations will receive larger transfers (all else equal), which will induce a larger share of workers to move to these cities and or into these sectors, raising aggregate emissions. However, the effect of the transfers on aggregate emissions also depends on substitution patterns across cities and sectors. For example, even if the correlation between wages and emissions is positive, progressive transfers may induce a large share of workers into a low-wage yet emissions-intensive city-sector. Thus, the effect of progressive transfers on aggregate emissions jointly depends on the correlation between wages and emissions and substitution patterns across city sectors.[35]

In Figure 5, I plot city-sector emissions per capita—defined as the sum, per capita, of firm and household emissions per—against city-sector wages.

[35] There are two exceptions to this: if there are only two choices (cities and or sectors), or if wages and emissions are perfectly correlated. In the first case, there is only one option for workers to switch into the choice with the higher transfers, and given the negative correlation between wages and emissions, this choice will be lower. In the latter case, lower-wage choices have strictly lower emissions. Thus any substitution to a lower wage choice would reduce aggregate emissions.

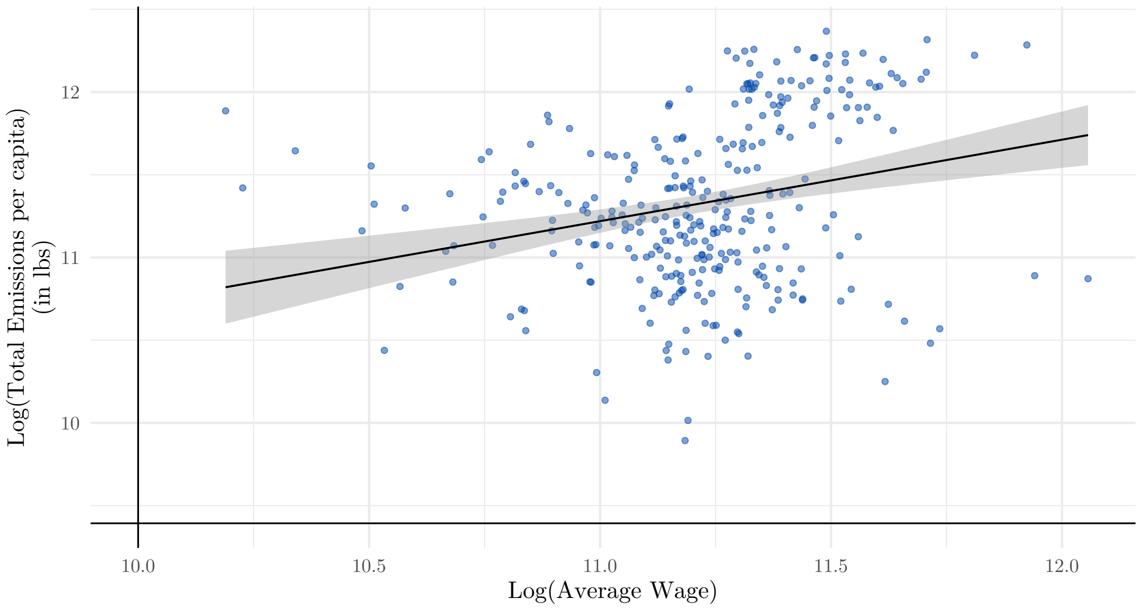

Figure 5: City-sector level household carbon emissions and firm emissions plotted against average wages. On the vertical axis, total emissions per capita are calculated as aggregated firm and household emissions divided by the respective city-sector employment count. On the horizontal axis, wages are estimated by city-sector-education group in Equation (24), then averaged by city-sector, weighted by the count of workers in that education group.

As Figure 5 indicates, the average household that lives and works in a lower-wage city-sector also tends to emit less carbon. In Appendix A.8, I disaggregate Figure 5 by education group to reveal that the positive relationship between emissions and wages holds for college and non-college workers considered separately.[36]

The positive cross-city correlation between emissions and wages has important implications for redistributing the revenue from a carbon tax. Often, policymakers and academics propose progressive transfers as a way to alleviate distributional concerns with pricing carbon.[37] However, whether or not these transfers increase or decrease aggregate emissions depends on both the correlation between wages and emissions and substitutions across the agent's choice sets.

Carbon Taxes with Transfer Payments. I extend the model so that the agent receives a transfer equal to $\mathcal{T}(w)$. The agent's post-transfer wage is then $\tilde{w}_{ejn} = w_{ejn} + \mathcal{T}(w)$. One of the primary

[36] Additionally, I disaggregate by education group and industry. For some industries, the relationship between emissions and wages is positive.

[37] See Carattini, Carvalho, and Fankhauser (2017) for an example.

goals of this paper is to capture the relationship between the progressivity of government transfers and aggregate carbon emissions. Thus, for the transfer function, I use the parsimonious specification employed by Heathcote, Storesletten, and Violante (2017) (henceforth HSV), which is given by:

$$\mathcal{T}(w) = \lambda w_{ejn}^{1-\gamma}$$

where $\lambda > 0$ is the overall level of the reimbursement and $\gamma \geq 1$ indexes the progressivity of the transfers.[38] Note that when $\gamma = 1$, transfers are proportional to wages, and when $\gamma \geq 1$, transfers are decreasing in wages. A higher value of γ implies higher-wage agents will receive smaller transfers. In counterfactuals with transfers, I append the definition of the model's equilibrium to include government-balanced budget condition. The balanced budget assumption implies that λ is endogenously determined in equilibrium; more details are included in Appendix A.2.3.

I use the model to numerically estimate the general equilibrium elasticity of aggregate emissions with respect to the relative progressivity of transfers. I define this elasticity as:

$$\epsilon_{\texttt{Emis},\gamma} = \frac{\partial \texttt{Emis}}{\partial \gamma} \frac{\gamma}{\texttt{Emis}}. \tag{21}$$

Note that the level of transfers an agent receives may change the agent's choice, which impacts the agent's emissions and thus aggregate emissions. Equation (21) is thus an implicit function of effectively all of the model's underlying parameters. If labor supply—especially non-college labor supply—is highly mobile and responsive to changes in wages, then an increase in γ will cause a larger change in emissions as more workers migrate or switch sectors. Firm production parameters (and hence labor demand), energy, and rental supply all govern the full extent of the price changes and hence aggregate emissions change. I estimate equation (21) numerically by simulating the model under $\gamma \in \{1, 1.2, 1.4, 1.6\}$. I display the result from this exercise graphically in figure 6 below.

[38] If $\lambda < 0$ and $\gamma < 1$ then this is the familiar HSV tax function.

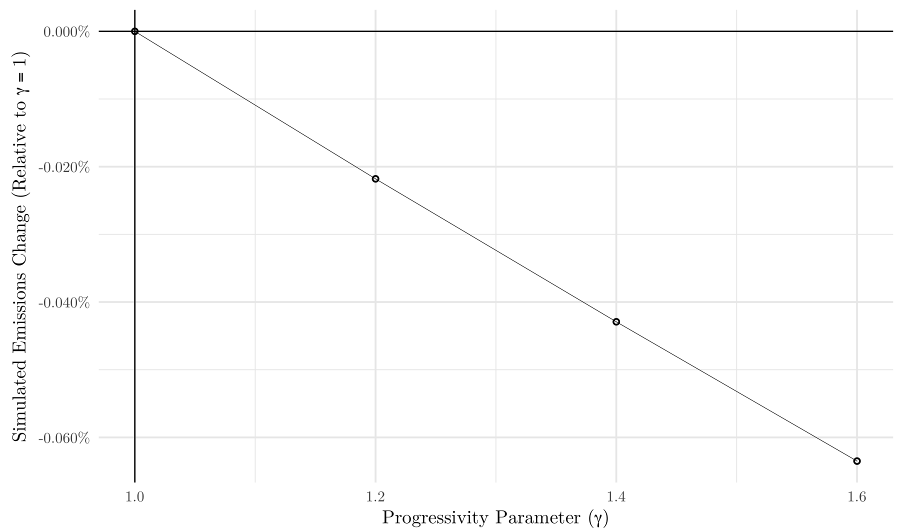

Figure 6: : Simulated total emissions relative to lump-sum transfers plotted against the progressivity parameter (γ). Simulated emissions are calculated in equilibrium as the sum of total emissions from agents and firms across all cities and sectors.

Figure 6 illustrates that in the US, equity-of-transfers and aggregate carbon emissions are inversely related. More specifically, I estimate $\epsilon_{\texttt{Emis},\gamma} = -0.00104$. Put differently, this indicates that a 1% increase in the progressivity of the transfer system would result in approximately a −0.001% decrease in aggregate emissions. I show the change in sectoral composition from a carbon tax with lump-sum transfers ($\gamma = 1$) and a carbon tax with progressive transfers ($\gamma = 1.2$) in Table 4.

$\gamma = \mathbf{1}$	%Δ Man. Emp	%Δ Ser. Emp	%Δ Con. Emp	%Δ Ag. Emp
Total	−11.8	2.42	1.57	−2.78
College	−13.7	1.99	0.07	−3.51
Non-College	−10.9	2.80	1.7	−2.62
$\gamma = \mathbf{1.2}$				
Total	−11.9	2.49	1.36	−1.86
College	−13.8	2.03	0.05	−2.78
Non-College	−11.1	2.91	1.5	−1.65

Table 4: Change in sectoral employment in aggregate and by education group for a $31 carbon tax with transfers relative to a $31 carbon tax with no transfers.

As shown in section 3, cities and sectors with lower wages also tend to have lower carbon emissions. Thus, more progressive transfers induce a larger share of agents to move into greener cities and sectors, lowering aggregate emissions.[39] When $\gamma = 1.2$, I find that manufacturing employment declines by 11.9% (compared to 11.8% with lump-sum transfers) and services employment increases by 2.49% (compared to 2.42% with lump-sum transfers). The model also predicts modest increases in construction employment (1.57%) and decreases in agricultural employment (2.78%). These results suggest that carbon tax policies with progressive transfers have the added benefit of modestly reducing aggregate emissions due to the compositional changes in the workforce the transfers induce.

7 Conclusions

In this paper, I estimate the distributional effects of a uniform national carbon tax. To accomplish this, I estimated a model of worker sorting across cities and sectors, in which imperfectly mobile agents that vary by education level consume a numeraire good, energy, and housing. The model incorporates the incidence of a carbon tax, including endogenous wages, rents, and electricity prices. To take the model to the data, I utilized a combination of estimation and calibration.

There are three main takeaways from the counterfactual exercises. First, the incidence of a carbon tax exhibits substantial spatial and sectoral heterogeneity- workers in manufacturing experience a much greater tax burden than workers in the less carbon-intensive services sector. Overall, I found that a carbon tax has a mean compensating variation of $926 for college workers and $1,417 for non-college workers.

Second, the share of this incidence attributable to coal varies across space. Coal has a larger share of the total burden in some coal-dependent regions, such as the Midwest, particularly for non-college-educated workers. Others, like New England, have a small share of the burden attributable to coal. These findings imply that policymakers will need to adjust expected compensation with tax revenues as the grid decarbonizes at potentially different rates across space. Lastly, I document a new relationship between equity and emissions: aggregate emissions fall as compensation becomes more equitable. Since lower-wage city-sectors are less carbon-intensive, progressive transfers induce a larger share of workers into these cities and sectors. This relationship suggests that progressive transfers may have the added benefit of helping achieve emissions targets.

Despite the detailed heterogeneity included in the model, I have made several simplifying assumptions in my analysis. I make two strong assumptions about capital in the production function. First, I assume the elasticity of substitution between capital and other inputs is one (e.g., the production function is Cobb-Douglas in capital and other inputs). Second, I assume

[39] If the relationship between wages and emissions were negative, then there would be an equity-emissions *trade-off*.

capital is traded on international markets, and there are no differences in local prices. Complementarity between capital and energy may have important implications for the distribution of carbon tax incidence. Third, I assume perfectly competitive input and output markets. Heterogeneity in market power across cities and sectors could bias my estimates of the tax incidence. In addition, I use natural gas and electricity as primary fuel inputs for firms; while this may be reasonable for many sectors, it certainly underestimates the effects of carbon pricing on agriculture since a large share of agricultural carbon emissions are from livestock. Future work could extend the model to extend the production function to incorporate these features.

My results speak to the importance of considering place-based incidence when designing federal policy. While much of the literature has identified negligible employment effects, I note that even if on net the number of jobs is the same or increases, reallocation is costly. My model provides insights on the mechanisms via which space-sectoral heterogeneity would arise from the tax, and my empirical results substantiate the claim of costly-re-allocation of labor. Understanding the heterogeneity in tax incidence is paramount for policymakers looking to reduce the current political headwinds with carbon pricing. As Sallee (2019) notes, "...the failure to create a Pareto improvement is due to a *prediction* problem; lump-sum transfers can only undo the distribution of burdens if they can be targeted precisely." Due to the rich level of heterogeneity in the model and hence results, the estimates from this paper may help design more precisely targeted compensation.

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A Appendix

A.1 Model Appendix

A.1.1 Firm FOC Derivation

This section derives the first order conditions for the firms. Recall that firms in city j and sector n produce according to

$$Y_{jn} = A_{jn} K_{jn}^{\eta} \mathcal{I}_{jn}^{1-\eta},$$

where $\mathcal{I}_{jn}$ is the CES aggregator between energy and labor inputs. Specifically,

$$\mathcal{I}_{jn} = \left(\alpha_{jn} \mathcal{E}_{jn}^{\rho_{el}^{n}} + (1-\alpha_{jn}) \mathcal{L}_{jn}^{\rho_{el}^{n}} \right)^{\frac{1}{\rho_{el}^{n}}},$$

where

$$\begin{aligned} \mathcal{E}_{jn} &= \left(\zeta_{jn} E_{jn}^{\rho_{e}^{n}} + (1-\zeta_{jn}) G_{jn}^{\rho_{e}^{n}} \right)^{\frac{1}{\rho_{e}^{n}}} \\ \mathcal{L}_{jn} &= \left(\theta_{jn} C_{jn}^{\rho_{l}} + (1-\theta_{jn}) L_{jn}^{\rho_{l}} \right)^{\frac{1}{\rho_{l}}}. \end{aligned}$$

Note that I assume factor markets are perfectly competitive so input prices are equal to their marginal products. The firm's profit function is given by:

$$\pi_{jn} = P_n A_{jn} K_{jn}^{\eta} \mathcal{I}_{jn}^{1-\eta} - W_{jn}^{C} C_{jn} - W_{jn}^{L} L_{jn} - P_{jn}^{G} G_{jn} - P_{jn}^{E} E_{jn}. \tag{22}$$

Differentiating equation 22 with respect to each of the firm's inputs yields the following expressions for energy prices (denoted by P_{jn}^{E} and P_{jn}^{G}) and pre-tax wages (W_{jn}^{C} and W_{jn}^{L}):

$$\begin{aligned} P_{jn}^{E} &= \left(\frac{Y_{jn}}{\mathcal{I}_{jn}} \right) \mathcal{I}_{jn}^{1-\rho_{el}^{n}} \alpha_{jn} (1-\eta) \zeta_{jn} E_{jn}^{\rho_{e}^{n}-1} \\ P_{jn}^{f} &= \left(\frac{Y_{jn}}{\mathcal{I}_{jn}} \right) \mathcal{I}_{jn}^{1-\rho_{el}^{n}} \alpha_{jn} (1-\eta)(1-\zeta_{jn}) G_{jn}^{\rho_{e}^{n}-1} \\ W_{jn}^{C} &= \left(\frac{Y_{jn}}{\mathcal{I}_{jn}} \right) \mathcal{I}_{jn}^{1-\rho_{el}^{n}} (1-\alpha_{jn})(1-\eta)(\theta_{jn}) C_{jn}^{\rho_{l}-1} \\ W_{jn}^{L} &= \left(\frac{Y_{jn}}{\mathcal{I}_{jn}} \right) \mathcal{I}_{jn}^{1-\rho_{el}^{n}} (1-\alpha_{jn})(1-\eta)(1-\theta_{jn}) L_{jn}^{\rho_{l}-1}. \end{aligned}$$

I assume that capital supply is perfectly elastic and has rental rate $\bar{r}$. The firm chooses its level of capital such that the price is equal to the marginal product. Specifically, this is given by

$$K_{jn} = \left(\frac{P_n A_{jn} \eta \mathcal{I}_{jn}^{1-\eta}}{\bar{r}} \right)^{\frac{1}{1-\eta}}. \tag{23}$$

Plugging equation 23 into the FOC's and rearranging yields the desired FOC's as in equation 8.

A.1.2 Firm Parameters

In this section, I outline my estimation and calibration of the production function parameters. I break this into the three following sections: labor, energy, and calibration.

Labor Parameters. I need city-sector wages, labor elasticity of substitution (σ_l), and factor intensities (θ_{jn}'s). Let $e \in \{C, L\}$ index worker education levels. A worker of demographic d's income in location j and sector n is given by

$$I_{ejn} = W_{ejn} \ell^e \tag{24}$$

where ℓ^e is the number of efficiency units of labor supplied by a worker of education level e. I parameterize ℓ^e as the probability that a worker of education level e in city j and sector n is unemployed (denoted by π_{ejn}) multiplied by the efficiency units. That is

$$\ell^e = \pi_{ejn} \hat{\ell}^e, \tag{25}$$

where I parameterize $\hat{\ell}^e$ as

$$\hat{\ell}^e = \text{white}_i^{\beta_1^e} \text{over35}_i^{\beta_2^e}. \tag{26}$$

Conditional on working, the workers pre-tax income is given by plugging in equation 25 into equation 24 and taking logs:

$$\log(I_{ejn}) = \log(W_{ejn}) + \beta_1^e \log(\text{white}_i) + \beta_2^e \log(\text{over35}_i). \tag{27}$$

I thus estimate city-sector-demographic wages using equation 27. Specifically, I estimate:

$$\log(I_{ejn}) = \nu_{ejn} + \beta_1^e \log(\text{white}_i) + \beta_2^e \log(\text{over35}_i) + \varepsilon_{ijn}, \tag{28}$$

where ν_{ejn} is a city-sector fixed effect (which estimates $\log(W_{ejn})$). I estimate equation 28 using individual data from the ACS. To account for variation in unemployment across city-sectors, I then weight the estimated wages by the employment rate in the CBSA-sector. This is calculated directly from the ACS data.

The remaining labor parameters to be calibrated are the labor elasticity of substitution σ_l and the labor input use intensities, θ_{jn}. Note that the log wage ratio is given by

$$\underbrace{\log\left(\frac{I^C_{jn}}{I^L_{jn}}\right)}_{\text{Estimated}} = \underbrace{-\frac{1}{\sigma_l}}_{\text{Calibrated}} \underbrace{\log\left(\frac{C_{jn}}{L_{jn}}\right)}_{\text{Data}} + \underbrace{\log\left(\frac{\theta_{jn}}{1-\theta_{jn}}\right)}_{\text{Unknown}}. \tag{29}$$

Note that the only unknowns in equation 29 are the θ_{jn} values. I can solve for these as:

$$\theta_{jn} = \frac{B_{jn}}{1 + B_{jn}} \tag{30}$$

where

$$B_{jn} = \left(\frac{I^C_{jn}}{I^L_{jnl}}\right)\left(\frac{C_{jn}}{L_{jn}}\right)^{\sigma_l}.$$

Energy Parameters. Similar to above, the log ratio of energy prices is given by

$$\underbrace{\log\left(\frac{P^E_{jn}}{P^G_{jn}}\right)}_{\text{data}} = \underbrace{-\frac{1}{\sigma_e}}_{\text{Calibrated}} \underbrace{\log\left(\frac{E_{jn}}{G_{jn}}\right)}_{\text{Data}} + \underbrace{\log\left(\frac{\zeta_{jn}}{1-\zeta_{jn}}\right)}_{\text{Unknown}}. \tag{31}$$

As with the labor parameters, I solve for the factor intensities using equation 31. Specifically,

$$\zeta_{jn} = \frac{Z_{jn}}{1 + Z_{jn}}, \tag{32}$$

where

$$Z_{jn} = \left(\frac{P^E_{jn}}{P^f_{jn}} \right) \left(\frac{E_{jn}}{G_{jn}} \right)^{\sigma_e}.$$

After recovering the ζ_n and θ_{jn}, I can recover the final set of input intensities: the α_{jn}. The ratio of the price of electricity to college educated labor is given by:

$$\underbrace{\log\left(\frac{P^E_{jn}}{W^C_{jn}} \right)}_{\text{data}} = \underbrace{\log\left(\frac{E^{\rho^n_e - 1}_{jn}}{C^{\rho_l - 1}_{jn}} \right)}_{\text{Data}} + \underbrace{\log\left(\frac{\mathcal{E}^{\rho_e l^n - \rho^n_e}_{jn}}{\mathcal{L}^{\rho^n_{el} - \rho_l}_{jn}} \right)}_{\text{data}} + \underbrace{\log\left(\frac{\zeta_{jn}}{\theta_{jn}} \right)}_{\text{Solved above}} + \underbrace{\log\left(\frac{\alpha_{jn}}{1 - \alpha_{jn}} \right)}_{\text{Unknown}}. \tag{33}$$

Thus I solve for these as:

$$\alpha_{jn} = \frac{Q_{jn}}{1 + Q_{jn}}, \tag{34}$$

where

$$Q_{jn} = \left(\frac{P^E_{jn}}{W^C_{jn}} \right) \left(\frac{C^{\rho_l - 1}_{jn}}{E^{\rho^n_e - 1}_{jn}} \right) \left(\frac{\theta_{jn}}{\zeta_{jn}} \right) \left(\frac{\mathcal{L}^{\rho^n_{el} - \rho_l}_{jn}}{\mathcal{E}^{\rho^n_{el} - \rho^n_e}_{jn}} \right). \tag{35}$$

The last set of parameters are the A_{jn} values. I pick these to match the data (e.g. I invert the first-order conditions now that I have all variables except for the TFP's).

A.1.3 Rent Paramaters

Hedonic Rents. I construct a rental index for each city in my sample to make comparisons in prices across CBSA'S more sensible. I regress individual gross log rent on a set of CBSA fixed effects and housing characteristics. I include the number of bedrooms, the number of rooms, household members per room, and the total number of units in the structure containing the household. Specifically, the equation I estimate for individual i is given by:

$$\log(R_i) = \beta_{CBSA(i)} + \beta_2 \text{Rooms}_i + \beta_3 \text{Units}_i + \beta_4 \text{Bedrooms}_i + \beta_5 \left(\frac{\text{members}_i}{\text{rooms}_i} \right) + \varepsilon_i. \tag{36}$$

I then take the average number of these characteristics across all CBSA's and hold them constant, and use the predicted value for each CBSA (generated from the fixed effects) as the hedonic rental index.

Rent Parameters. After obtaining the rental index, I can calculate the remaining parameters in the housing supply curve. The reduced-form relationship for the housing supply curve is given by

$$\log(R_j) = \frac{\beta_j}{1+\beta_j}\log\left(\sum_e \sum_n N_{ejn}\frac{\left(\alpha_e^H \times w_{ejn})\right)}{\alpha_{ejn}}\right) + \eta_j \tag{37}$$

I first calculate R_j using equation 36. I then calibrate β_j using the values in Saiz (2010).[40] For the two CBSA's in my model in which do not overlap with Saiz's elasticities (Honolulu & Sacramento), I compute $\beta_j = \beta_0 + \beta_1 \text{WRI}_j$ where WRI_j is the WRI for city $j \in \{\text{Sac}, \text{Hono}\}$. I take parameter estimates of β_0 and β_1 from column VI, table III of Saiz (2010). I then choose $\eta_j s$ to match the data.

A.2 Household Energy

A.2.1 Baseline Consumption

I follow very closely to Glaeser and Kahn (2010) in constructing household emissions across CBSAs. I estimate household level regressions using CBSA fixed effects to impute the predicted energy use by CBSA. Specifically, I estimate:

$$x_i^m = \gamma_{\text{CBSA(i)}} + \beta_1 \log(\text{Income}_i) + \beta_2 \text{HHsize}_i + \beta_2 \text{Agehead}_i + \varepsilon_i. \tag{38}$$

where x_i^m is household i's consumption of fuel type $m \in \{\text{gas, elec, oil}\}$, $\gamma_{\text{CBSA(i)}}$ is a fixed effect for the household's CBSA, $Income_i$ is the households income obtained from equation 29 and the other variables are the same controls used in Glaeser and Kahn (2010). I adjust the estimated coefficients by the composition of a cities single unit/multi-unit and home owned/rented composition to address the concern that rented homes and multi-family homes are less likely to pay for energy themselves. The ACS has flags for whether the individual owns or rents the house, and if they live in a single or multi-family home. I reweight the estimated coefficients by the fraction of each of the four groups in every CBSA.

A.2.2 Energy Expenditure Shares

This section contains summary statistics for the model's energy expenditure shares, or $\tilde{\alpha}^m = \frac{P^m \times x^m}{W}$. The estimates can be found in Table 6.

[40] Specifically, I use the estimates reported in Table VI.

Expenditure Share on:	College	Non-College
Electricity		
Mean (SD)	0.025 (0.013)	0.046 (0.018)
Range	[0.005, 0.084]	[0.014, 0.133]
Natural Gas		
Mean (SD)	0.03 (0.03)	0.04 (0.05)
Range	[0.00, 0.39]	[0.00, 0.36]
Fuel-Oil		
Mean (SD)	0.001 (0.003)	0.003 (0.005)
Range	[0.000, 0.021]	[0.000, 0.025]

Table 6: Estimated energy-expenditure shares for college and non-college workers, respectively. Summary statistics are taken over the choice set (N=395). Estimates of energy use of type m come from equation 38. Estimates of wages come from equation 28. State-level electricity prices come from EIA data.

A.2.3 HSV Transfers

Let post-transfer income be given by:

$$\tilde{w}_{ij} = w_{ij} + \lambda w_{ij}^{1-\gamma},$$

where $\lambda > 0$ is the overall level of the reimbursement and $\gamma > 1$ indexes the progressivity of the transfers.[41] Note that the government's total revenue from a carbon tax of τ is given by $\mathcal{T} = \tau \sum_n \sum_j \delta_j \hat{f}_{jn}$ where again $\hat{f}_{jn}$ is total energy use in jn. Denote the household's transfer as $g_i = w_{ij}^{1-\gamma}$. In equilibrium, the sum of government transfers, $\mathcal{G} = \sum_i g_i$ must be equal to total revenue. I can solve for λ that satisfies the government budget constraint, $\lambda^\star$, by equating total payments to total revenues:

$$\lambda^\star \sum_e \sum_j N_{ejn}^\star w_{ejn}^{1-\gamma} = \tau \sum_n \sum_j \sum_m \delta_j^m \hat{f}_{jn}^m$$

$$\lambda^\star = \frac{\tau \sum_n \sum_j \sum_m \delta_j^m \hat{f}_{jn}^m}{\sum_e \sum_j N_{ejn}^\star w_{ejn}^{1-\gamma}}.$$

Note that the allocation of workers across cities, N_j and energy consumption, $\hat{f}_{jn}$ are functions of λ in equilibrium. Computationally, I guess a value of λ_g and shares, calculate the

[41] If $\lambda < 0$ and $\gamma < 1$ then this is a tax function.

implied $\lambda^\star$ and check if $\lambda^\star = \lambda_g$. If they are not equal I update my guess as a convex combination of my original guess and $\lambda^\star$.

A.2.4 Model Fit: Energy Consumption

Figure 7 demonstrates model's baseline fit for the three different fuel types for households: electricity, natural gas, and fuel-oil.

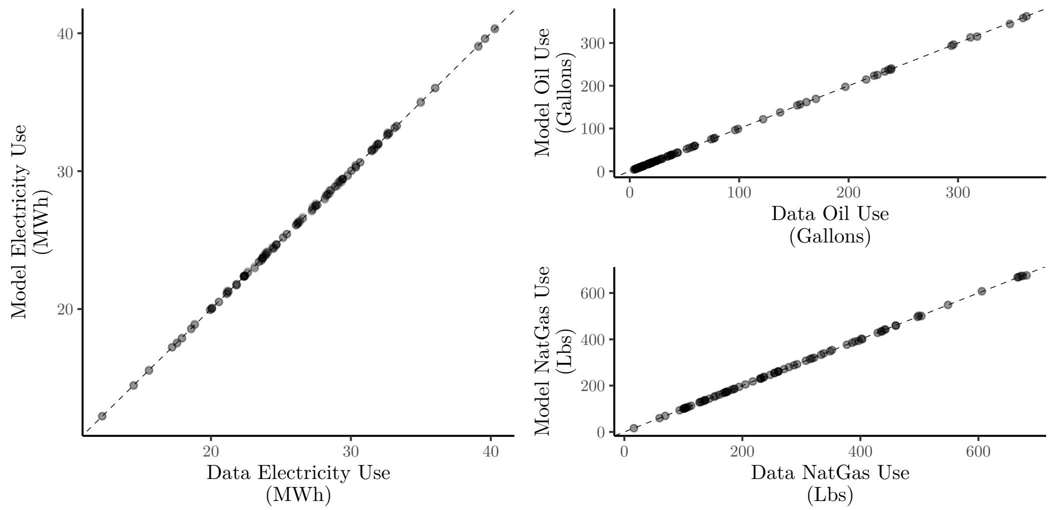

Figure 7: Baseline model fit for electricity, natural gas, and fuel-oil. The x-axis' contains the data city-sector fuel consumption (predicted from equation 38), and the y-axis has the baseline equilibrium energy consumption in the model.

A.3 Energy Adjusted Budget Income

In this section, I derive the "energy-adjusted budget income," $w^{EA}_{ejnt} = \frac{\log(w_{ejnt}) - \sum_m \left(\tilde{\alpha}^m_{ejnt} \log(P_{jt})\right)}{1 - \sum_m \tilde{\alpha}^m_{ejnt}}$, used in estimating equation 18, following Colas and Morehouse (2021). Recall that the mean utility is given by:

$$\delta_{ejnt} = \left(\frac{1 + \alpha^H_e + \sum_m \alpha^m_{ej}}{\sigma_e}\right) \log(w_{ejnt}) - \frac{\alpha^h_e}{\sigma_e} \log(R_{jt}) - \sum_m \frac{\alpha^m_{ej}}{\sigma_e} \log P^m_{jt} + \xi_{ejnt},$$

Note that $\tilde{\alpha}^m_{ejnt} = \frac{\alpha^m_{ejnt}}{\alpha_{ejnt}}$ implies that $\sum_{m'} \tilde{\alpha}^{m'}_{ejt} = \frac{\sum_{m'} \tilde{\alpha}^{m'}_{ejt}(1+\alpha^h_e)}{1-\sum_{m'} \alpha^{m'}_{ejt}}$ and thus $\alpha^m_{ejt} = \frac{\tilde{\alpha}^m_{ejt}(1+\alpha^h_e)}{1-\sum_{m'} \tilde{\alpha_{ejt}}^{m'}}$. I can plug these into the mean utility equation to get:

$$\delta_{ejnt} = \left(\frac{1 + \alpha_e^h + \frac{\tilde{\alpha}_{ejt}^m (1+\alpha_e^h)}{1 - \sum_{m'} \tilde{\alpha_{ejt}}^{m'}}}{\sigma_e} \right) \log(w_{ejnt}) - \frac{\alpha_e^h}{\sigma_e} \log(R_{jt}) - \frac{(1 + \alpha_e^h)}{1 - 1 - \sum_{m'} \tilde{\alpha_{ejt}}^{m'}} \sum_m \frac{\tilde{\alpha}_{ej}^m}{\sigma_e} \log P_{jt}^m + \xi_{ejnt}.$$

Rearranging yields:

$$\delta_{ejnt} = \Theta_{et}^w \log(w_{ejnt}^{EA}) + \Theta_{et}^r \log(R_j) + \epsilon_{ejn},$$

where $w_{ejnt}^{EA} = \dfrac{\log(w_{ejnt}) - \sum_m \left(\tilde{\alpha}_{ejnt}^m \log(P_{jt}) \right)}{1 - \sum_m \tilde{\alpha}_{ejnt}^m}$,$\Theta_e^w = \frac{1+\alpha_e^h}{\sigma_e}$, $\Theta_e^r = \frac{\alpha_e^h}{\sigma_e}$. Note that given estimates of Θ_e^w and Θ_e^r, I can solve for α_e^h and σ_e using the above equations.

A.4 Estimation Summary

Parameter Name	Notation	Source
Labor Supply		
Moving Costs	$\Theta_e^{div}, \Theta_e^{dist}, \Theta_e^{dist2}$	MLE (equation 16)
Marginal Utility of Income/Rents	$\Theta_e^{w}, \Theta_e^{r}$	IV (equation 18)
Variance of pref. shock	σ_e	Algebra
Housing Parameter	α_e^H	Algebra
Utility of Energy param	α_{ejn}^m	Algebra
Wage Index	W_{ejn}	OLS (equation 28)
Firm Parameters		
Energy-Lab EoS	σ_{el}^n	(Koesler and Schymura, 2012)
Gas- Elec EoS	σ_e^n	(Serletis, Timilsina, and Vasetsky, 2010)
College-No College EoS	σ_l	(Card, 2009)
Factor Intensities	$\alpha_{jn}, \theta_{jn}, \zeta_{jn}$	Relative demand curves
TFP	A_{jn}	Firm FOCs
Energy and Rent Parameters		
Intercepts	β_j, a_{mj}	Algebra
Energy Supply Elasticity	κ	(Dahl and Duggan, 1996)
Rent Supply Elasticity	γ_j	(Saiz, 2010)
Carbon Emissions Factor	δ^m	Data
Rent Index	R_j	OLS (equation 36)

Table 7: Overview of calibration and estimation strategy for the model's parameters.

A.5 NERC Region Emissions Factors

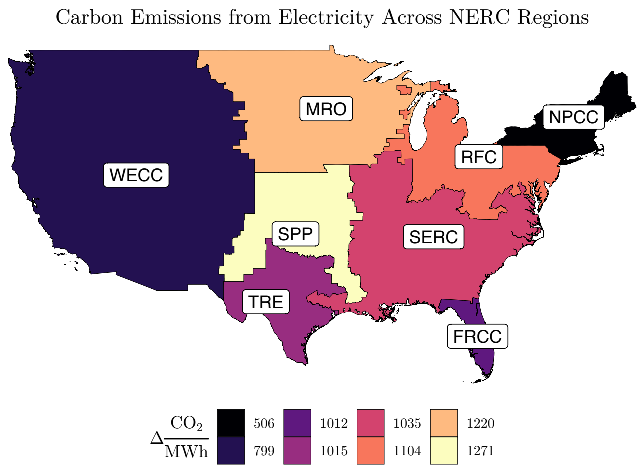

Figure 8: NERC regional electricity emissions factors. Emissions factors are calculated as output-weighted averages of individual plant's emissions rates.

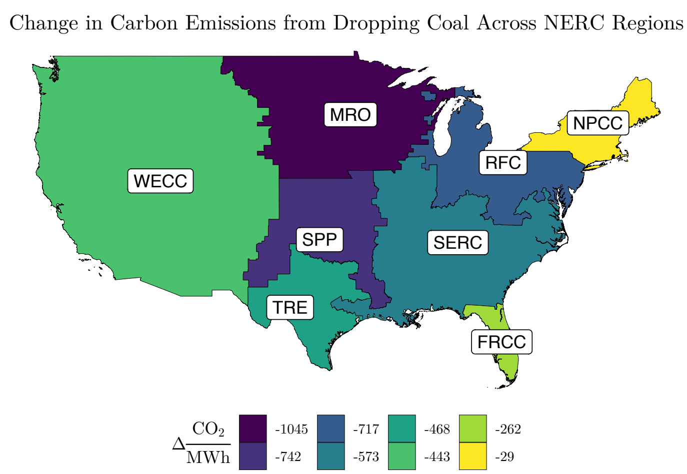

Figure 9: Change in NERC region emissions factors from electricity in the absence of coal fueled power plants. Emissions factors are calculated as output-weighted averages of individual plant's emissions rates, for all plants in a region excluding coal.

A.5.1 Heterogeneity in Incidence Across Space

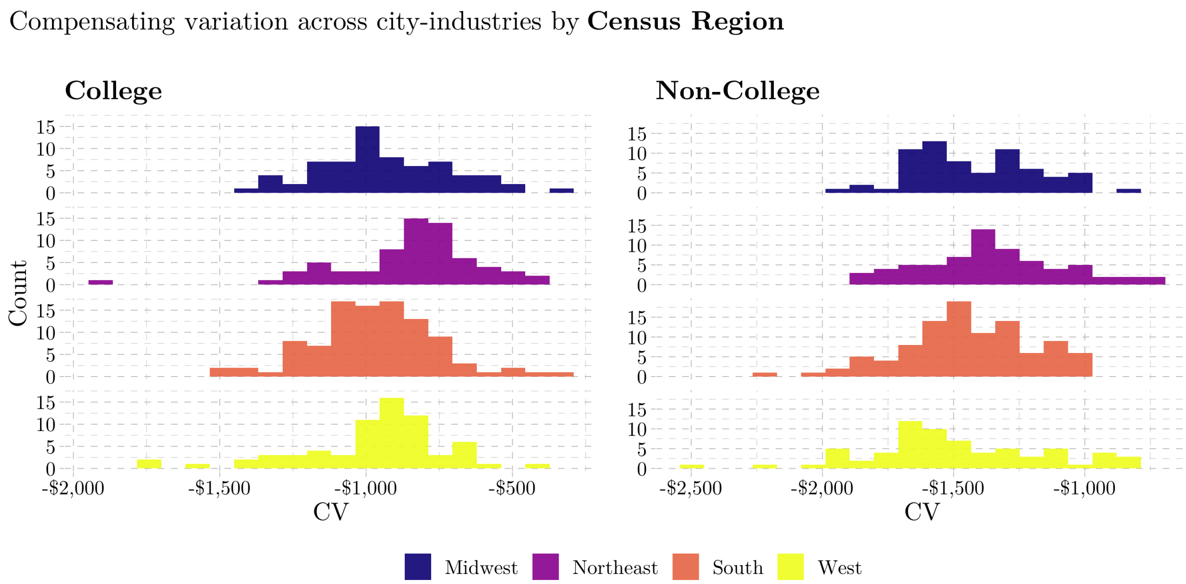

Figure 10: The distribution of mean compensating variation across cities and sectors by Census Region from a $31 per ton carbon tax. CV is measured in dollars.

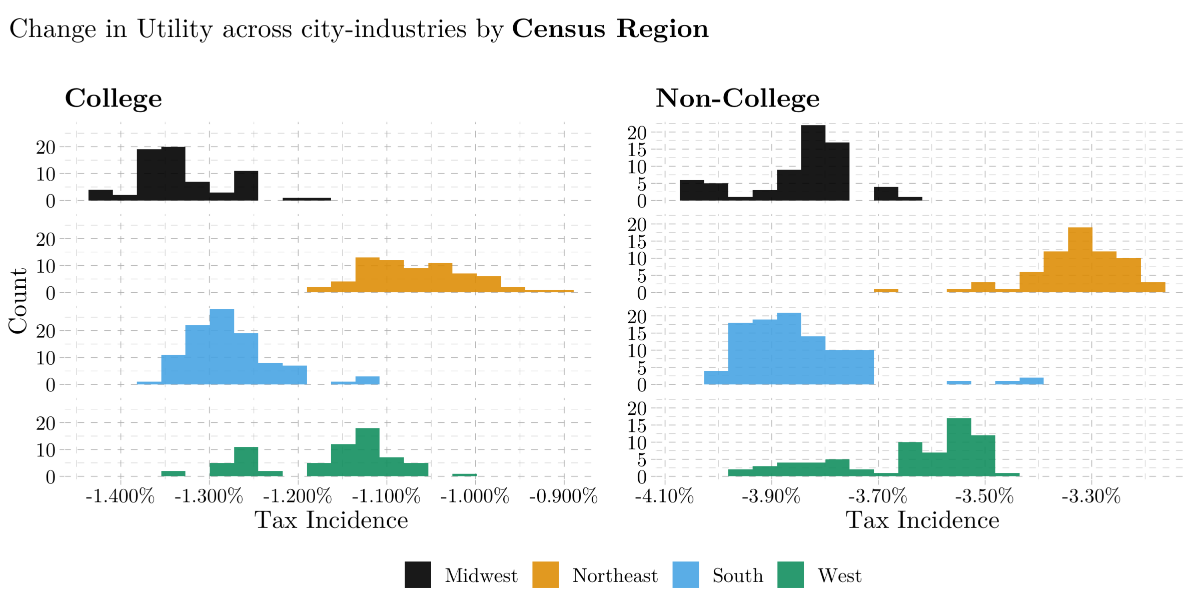

Figure 11: The distribution of tax incidence (non-monetized) in utility across cities and sectors by Census Region from a $31 per ton carbon tax.

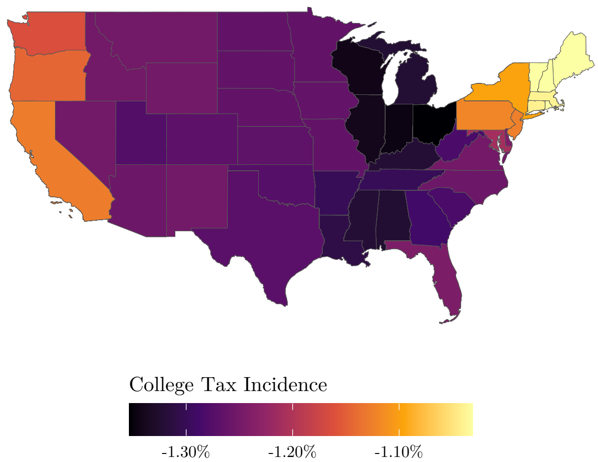

Figure 12: Tax incidence (non-monetized) across states from a $31 per ton carbon tax for college educated households.

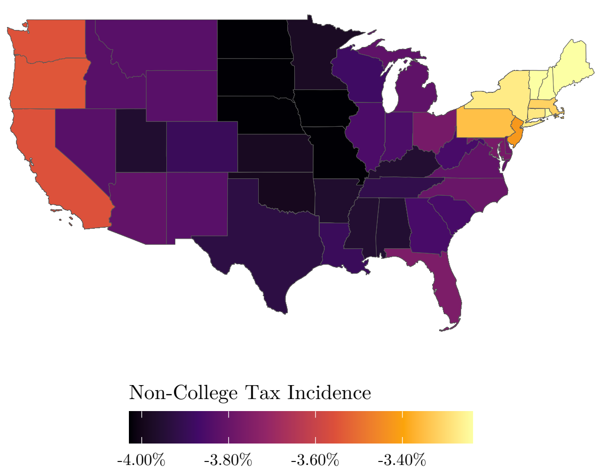

Figure 13: Tax incidence (non-monetized) across states from a $31 per ton carbon tax for non-college educated households.

τ = $31/ton: **No Transfers**	Midwest	Northeast	South	West
All	−1,290	1,195	1,255	1,291
	(309)	(315)	(321)	(355)
College	971	967	962	178
	(181)	(218)	(178)	(257)
Non-College	−1,471	1,404	1,455	1,508
	(203)	(235)	(230)	(257)

Table 8: Mean compensating variation across cities and sectors by Census Region from a $31 per ton carbon tax. Standard deviations are in parenthesis.

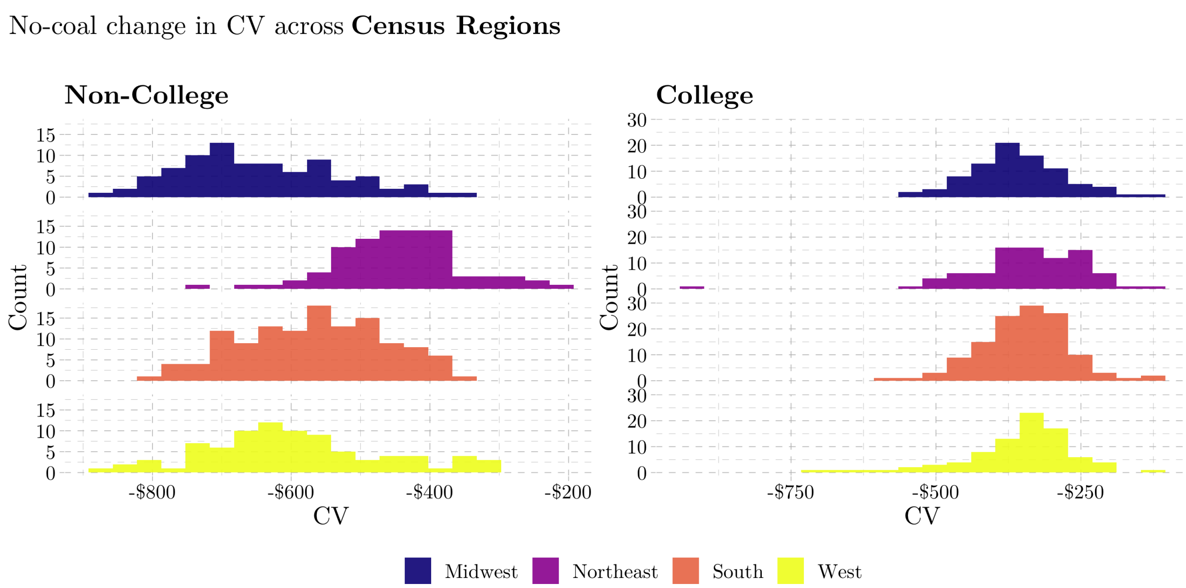

Table 9: Change in compensating variation from dropping coal across census regions from a $31 per ton carbon tax.

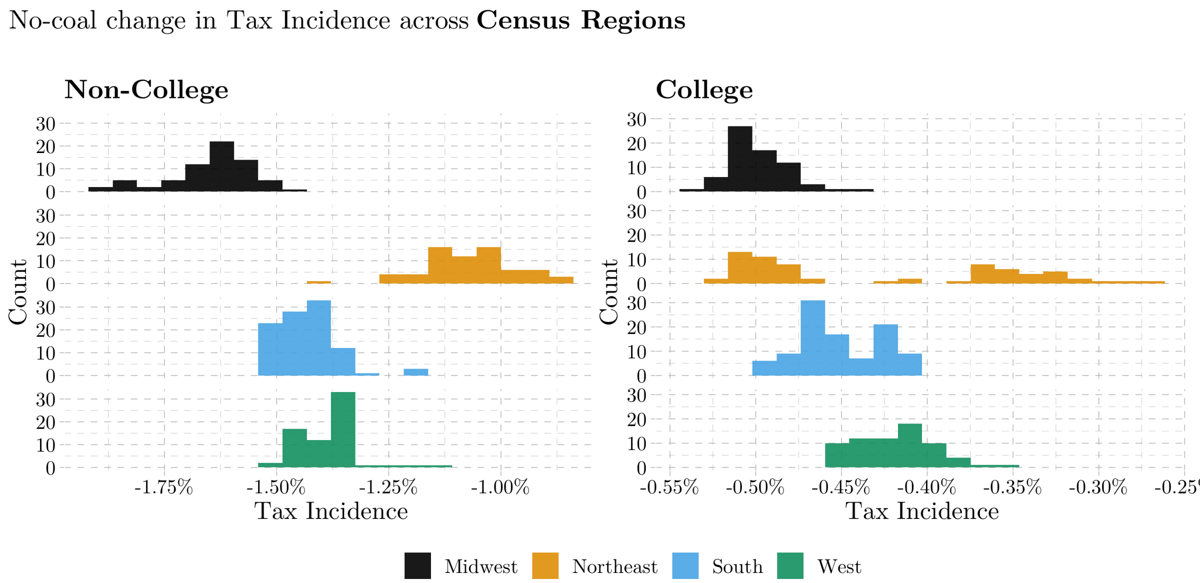

Table 10: Percent change in tax incidence (non-monetized) from dropping coal across census regions from a $31 per ton carbon tax.

A.5.2 Heterogeneity in Incidence Across Industries

In this section, I decompose the monetized (compensating variation) and non-monetized incidence from a $31 dollar per ton carbon tax.

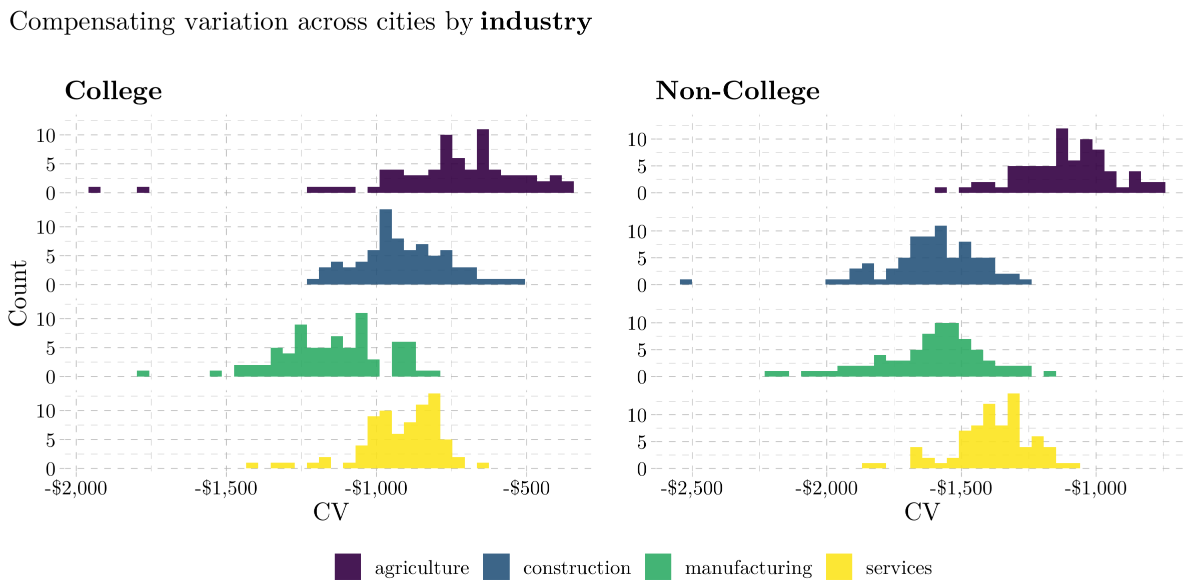

Figure 14: The distribution of mean compensating variation across cities by industries from a $31 per ton carbon tax. CV is measured in dollars.

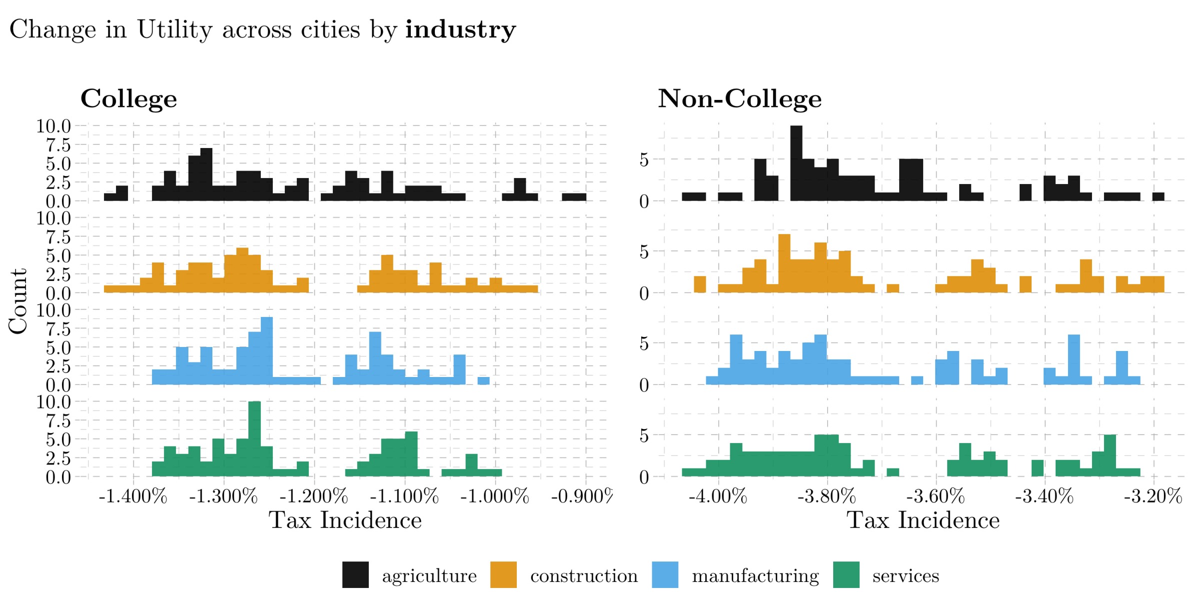

Figure 15: The distribution of tax incidence (non-monetized) across cities by industries from a $31 per ton carbon tax.

τ = \$31/ton: **No Transfers**	Manufacturing	Services	Construction	Agriculture
All	−1,446	1,156	1,491	1,012
	(263)	(271)	(304)	(217)
College	1,170	949	916	708
	(224)	(187)	(151)	(171)
Non-College	−1,565	1,360	1,598	1,094
	(174)	(168)	(180)	(142)

Table 11: Mean compensating variation across cities by industry from a \$31 per ton carbon tax. Standard deviations are in parenthesis.

A.5.3 Migration

In this section, I map out changes in population across cities from a $31 per ton carbon tax, aggregated to the state level. My sample only includes 34 states, I use changes in population at the Census division level for states with missing data, excluding the population changes from the included CBSAs within the respective census division.

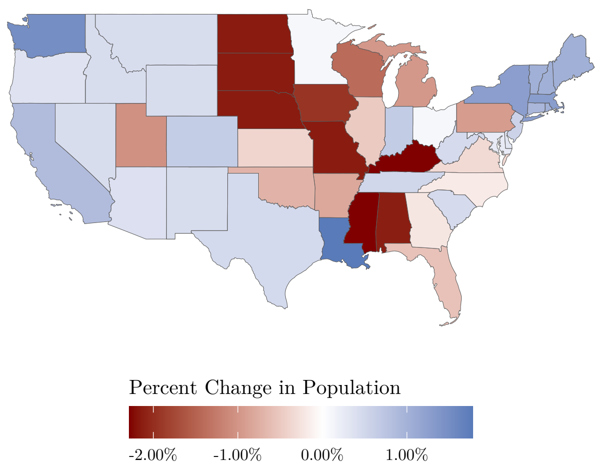

Figure 16: Population changes are computed using the equilibrium arising from the model using a $31 per ton carbon tax.

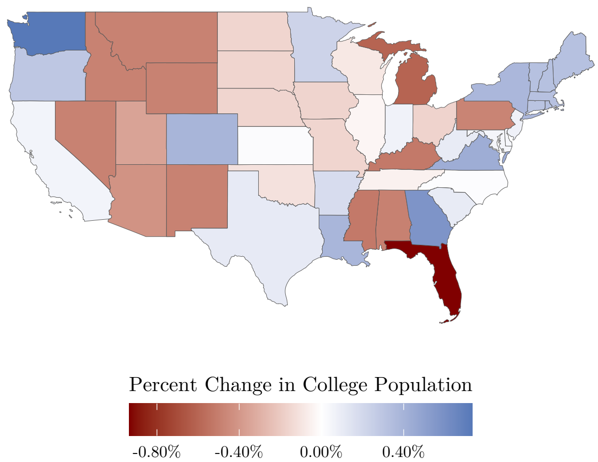

Figure 17: Population changes are computed using the equilibrium arising from the model using a $31 per ton carbon tax.

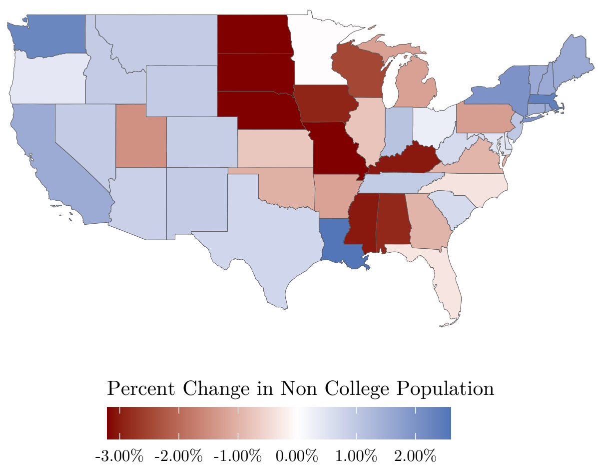

Figure 18: Population changes are computed using the equilibrium arising from the model using a $31 per ton carbon tax.

A.5.4 Voting and Tax Incidence

This section provides plots that explore the relationship between carbon pricing incidence and the share of the given CBSA that voted for Trump in the 2016 presidential election.

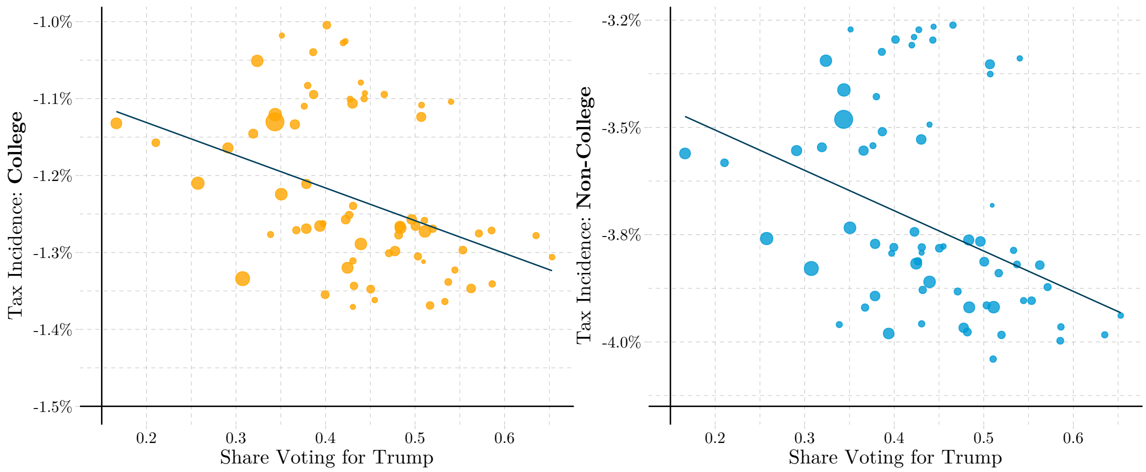

Figure 19: An observation is a CBSA; the size of each observation reflects the total number of *voters* in the 2016 presidential primary election in the CBSA. Tax incidence is measured as the relative change in utility from a $31 per ton carbon tax, calculated using equation 20.

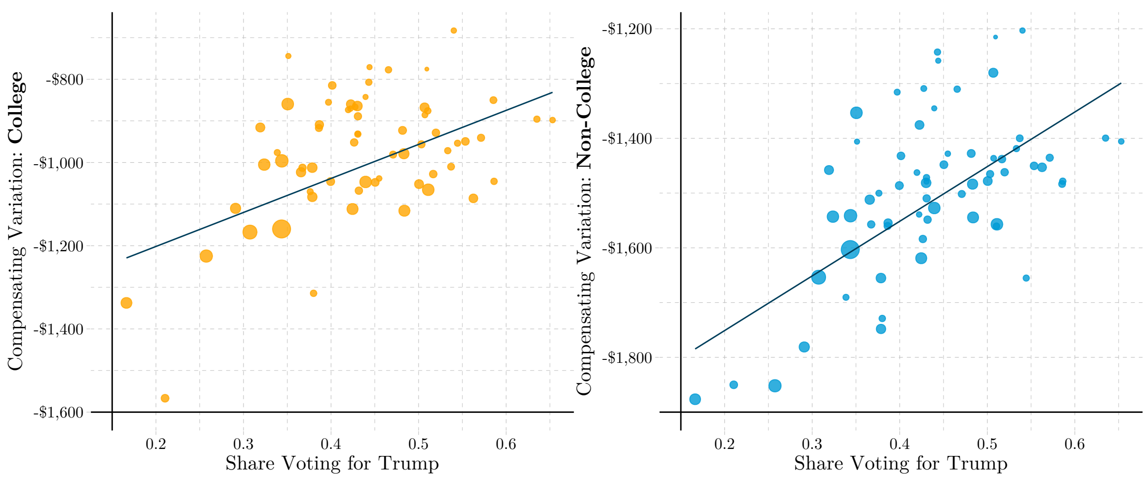

Figure 20: An observation is a CBSA; the size of each observation reflects the total number of *voters* in the 2016 presidential primary election in the CBSA. Compensating variation is measured as the average dollar amount required to make a household indifferent to a $31 per ton carbon tax, calculated using equation 20.

A.6 Computational Appendix

A.6.1 Nested-Fixed-Point Algorithm

In this section, I outline the nested-fixed-point algorithm I use to obtain the preference parameters:

$$\mathbf{\Theta}^* = \arg\max \sum_{i=1}^{N^d} \sum_{n \in N} \sum_{j \in J} \mathbb{I}_i(j,n) \log(\delta_{ejn}, P_i(\mathbf{\Theta}^{et})),$$

where $P_i(\delta_{ejn}, \mathbf{\Theta}^{\gamma_e})$ is defined in equation 15. In what follows, let t denote iteration number (**not time**). I proceed in the following manner:

Outer-Loop

(1) Start with an arbitrary guess of the parameter vector, $\mathbf{\Theta}^{*,0}$

Inner-Loop

(2) Guess an arbitrary level of mean utilities for each city-sector combo and education level, δ^0_{ejn}

(3) Given the guess of the parameter vector and mean utility, compute the model's predicted share of agent's in each sector-city combo. This is given by

$$S^0_{\text{model}_{ejn}} = \sum_{i}^{N^d} P_i(\delta_{ejnt}, \mathbf{\Theta}_{et}),$$

(4) Use the Nevo speedup (Nevo, 2000) of the contraction mapping from Berry (1994):

$$\exp(\delta^1_{ejn}) = \exp(\delta^0_{ejn}) \times \left(\frac{S_{\text{data}_{ejn}}}{S^0_{\text{model}_{ejn}}} \right), \tag{39}$$

where $S_{\text{data}_{ejn}}$ is the share of agents of education level e that choose city j and sector n in the data. Note that equation 39 will converge for any guess of the parameter vector and initial delta.

(5) Check for convergence of equation 39. Specifically, I check

$$\sup \left| \delta^1_{ejn} - \delta^0_{ejn} \right| < \epsilon.$$

If the equation hasn't converged, update the new guess of δ to δ^1 and go back to step (3). Repeat 3-5 until delta has converged. This ends the inner-loop

(6) After obtaining the unique δ_{ejn} for the guess of $\mathbf{\Theta}^{*,0}$, we can compute the value of the likelihood function. Check to see if the likelihood function is maximized. If not, go back to step (1). To update the guess of $\mathbf{\Theta}^{*}$, I use the Nelder-Mead algorithm.

A.6.2 Equilibrium Simulation

In this section, I outline how I solve for the counterfactual equilibrium.

(1) Guess a vector of wages, rents, residential electricity prices, industrial electricity demand, and industrial natural gas demand.

(2) Given these guesses, calculated labor supply in each city using the implied choice shares multiplied by the total population of college and non-college workers

(3) Calculate the value of the labor aggregator, the energy aggregator, and finally, the input aggregator using the implied populations from step 2 and the guesses of industrial energy consumption

(4) Calculate total housing demand using equation 37.

(5) Check if the new vectors of wages, rents, and residential energy prices and industrial energy consumption from steps 3 and 4 are within ϵ of the guess made in step 1. If not, return to step 1, using updated guesses that are convex combinations of the old guess and new prices that come from the firm's FOC and rent equations. To update the guess of industrial gas demand, I check if the price from the firm's FOC matches the data prices. If not, I update the new guess of industrial gas to be larger than the old. If so, I update it to be smaller. For electricity, I use the same process but compare the firm's FOC prices to city-level supply prices (generated by the supply curve) and update accordingly.

A.7 Data Appendix

A.7.1 Labor Supply & Demand

Cleaning. My sample consists of all non-military, non-institutionalized, employed, (16-64) individuals. I drop all observations with missing or negative incomes. Additionally, I drop all workers, not in the 10 sectors described in the model section. A household is defined by the ACS variable *SERIAL*, which assigns all individuals in a household the same number. The decision-maker in the model is the "household head" (given by the IPUMS variable *RELATE*).

Geography. I construct the labor supply and demand from the 5-year aggregated ACS 2012-2016 data. My geographic unit of observation is a "Core-Based Statistical Area" (CBSA). I follow closely in other literature in constructing the sample to make it more comparable to other papers. Specifically, I choose the 70 largest CBSA's, as defined by the population in 1980. I then map individuals that do not live in one of these 70 CBSA's into their corresponding census division, creating an additional 9 choices. Thus the model consists of 79 unique, geographic choices. All wage estimates and choice counts are weighted by the exogenous sampling weights provided by the ACS.

Industry. To construct the model's industries, I use the "INDNAICS" variable from the ACS. While the ACS has NAICS codes at the 6-digit (least aggregated), I constrain the model to contain 10 sectors: services, construction, transportation, the balance of manufacturing, agriculture, metals, foods, chemicals, mining, and plastics. These sectors contain over 80% of total US employment.

A.7.2 City-Sector Energy Use

In this section, I detail how I assign energy consumption by city-sector to firms in the baseline case. I observe energy consumption by sector at the national level from the EIA data. Additionally, the EIA has utility-level electricity and natural gas use by aggregated industrial, commercial, and residential sectors. I construct a sector n's consumption of electricity (natural gas) as proportional to the city-sectors share of aggregate employment. Note that for sectoral employment, L_n, I use BLS data. For the numerator, L_{jn}, I use counts from my sample. Since E_n is aggregated across all US cities, using the fraction of workers in my sample across the whole US adjusts firm energy consumption to my match my subset of households. Specifically, firm electricity and gas consumption is given by:

$$E_{jn} = \frac{L_{jn}}{L_n} * E_n$$
$$G_{jn} = \frac{L_{jn}}{L_n} * G_n.$$

A.8 Additional Scatterplots

In this section I disaggregate figure 5 by education group in figure 21 and then by education group and sector in 22.

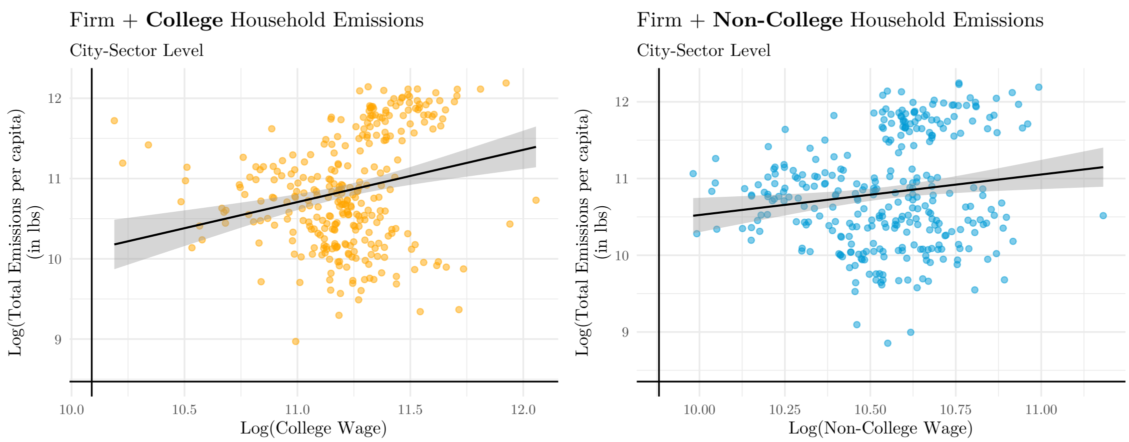

Figure 21: Total emissions per capita across city-sector plotted against wages. Wages are constructed as city level averages estimated from equation 28. Emissions are the sum of firm emissions per capita and household emissions for a given education group.

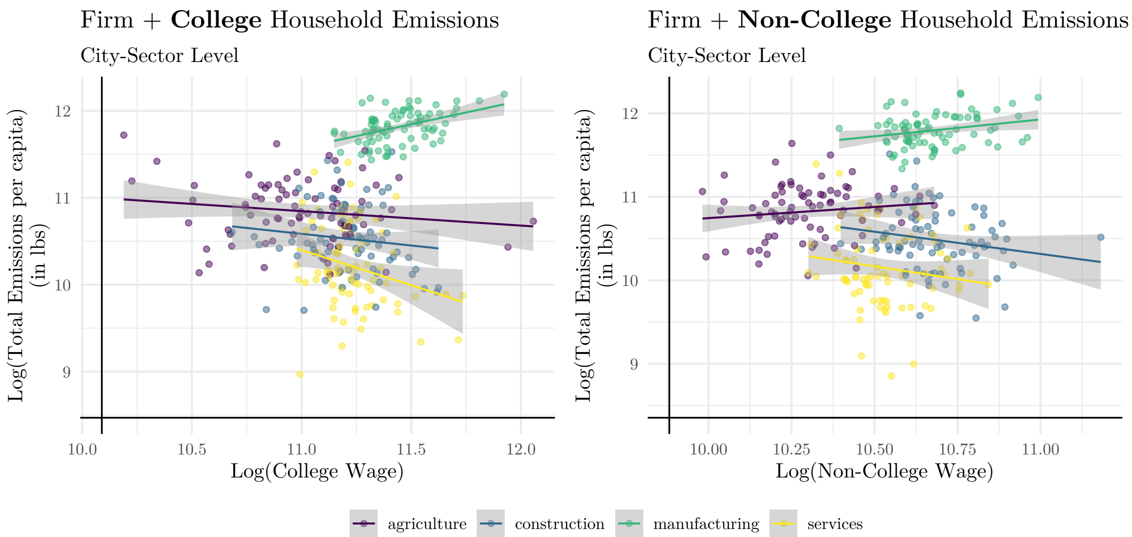

Figure 22: Total emissions per capita by city across industries plotted against wages. Wages are constructed as city level averages estimated from equation 28. Emissions are the sum of firm emissions per capita and household emissions for a given education group.

A.9 Sector Energy Demand

The EIA classifies the Industrial and Commercial sector in the following manner:

- **Industrial sector**: An energy-consuming sector that consists of all facilities and equipment used for producing, processing, or assembling goods. The industrial sector encompasses the following types of activity manufacturing (NAICS codes 31-33); agriculture, forestry, fishing and hunting (NAICS code 11); mining, including oil and gas extraction (NAICS code 21); and construction (NAICS code 23). Overall energy use in this sector is largely for process heat and cooling and powering machinery, with lesser amounts used for facility heating, air conditioning, and lighting. Fossil fuels are also used as raw material inputs to manufactured products. Note: This sector includes generators that produce electricity and/or useful thermal output primarily to support the above-mentioned industrial activities. Various EIA programs differ in sectoral coverage.

- **Commercial Sector**: An energy-consuming sector that consists of service-providing facilities and equipment of businesses; Federal, State, and local governments; and other private and public organizations, such as religious, social, or fraternal groups. The commercial sector includes institutional living quarters. It also includes sewage treatment facilities. Common uses of energy associated with this sector include space heating, water heating, air conditioning, lighting, refrigeration, cooking, and running a wide variety of other equipment. Note: This sector includes generators that produce electricity and/or useful thermal output primarily to support the activities of the above-mentioned commercial establishments.