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The Environmental Cost of Land Use Restrictions*

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Abstract

Cities with cleaner power plants and lower energy demand have stricter land use restrictions; these restrictions increase housing prices and disincentivize living in these lower polluting cities. We use a spatial equilibrium model to quantify the effect of land use restrictions on household carbon emissions. Our model features heterogeneous households, cities that vary by power plant technology and the benefits of energy usage, as well as endogenous wages and rents. Relaxing restrictions in California to the national median leads to a 2.3% drop in national carbon emissions. The burden of a carbon tax differs substantially across locations.

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Keywords: Greenhouse gasses, local labor markets, spatial equilibrium

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1 Introduction

The negative effects of carbon dioxide (CO_2) are well understood; higher levels of CO_2 in the atmosphere are affiliated with a multitude of environmental issues. The amount of energy an individual uses, and therefore the amount of carbon emissions one is responsible for, depends partially on where the individual lives.[1] For example, Oklahoma City has both high summer temperatures and relies heavily on coal power plants while San Francisco has a moderate climate and uses electricity largely produced in clean hydroelectric plants. As a result, households in Oklahoma City consume high levels of air conditioning using electricity produced from high-polluting power plants while households in San Francisco will use less electricity from lower-polluting plants. Therefore, government policy which shapes the distribution of workers across cities has important implications for national carbon emissions.

Local land use restrictions are often employed to improve the "greenness" of a city. However, these restrictions increase costs to new construction and therefore limit population growth in many of the most desirable cities (Glaeser, Gyourko, and Saks, 2005).[2] Further, Glaeser and Kahn (2010) document that cities with lower carbon usage per household have stricter land use restrictions; suggesting that these restrictions discourage people from living in lower polluting cities. The goal of this paper is to quantity the effect of land use restrictions on national residential carbon emissions.

To this end, we specify a spatial equilibrium model with power plant technology and demand for energy that varies across cities. Heterogeneous and imperfectly mobile households choose which city to live in and how much housing, electricity, natural gas, and fuel oil to consume. Rents and wages are determined in equilibrium by the location and consumption choices of these households. Furthermore, cities vary in the restrictiveness of local land use regulations. All else equal, stricter land use restrictions imply higher costs of living which disincentivize

[1] For example, Glaeser and Kahn (2010) show that the median household in Memphis is responsible for nearly twice as much carbon emissions as an median household in San Francisco.

[2] These restrictions are often popular among local homeowners as they keep house prices high (Glaeser, 2014). Albouy and Ehrlich (2018) find that land use restrictions increase the cost of construction without improving local amenities.

households from living in these cities.[3]

Our model allows carbon output to vary across cities for two reasons. First, we allow the marginal benefit of usage of electricity, natural gas, and fuel oil to vary by city. Second, due to spatial variation in the technology of power plants across the US, electricity production has heterogeneous emissions. If land use regulations are stricter in cities with more carbon efficient power plants and lower energy demand, households will be incentivized to live in "dirtier" cities, thus increasing national carbon emissions.

For our analysis, we combine data from three main sources. We utilize data on household location, income, rents and expenditures on electricity, natural gas, and fuel oil from over 5 million households from the five-year aggregated American Community Survey (ACS) from 2012 - 2016. We combine household expenditure data with state-level prices from the Energy Information Association (EIA) to impute household usage of each of these three energy types. Next, we use data from the Emissions & Generation Resource Integrated Database (eGrid) on the energy output, CO_2 emissions rates and locations of all power plants in the United States to estimate carbon emissions associated with electricity production across the US. We update the descriptive results in Glaeser and Kahn (2010) with this more recent data and document substantial variation in carbon emissions across cities. For example, we show that a household in Memphis is responsible for over three times as much annual carbon emissions as a household with the same demographics in Honolulu. Additionally, we show that household carbon emissions are negatively correlated with a standard measure of land use restrictions, the Wharton Land-Use Regulation Index—greener cities tend to have stricter land use restrictions.

Next, we use these data sources and a combination of calibration and estimation to take our quantitative model to the data. The household sorting and energy demand component is estimated via maximum likelihood, using data on locations and energy expenditures from the ACS. We use data from eGrid to estimate the carbon emissions associated with electricity production across regions and estimates from Saiz (2010) to calibrate the parameters of housing supply curves as a

[3]We use the terms "land use restrictions" and "land use regulations" interchangeably throughout the paper.

function of land use restrictions.

California legislators are currently debating SB-50, a bill that would relax local land use restrictions in California cities.[4] We use the estimated model to simulate the effects of such a policy, specifically, by setting land use regulations in California cities to the median level in the United States. Due to the moderate climate and carbon efficient power plants, California cities are remarkably green. However, land use regulations are strict—the San Francisco MSA is in the 86th percentile of the Wharton Index while Los Angeles CBSA is the 78th. As a result of relaxing these restrictions, we find that the long run population in California cities increases by nearly 68% and national usage of natural gas and electricity drop by 1.1% and 1.7%, respectively, as demand for both types of energy are lower in California. Overall, this leads to a 2.3% decrease in national carbon emissions. This is driven by a decrease in energy usage and a greater portion of total electricity consumption coming from clean power plants in California. Furthermore, as California cities have high productivity levels, this leads to increase in average wages for both unskilled and skilled workers. In total, this shift towards more productive and lower polluting cities increases the output to emissions ratio by 4.7%.

Next, we entirely remove the negative correlation between land use restrictions and carbon emissions by setting the Wharton Index in all cities to the national median. Households respond by leaving the Midwest and South and move to the West Coast and Northeast. Demand for natural gas is high and demand for electricity is low in the cold Northeast, resulting in an increase in national gas usage and a decrease in total electricity usage. Overall, these changes in household sorting and energy usage lead to an 8% drop in national carbon emissions and nearly a 20% increase in the national carbon efficiency of output.

Finally, we simulate the effects of a carbon tax equal to the social cost of carbon emissions.[5] We find this carbon tax leads to over a 10% decrease in residential carbon emissions, both via its effect on household sorting and decreased usage

[4]SB-50 is appropriately referred to as the "More HOMES Act" (Housing, Opportunity, Mobility, Equity, and Stability). The bill focuses on relaxing density restrictions and reducing the number of areas zoned for single-family homes, particularly in areas near public transit and in commercial areas.

[5]We use $31 per ton of carbon based on the estimates of the social cost of carbon in Nordhaus (2017).

conditional on location. The direct effect of the tax reduces average household welfare by $305, raises a tax revenue of $269 per household, and leads to a reduction in the social cost of carbon valued at $38 per household. However, the carbon tax has significant distributional consequences: the tax burden of households in the Midwest is nearly 50% larger than that of households in the West.

Our paper relates to two recent papers, Hsieh and Moretti (2019) (HM) and Herkenhoff, Ohanian, and Prescott (2018), who find that relaxing land use regulations in high productivity cities would lead to large increases in GDP.[6] Methodologically, our approach is closer to HM. Our model focuses on an entirely different set of outcomes and incorporates energy demand, energy production, and emissions. Furthermore, workers in our model vary in terms of education, family composition, age, race and the state in which they were born. Therefore, our model allows for richer substitution patterns across cities and allows us to analyze how changes in land use restrictions affect both the population and demographic composition across cities. In Section 6, we demonstrate that our predicted changes in aggregate population are similar to those in HM, however, we also show that relaxing land use regulations leads to important changes in the composition of households within a city.

Our work builds on the descriptive findings in Glaeser and Kahn (2010) (GK). GK measure predicted carbon emissions associated with living in different cities across the country and documents a negative correlation between emissions and land use regulations. Relative to GK, the primary contribution of this paper is to utilize a structural model to quantify the effects of land use restrictions on national carbon emissions. National carbon emissions are an equilibrium object; household sorting, energy demand, and housing supply/demand all determine the extent to which land use restrictions affect national carbon emissions. Estimating the effects of a counterfactual change in land use restrictions necessitates a structural equilibrium model.

This paper is also related to a large literature on how exposure to environmental externalities varies by location (See Chay and Greenstone (2005); Currie et al.

[6] Albouy and Stuart (2014) also find that relaxing land use regulations would lead to large redistribution of households across cities but are less concerned with the effect on national productivity.

(2015); Muehlenbachs, Spiller, and Timmins (2015); or Fowlie, Rubin, and Walker (Forthcoming), for example). In our setting, exposure to the carbon emissions does not depend on the household's location—the effects of carbon emissions and global warming are predominantly felt globally, not locally. However, the amount of carbon emitted generated depends on where the household lives. Finally, in complementary work, Mangum (2016) analyzes the effects of housing and land stock allocations on carbon emissions.[7]

The remainder of the paper proceeds as follows. In Section 2, we describe the data and in Section 3 we document several stylized facts regarding emissions and land use restrictions across cities. We present our quantitative spatial equilibrium model in Section 4. We describe how we take the model to the data in Section 5 and discuss model validation in Section 6. Section 7 presents the main counterfactual results. Section 8 presents robustness and model extensions and Section 9 concludes.

2 Data

This paper utilizes individual data on household sorting and energy expenditures from the ACS, detailed data on power plants from eGrid, and state level energy pricing data from the EIA. In what follows, we briefly describe each of the main data sources and how they are used in our analysis. Further details on the data can be found in Appendix A.

CBSA Level Data We utilize Core Based Statistical Areas (CBSAs) as our definition of a geographic area. CBSAs correspond to distinct labor markets and are the Office of Management and Budget's official definition of a metropolitan area. To measure land use regulations in each CBSAs we utilize a standard metric developed by Gyourko, Saiz, and Summers (2008), the Wharton Land-Use Regulation Index (WLURI). This index was created from a survey sent to 6896 municipalities across the US, with questions that range from how many

[7]Compared to Mangum (2016), our paper focuses more on the workers sorting across cities and energy usage. Mangum's focus on the housing construction process allows for a more nuanced understanding of how different land use restrictions affect the housing stock.

regulatory boards one must clear before construction to city-specific density and open space requirements. A higher value of the Wharton-Index implies more stringent regulations and higher costs of developing land and has been shown to lead to more inelastic housing supply curves (e.g. Saiz (2010), Albouy and Ehrlich (2018), or Diamond (2016)).

Individual Data Individual-level data comes from US Integrated Public Use Microdata Series (IPUMS); we utilize the 5% five-year American Community Survey (ACS) from 2012 - 2016 (Ruggles et al., 2010). Since we are allowing for a rich-level of agent heterogeneity, a large data-set is imperative for our analysis. Our sample consists of over 5 million households and provides demographic, location, and housing information. Crucially, the ACS contains yearly expenditures data on natural gas, electricity, and fuel oil.

Our model is concerned with emissions generated at home, we therefore focus on three primary **energy types**: natural gas, electricity, and fuel oil.[8] We combine data on expenditures on these three energy types with state level price data from the US Energy Information Administration (EIA)[9] to impute household consumption of natural gas, electricity, and fuel oil.

Power Plants and Emissions For each of the three energy types we consider, we use conversion factors to convert usage of each energy type to carbon emissions. We assume 117 lbs of CO_2 are emitted per thousand cubic feet of natural gas consumed and 17 lbs of CO_2 are emitted per gallon of fuel oil consumed.[10] Carbon emissions associated with electricity usage depend on where the electricity is consumed—electricity used in areas which generate electricity via coal plants will lead to more carbon emissions than in areas which rely more heavily on hydroelectric power.

We therefore turn to power plant-level data from the Emissions & Generation Resource Integrated Database (eGRID). This dataset contains information on

[8] GK also examine the role of differences across cities in emissions produced by cars. They find that differential usage of cars does little to explain total differences in emissions across cities. Furthermore, data on driving across cities is limited.

[9] https://www.eia.gov/state/seds/

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

every power plant in the US's location, primary fuel input, emissions rate, and total megawatt hours of electricity generated each year. To assign households to power plants, we use the eight North American Electric Reliability Council (NERC) regions. These eight regions can be thought of as closed markets as transmissions of electricity within a region is common but electricity is rarely transferred across regions (Holland and Mansur, 2008; Glaeser and Kahn, 2010).

We calculate the emissions factor associated with each NERC region as the weighted average CO_2 emissions of all plants in the NERC region. The emissions factors range from roughly 800 to 1550 lbs of CO_2 emitted per megawatt hour of electricity consumed.[11] All CBSAs within a NERC region are assigned this conversion factor.

3 Descriptive Statistics

In this section we calculate predicted household usage of electricity, natural gas and fuel oil usage across cities and the associated carbon emissions. We follow GK closely in construction of CBSA level measures.

Our goal is to construct a measure of predicted energy usage in each CBSA, controlling for differences in household composition and demographics. First, we calculate each household's imputed energy usage in natural gas, electricity and fuel oil as their reported expenditure on each of these energy types divided by the state-level price of each energy type. We then regress household energy usage on demographic variables and CBSA fixed effects and compute the predicted usage of a household with median demographic characteristics in each city.[12] Details on the regression can be found in Section A.5.

Once we obtain predicted per-capita energy use for each CBSA and energy type, we turn to emissions. We multiply the predicted usage for each fuel type with the respective emissions factor. As discussed in Section 2, we assume a constant emissions factor for fuel oil and natural gas. The emissions factor for electricity use varies across NERC regions.

[11]For the full distribution of emissions factors, see Table 9 in Section A.4.

[12]Results where we do not control for demographics are qualitatively similar. In our main specification, we control for log income, household size, and age of the household head.

CBSA	Rank	Emissions (1000 lbs)	Gas Emissions (1000 lbs)	Fuel Emissions (1000 lbs)	Electricity Use (MwH)	Electricity Conversion (1000 lbs per MwH)	Electricity Emissions (1000 lbs)
Lowest							
Honolulu, HI	1	9.65	0.30	0.07	6.10	1.52	9.29
Oxnard, CA	2	11.14	5.29	0.11	7.18	0.80	5.75
San Diego, CA	3	11.28	4.65	0.15	8.10	0.80	6.48
Los Angeles, CA	4	11.31	4.95	0.08	7.85	0.80	6.28
San Jose, CA	5	12.27	5.70	0.11	8.08	0.80	6.46
San Francisco, CA	6	12.50	5.94	0.13	8.04	0.80	6.43
Middle							
Austin, TX	33	20.96	3.87	0.13	16.71	1.01	16.96
Charlotte, NC-SC	34	21.05	4.91	0.24	15.36	1.04	15.90
Houston, TX	35	21.81	3.92	0.10	17.52	1.01	17.78
Virginia Beach, VA	36	21.98	4.51	0.43	16.46	1.04	17.04
Richmond, VA	37	22.08	4.39	0.69	16.41	1.04	16.99
Dallas-Fort, TX	38	22.33	3.89	0.13	18.04	1.01	18.31
Highest							
Tulsa, OK	65	27.61	7.54	0.16	15.67	1.27	19.92
Detroit, MI	66	27.99	14.97	0.28	11.53	1.11	12.75
Kansas City, MO-KS	67	28.90	8.77	0.18	15.69	1.27	19.95
Omaha, NE	68	29.96	13.02	0.26	13.66	1.22	16.68
Oklahoma City, OK	69	30.46	7.21	0.19	18.14	1.27	23.06
Memphis, TN-MS-AR	70	30.66	6.70	0.15	23.00	1.04	23.81

Table 1: Predicted CBSA level CO_2 emissions by fuel type for the six lowest emissions cities, the six median cities, and the six highest emissions cities. The third column ("Emissions") shows the sum of predicted CO_2 emissions from natural gas, fuel oil and electricity for the CBSA. The next two columns show emissions from gas and fuel oil respectively, which are equal to predicted usage multiplied by the appropriate emissions factor. The last three columns show predicted electricity usage, the electricity emissions factor, and predicted electricity emissions, equal to predicted electricity usage multiplied by the emissions factor. Use is measured in 1000 pounds per megawatt hour.

3.1 Predicted Emissions

The predicted usage and emissions for selected cities are shown in Table 1. We show results for the six lowest emissions cities, the six highest emissions cities, and the six median cities. The third column ("Emissions") shows the sum of predicted emissions from natural gas, fuel oil and electricity for the CBSA. There is a huge range in predicted household emissions across cities. In Honolulu, predicted emissions are only 9.65 tons, whereas in Memphis they are over 30 tons.

The next two columns show emissions from gas and fuel oil respectively, which are equal to predicted usage multiplied by the appropriate emissions factor. Natural gas emissions are generally largest in colder regions.[13] Emissions from fuel oil are generally quite small in magnitude compared to emissions from the other two energy types. The last three columns show predicted electricity usage, the electricity emissions factor, and predicted electricity emissions, equal to predicted electricity usage multiplied by the emissions factor.

Spatial variation in carbon emissions comes from multiple sources. For example, power plants utilized in Memphis emit less CO_2 than Kansas City (1.04 lbs per MwH in Memphis compared to 1.27 in Kansas City). However, electricity usage in Memphis is so much higher than in Kansas City that overall average household carbon emissions are higher in Memphis, despite greater consumption of fuel and natural gas in Kansas City. Conversely, consider emissions resulting from electricity in Houston compared to Tulsa. Households in Houston use more electricity than those in Tulsa. However, power plants utilized in Tulsa are less carbon efficient than those utilized in Houston. Therefore, carbon emissions from electricity use are higher in Tulsa. This underscores an important feature of the data: spatial variation in individual electricity emissions is driven both by differences in energy usage and heterogeneity in power plants across regions.

3.2 Policy and Emissions

Spatial variation in carbon emissions implies that any policy that has an effect on where people live will also impact national carbon emissions. The primary policy we are interested in is land use regulations. Figure 1 shows a scatterplot between CBSA-level predicted emissions and the Wharton Land-Use Regulation Index. The Wharton Index is displayed on the horizontal axis; higher values of this index correspond to stricter land use restrictions. The vertical axis displays predicted per household carbon emissions, measured in pounds.[14]

[13]In Section A.7, as in GK, we show that colder winter temperatures are highly predictive of natural gas usage.

[14]This statistic is the same as that displayed in the "Emissions" column of Table 1.

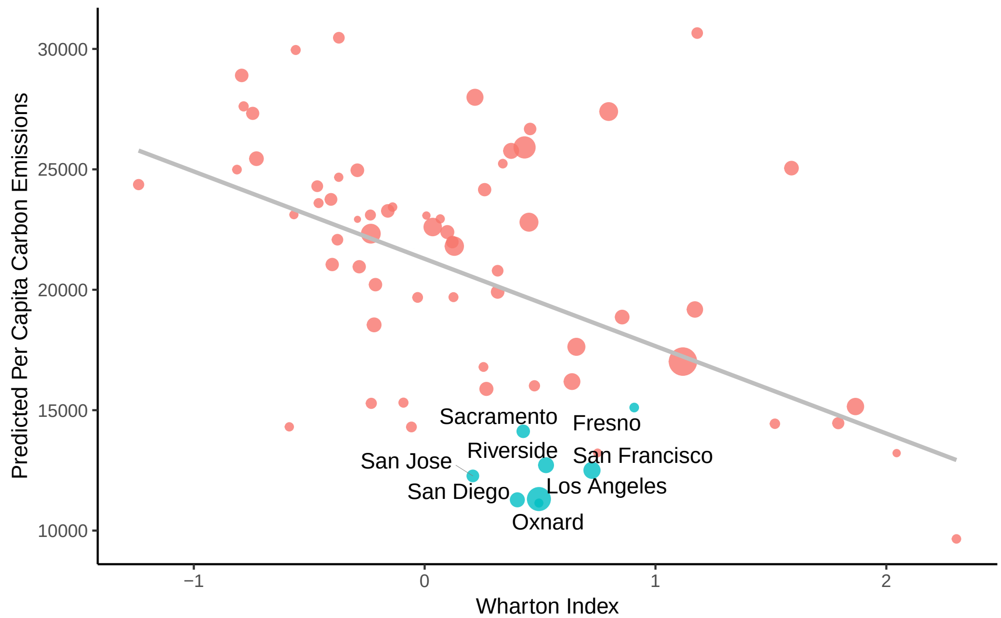


Figure 1: Emissions are measured in pounds. Each circle is a CBSA; highlighted are California cities. The size of each circle reflects CBSA population.

Generally, higher land use regulations are associated with lower per-capita carbon emissions. California cities are remarkably "green" due to a combination of temperate climate and clean power plants. These cities also have very high-land use regulations, which inflates housing prices and incentivizes individuals to live away from California. As we have documented, the spatial distribution of individuals has a large impact on aggregate carbon emissions. We proceed by building a spatial equilibrium model to glean insight on the effect on land use restrictions on national carbon emissions.

4 Model

We employ a static spatial equilibrium featuring heterogeneous households, with endogenous wages and rents, similar to those used in Diamond (2016), Piyapromdee (2017), and Colas and Hutchinson (2018). We extend this class of model by allowing locations to vary by carbon output of regional power plants and the marginal benefits of energy usage. Therefore, our model is able to map changes in the distribution of households across locations to carbon emissions.

Household sorting is a static, discrete choice—households choose the city which provides the highest utility in terms of wages, rents, amenities, and energy prices. Households purchase three **energy types**—electricity, natural gas and fuel oil—which they use to produce **energy services** (e.g. air conditioning, home heating). The benefit of energy services varies by city. For example, the benefit of air conditioning and therefore electricity are high in Oklahoma City while the benefit of home heating (and therefore natural gas) are high in Minneapolis. Each location has an upward sloping housing supply curve whose elasticity depends on local land use restrictions. Cities with stricter land use restrictions will have more inelastic housing supply curves and higher rents, all else equal. Competitive firms combine high and low skilled workers using a CES production function. Thus, local wages and rents are endogenous to the distribution of workers across cities. Changes in land use restrictions across cities will change housing supply curves across cities and impact the equilibrium distribution of households.

As we show in Section A.8, emissions vary across household types. Furthermore, a number of studies have shown that workers of various education levels vary in their mobility and sorting patterns across cities.[15] We allow households in the model to vary in their education level, race, age group, martial status and number of children. These households types vary in their preferences over locations, energy services, and housing. Within this demographic group, households also receive a premium for living in cities close to their birth state. This allows for rich substitution patterns in response to policy changes—a decrease in rents in San Francisco, for example, will lead to larger inflows of households who are born in California. Finally, households receive an idiosyncratic preference draw over each location, where the variance of the draw varies by household demographics. Therefore, households are imperfectly mobile across cities.

The amount of carbon emissions generated by a household varies for two reasons in the model. First, the marginal benefit of energy usage varies by city. Cities with higher marginal benefit of energy usage will have higher levels of energy usage, all else equal. Second, the production technology and carbon efficiency of

[15]See, for example, Bound and Holzer (2000) or Diamond (2016).

power plants varies across NERC regions. Electricity used at a given city must be purchased from a power plant in the associated NERC region. Therefore, electricity usage in cities with more carbon efficient power plants will lead to lower emissions.

4.1 Households

Let j index cities and i index households. Households are endowed with a demographic type d, which includes the household head's education, marital status, race, number of children and age group. Demographic groups vary in both preferences and wages. Locations vary by amenities, which we denote λ_{ij}. To solve their decision problem, the household chooses a location j that yields maximal benefits from amenities and consumption of the numeraire c, housing H, and energy services E^m, such as heating or air-conditioning.

We parameterize the household's utility function as:

$$u_{ij} = \alpha_d^c \log c + \alpha_d^H \log H + \sum_m \hat{\alpha}_{jd}^m \log E^m + \lambda_{ij} \tag{1}$$

where α_d^c, α_d^H, and $\hat{\alpha}_{jd}^m$ are parameters which scale the marginal benefit of consumption, housing and energy services. We allow $\hat{\alpha}_{jd}^m$ to vary across cities to reflect differences in the marginal benefit of energy services across cities, perhaps due to differences in weather.[16]

We assume energy services are produced by the household using a fixed proportions energy production function which maps energy types into energy services. Let x^m denote usage of energy type m, where $m \in \{Elec, Gas, Fuel\}$. The energy service production function takes the form:

$$E^m = f\left(x^m\right) = \delta^m x^m \tag{2}$$

where δ^m is a parameter that maps units of energy units into energy services.

[16] In Section A.7, we show that local temperature is highly predictive of energy usage. We assume that these parameters are not function of local population or population density. In Appendix A.6, we provide evidence that population is not a significant predictor of energy demand.

Substitution of 2 into 1 yields:

$$u_{ij} = \alpha_d^c \log c + \alpha_d^H \log H + \sum_m \alpha_{jd}^m \log x_m + \lambda_{ij} \tag{3}$$

where $\alpha_{jd}^m = \hat{\alpha}_{jd}^m \delta^m$.

The agents' budget constraint is given by:

$$I_{jd} = c + R_j H + \sum_m P_j^m x^m$$

where I_{jd} is the income level of agents of demographic d living in city j and x^m is usage of energy type m. R_j and P_j^m represent the prices of housing and the price of energy of type m in city j. We normalize the price of consumption c to one.

We decompose the amenity term, λ_{ij}, into five distinct components. In particular, we let:

$$\lambda_{ij} = \gamma_d^{hp} \mathbb{I}\left(j \in Bstate_i\right) + \gamma_d^{\text{dist}} \phi\left(j, Bstate_i\right) + \gamma_d^{\text{dist2}} \phi^2\left(j, Bstate_i\right) + \xi_{jd} + \sigma_d \epsilon_{ij} \tag{4}$$

where $\mathbb{I}\left(j \in Bstate_i\right)$ is an indicator for location j being in worker i's birth state, $\phi\left(j, Bstate_i\right)$ and $\phi^2\left(j, Bstate_i\right)$ are the distance and squared distance, respectively, between agent i's birth state and location j. ξ_{jd} is a shared unobservable component of amenities and ϵ_{ij} is an idiosyncratic preference shock with dispersion parameter σ. Differences in ϵ_{ij} across individuals and cities reflect unobservable variation in attachment to a location that an individual might have. We assume that ϵ_{ij} follows a Type 1 Extreme Value distribution.

We make an important assumption that unobserved amenities, ξ_{jd}, are taken as exogenous and are not function of land use restrictions, as is relatively standard.[17] This assumption is supported by the findings in Albouy and Ehrlich (2018), who find that land use restrictions increase the cost of housing production without improving local quality of life.

Solving the agent's maximization problem yields constant income shares on

[17] See Hsieh and Moretti (2019), Piyapromdee (2017), or Colas and Hutchinson (2018), for example. Diamond (2016) and Herkenhoff, Ohanian, and Prescott (2018) allow amenities to be endogenous to household composition, but not land use restrictions directly.

housing and energy of all types. We write a household of demographic group d's optimal choice of housing, conditional on living in a city j as,

$$H_{jd}^{\star} = \frac{\alpha_d^H I_{jd}}{\boldsymbol{\alpha}_{jd} R_j}$$

where we define

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

Optimal usage of energy type m is also a constant fraction of income:

$$x_{jd}^{m\star} = \frac{\alpha_{jd}^m I_{jd}}{\boldsymbol{\alpha}_{jd} P_j^m}.$$

We then solve for the indirect utility function associated with location j:

$$V_{ij} = (\boldsymbol{\alpha}_{jd}) \log I_{jd} - \alpha_d^H \log R_j - \sum_m \alpha_{jd}^m \log P_j^m + \hat{\lambda}_{ij} \tag{5}$$

where

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

The household's problem can therefore be thought of as a discrete choice over all the locations, conditional on optimal quantities of housing and energy consumption. We write the total number of workers of demographic d who choose to live in location j as

$$N_{jd} = \sum_{i \in I_d} \text{argmax}_{j'} V_{ij'}.$$

Given that the idiosyncratic preference draws are distributed as Extreme-Value Type I, we can write the probability that an individual i chooses a location j as

$$P_{ij} = \frac{\exp\left(\bar{u}_{ij}/\sigma_d\right)}{\sum_{j' \in J} \exp\left(\bar{u}_{ij'}/\sigma_d\right)} \tag{6}$$

where $\bar{u}_{ij} = u_{ij} - \sigma_d \epsilon_{ij}$ is the agent's indirect utility of choosing location j minus the idiosyncratic preference draw.

4.2 Housing Supply

Each city has an upward sloping housing supply curve. The elasticity of the housing supply curve is allowed to vary by city as a function of the amount of available land and the strictness of land use restrictions. Specifically, we follow Kline and Moretti (2014) and parameterize the inverse housing supply curve in city j as:

$$R_j = z_j H_j^{k_j}, \tag{7}$$

where H_j is quantity of housing supplied, z_j is a scale parameter, and k_j is a parameter equal to the inverse elasticity of the housing supply curve $\left(\text{i.e., } \frac{\partial \log R_j}{\partial \log H_{jt}} = k_j\right)$. Taking logs of equation 7, we obtain

$$\log(R_j) = k_j \log(H_j) + \log(z_j). \tag{8}$$

The term k_j plays a crucial role in our analysis. Higher values of k_j imply more inelastic housing supply curves and higher rent levels. Therefore, cities with higher values of k_j will have lower equilibrium population levels, all else equal.

As shown by Saiz (2010), local land use restrictions, as measured by the Wharton Land Use Index, and the fraction of land that is unavailable for development due to geographic constraints are strong determinants of more inelastic housing supply curves. We follow Saiz (2010) and parameterize k_j as a function of land use restrictions and geographic constraints:

$$k_j = \nu_1 + \nu_2 \psi_j^{WRI} + \nu_3 \psi_j^{GEO}$$

where ψ_j^{WRI} is the Wharton Land Use Index and ψ_j^{GEO} measures the amount of land that is unavailable for development due to geographic restrictions. A higher value of ν_2 implies that cities with stricter land use restrictions will have more inelastic housing supply. As shown in Section 3.2, cities with higher values of ψ_j^{WRI} generally have lower carbon emissions per household. In the model, this disincentivizes households from living in "greener" cities and encourages households to live in "dirtier" cities.

Specifically, given that the idiosyncratic preferences draws are distributed as Extreme-Value Type I, the partial equilibrium elasticity of location choice with respect to rents is approximately equal to:[18]

$$\frac{\partial \log P_{ij}}{\partial \log R_j} \approx -\frac{\alpha_d^H}{\sigma_d}.$$

We can solve for the partial equilibrium effect of a household's choice probability with respect to land use restrictions as

$$\frac{\partial \log P_{ij}}{\partial \psi_j^{WRI}} \approx -\nu_2 \frac{\alpha_d^H}{\sigma_d} \log(H_{jt})$$

The partial equilibrium effect of land use restrictions is proportional to the expenditure share on housing and the importance of land use restrictions in dictating the housing supply elasticity ν_2, and inversely proportion to σ_d, the dispersion in the idiosyncratic preference draw. Higher values of σ_d imply household location choices are less responsive to changes in rents; thus, variation in land use restrictions will have smaller effects on household sorting.

4.3 Energy Production and Emissions

We allow for three types of energy in our analysis, natural gas, fuel oil and electricity. We assume fuel oil and natural gas are purchased on an international market and treat supply for these types of energy as perfectly elastic. We assume that the carbon byproduct of fuel oil and natural gas are constant regardless of where the energy is used. Total household emissions of carbon from natural gas and fuel oil usage in city j is the sum of usage of the energy type multiplied by the appropriate conversion factor:

$$CO_{2j}^{m} = \hat{\delta}^m \sum_d N_{jd} x_{jd}^m, \quad m \in \{Gas, Fuel\}$$

[18] Differentiating P_{ij} with respect to rents yields $\frac{\partial \log P_{ij}}{\partial \log R_j} = -\frac{\alpha_d^H}{\sigma_d}(1 - P_{ij}) \approx -\frac{\alpha_d^H}{\sigma_d}$ for small values of P_{ij}.

where $\sum_d N_{jd} x^m_{jd}$ is the total amount of fuel of type m consumed by people living in city j, $\hat{\delta}^m$ is the amount of carbon emissions per unit of fuel of type m and N_{jd} is the number of households of demographic d living in j.

We assume electricity is generated across NERC regions in the United States and then is transmitted to local labor markets within those regions. Within each NERC region, perfectly competitive electricity companies produce energy.[19] In our baseline specification, we assume that the marginal cost of energy production is constant.[20] In Section 8.3, we consider a model extension with increasing marginal cost. We find that the qualitative results are similar in both cases.

We allow the conversion factor for electricity to vary by NERC regions to reflect differences in the technology of power plants across regions in the United States. For example, a larger percentage of power in the Western NERC region (WECC) comes from hydroelectric dams, whereas the Southern NERC region (SERC) relies more heavily on coal power.

Let $\hat{\delta}^m_{\mathcal{R}}$ represent the conversion factor of electricity to carbon emissions in NERC region $\mathcal{R}$ and let $\mathcal{R}(j)$ map cities to their corresponding NERC regions. We write carbon emission resulting from electricity usage in CBSA j as

$$CO_{2}{}^m_j = \hat{\delta}^m_{\mathcal{R}(j)} \sum_d N_{jd} x^m_{jd}, \quad m \in \{Elec\}$$

For simplicity, we use the following notation for carbon emissions factors:

$$\delta^m_j = \begin{cases} \hat{\delta}_m & m \in \{Gas, Fuel\} \\ \hat{\delta}^m_{\mathcal{R}(j)} & m \in \{Elec\} \end{cases}$$

Local carbon emission of each energy type m can then be written as

$$CO_{2}{}^m_j = \delta^m_j \sum_d N_{jd} x^m_{jd}$$

[19]Electricity is a homogeneous good with a large number of with many producers. However, when transmission constraints bind, generation companies may have local market power. See Joskow and Tirole (2000) for a discussion.

[20]The short run supply of electricity is often modeled as a dispatch curve with constant marginal or linear marginal cost curves. However, as we are considering a long-run equilibrium, the supply curve is given by the long run marginal cost curve, allowing for the construction of new reactors or the entry of new plants.

The main outcome of interest is national carbon emissions. Total national emissions from all energy type m is the given by $CO_2^m = \sum_j CO_{2j}^m$, and national emissions across all energy types is simply the sum of the energy specific pollution levels, $CO_2 = \sum_m CO_2^m$.

From here it is relatively straightforward to see how the distribution of households across cities can affect the level of national carbon emissions. We rewrite national emissions in terms of the covariance between the distribution of households and the efficiency of local electricity usage multiplied by the local energy usage:

$$CO_2 = \sum_m \sum_d \left(J\text{Cov}\left(N_j^d, x_{jd}^m \delta_j^m\right) + N^d \mathbb{E}\left[x_{jd}^m \delta_j^m\right]\right),$$

where N^d, the total number of households of group d, and J, the total number of cities, are both model primitives. The expectation $\mathbb{E}\left[x_{jd}^m \delta_j^m\right]$ is taken over cities j.

National emissions are increasing in the covariance of population and the product of energy usage and energy conversion factors. Therefore, policies which lead households to live in areas with higher energy usage and less carbon efficient power plants will lead to increases in national carbon emissions.

As demonstrated in Section 3.2, land use regulations are negatively correlated with local average CO_2 emissions levels. Furthermore, stricter land use regulations increase local rents and lead to lower equilibrium population levels, this strengthens the relationship between local population levels and local emissions. In Section 7, we examine the quantitative implications of this relation between land use regulations, energy demand, and power plant technology on national carbon output.

4.4 Wages

Perfectly competitive firms in each city combine skilled and unskilled labor in a CES production function to produce the numéraire consumption good, where we define household heads with a college degree as skilled and household heads with less than a college degree as unskilled. Therefore, wages for skilled and unskilled workers in each city are determined endogenously by the ratio of skilled to unskilled workers. Specifically, firms use a combination of skilled (S) and unskilled labor (U), as inputs in the following production function:

$$Y_j = A_j[(1-\theta_j)U_j^{\frac{\sigma-1}{\sigma}} + \theta_j S_j^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}} \tag{9}$$

where U_j and S_j are defined as the total efficiency units of labor supplied by unskilled and skilled workers in city j, respectively. A_j is the total factor productivity in city j and θ_j is the relative factor intensity of skilled workers. The elasticity of substitution between skilled and unskilled workers is given by σ.[21]

Firms take wages as given and choose skilled and unskilled labor quantities to maximize profits. We derive labor demand curves as a result of the firms skilled and unskilled labor first order conditions for profit maximization:

$$\begin{aligned} W_{js} =& A_j \left(\frac{Y_j}{A_j}\right)^{\frac{1}{\sigma}} \theta_j S_j^{-\frac{1}{\sigma}} \\ W_{ju} =& A_j \left(\frac{Y_j}{A_j}\right)^{\frac{1}{\sigma}} (1-\theta_j) U_j^{-\frac{1}{\sigma}}, \end{aligned} \tag{10}$$

where W_{js} and W_{ju} are the wage rates for skilled and unskilled labor, respectively.

Within education groups, demographic groups are perfectly substitutable in production but vary in their productivity and therefore supply different amounts of efficiency units of labor. Income levels for an individual household are given by the amount of efficiency units of labor supplied by the household multiplied by the appropriate wage rate. Income for a household of demographic group d living in city j is given by $I_j^d = W_{ju}\ell^d$ for unskilled workers and $I_j^d = W_{js}\ell^d$ for skilled workers, where ℓ^d represents the amount of efficiency units supplied by agents of demographic group d.

[21] One straightforward way to introduce capital into the model is the assume that production is Cobb-Douglas in capital and a CES labor supply such that $Y_{jt} = A_{jt}K_{jt}^{\eta}\left([(1-\theta_j)U_j^{\frac{\sigma-1}{\sigma}} + \theta_j S_j^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}}\right)^{1-\eta}$ where η is a parameter. If capital supply is perfectly elastic, this production function implies wage equations that are equivalent to those here. See Colas (2019) for details.

4.5 Equilibrium

In this environment, an equilibrium is characterized by household and firm optimization, and market clearing in the housing and labor markets.[22]

More specifically, as we have shown in Section 4.1, given prices, household i's optimal choice maximizes utility. Household optimization defines housing demand, energy demand, and labor supply. Housing demand in a city j is given by the sum of housing demand of all agents living in that city. We can write this as

$$H_j^D = \sum_d N_{jd} \frac{\alpha_d^H I_{jd}}{R_j \boldsymbol{\alpha}_{jd}}, \tag{11}$$

where, as before, N_{jd} is the total number of workers of demographic d who choose to live in city j, and where we allow D and $\mathcal{S}$ superscripts to denote demand and supply quantities, respectively. Similarly, energy demand is the sum of energy demand of all individuals living in a city:

$$X_j^{mD} = \sum_d N_{jd} \frac{\alpha_{jd}^m I_{jd}}{P_j^m \boldsymbol{\alpha}_{jd}}. \tag{12}$$

Labor supply is the sum of efficiency units of labor supplied by all agents of a given skill level in city j:

$$S_j^{\mathcal{S}} = \sum_{d' \in d^S} N_{jd} \ell^{d'}$$

for skilled workers and

$$U_j^{\mathcal{S}} = \sum_{d' \in d^U} N_{jd} \ell^{d'}$$

for unskilled workers where d^S and d^U are the sets of demographic groups that with a college degree and without a college degree, respectively.

Labor demand for skilled and unskilled workers are implicitly defined by equations 10, the first-order conditions of the production firms. Housing supply is given by equation 8.

Finally, an equilibrium is defined by the two market clearing conditions:

[22] In Section 8.3 we consider the case when energy prices are determined in equilibrium. In this case, an equilibrium is also defined by market clearing in the energy markets.

1. Housing Market Clearing: $H_j^{\mathcal{S}} = H_j^D$, for all cities, j.

2. Labor Market Clearing: $S_j^{\mathcal{S}} = S_j^D$ for skilled workers and $U_j^{\mathcal{S}} = U_j^D$ for unskilled workers in all cities.

5 Data Inference

To take the model to the data, we calibrate some parameters from the literature and estimate the remainder of the parameters. We focus most of our exposition on the estimation of household location choice and energy use. Estimation of the housing supply and production are relatively standard and details are therefore included in appendices B.1 and B.2. The carbon emissions factors are calculated as in Section 2.[23]

5.1 Households

Recall that the workers' utility function can be written as:

$$u_{ij} = \alpha_d^c \log c + \alpha_d^H \log H + \sum_m \alpha_{jd}^m \log x_m + \gamma_d^{hp} \mathbb{I}\left(j \in Bstate_i\right) + \\ \gamma_d^{\text{dist}} \phi\left(j, Bstate_i\right) + \gamma_d^{\text{dist2}} \phi^2\left(j, Bstate_i\right) + \xi_{jd} + \sigma_d \epsilon_{ij}$$

Therefore, the set of parameters to be estimated are α_d^c, α_d^H, and α_{jd}^m, the parameters governing the budget shares of consumption, housing and energy spending, respectively; γ_d^{hp}, γ_d^{dist} and γ_d^{dist2}, the parameters governing the strength of home premium and the disutility of living further away from one's birth state; ξ_{jd}, the unobserved city-level amenities; and σ_d, the parameters that govern the variance of idiosyncratic preference draws.

We calibrate α_d^H and α_d^c to match the national expenditure shares on housing and non-energy, non-housing expenditure, respectively. We set $\alpha_d^H = .4$ and

[23] That is, we assume 117 lbs of CO_2 emitted per thousand cubic feet of natural gas consumed and 17 lbs of CO_2 emitted per gallon of fuel oil consumed. We calculate the weighted average CO_2 emissions of all plants in a NERC region. We then assign each of the CBSAs to a NERC region, thus assigning all individuals in our sample an emissions factor for electricity.

$\alpha_d^c = .55$ for all demographic groups.[24] Next, we choose the parameters governing the expenditure share on each energy type, α_{jd}^m, to match the expenditure share on each fuel type by each demographic group in each city. Specifically, given the Cobb-Douglas utility function, the expenditure share on fuel type m of demographic group d in city j will be given by

$$\frac{E_{jd}^m P_j^m}{I_{jd}} = \frac{\alpha_{jd}^m}{\alpha_c^d + \alpha_d^H + \sum_m \alpha_{jd}^m}$$

The expenditure share on each type of fuel by city and demographic group can be calculated directly using income data and energy expenditure data on households from the ACS. The parameters α_c^d and α_d^H have already been calibrated, and all of the α_{jd}^m's are unknowns. This defines a system of equations for each city with M equations and M unknowns. We choose the set of α_{jd}^m parameters to match the city-specific expenditure shares on each fuel type for each demographic group in the ACS.

The next parameter we calibrate is σ_d, the variance of the idiosyncratic location draw. This parameter dictates the elasticity of household location choices with respect to local prices and therefore plays an important role in our analysis. For example, our main counterfactuals depend crucially on the elasticity of worker choices with respect to local rents. For large values of σ_d, worker location choices depend more on idiosyncratic preference draws, and therefore workers choices will be less sensitive to changes in local prices. Smaller values of σ_d imply that idiosyncratic draws only play a small role in location choices and thus the elasticity of location choices with respect to prices will be high. We use the values estimated in Diamond (2016), who uses labor demand shocks across cities to identify the elasticity of worker choices to local prices.[25] Specifically we set $\sigma_d = \frac{1}{4.15}$ for unskilled workers and $\sigma_d = \frac{1}{5.52}$ for skilled workers. In Section 8.1, we examine the sensitivity of our results to alternative values of α_c^H and σ_d.

We estimate the parameters that govern the strength of the home premiums, γ_d^{hp}, γ_d^{dist} and γ_d^{dist2} and unobserved amenities, ξ_{jd}, via maximum likelihood. As

[24]In Section 8.1, we examine the robustness of our results to alternative values of these parameters.

[25]This parameter has been estimated extensively in the literature. For example, see Piyapromdee (2017), Suarez Serrato and Zidar (2016), or Colas and Hutchinson (2018).

shown in section 4.1, we write the probability that an individual i chooses a location j as

$$P_{ij} = \frac{\exp\left(\bar{u}_{ij}/\sigma_d\right)}{\sum_{j' \in J} \exp\left(\bar{u}_{ij'}/\sigma_d\right)} \tag{13}$$

where $\bar{u}_{ij} = u_{ij} - \sigma_d \epsilon_{ij}$ is the agent's indirect utility asscoiated with location j minus the idiosyncratic preference draw. The log-likelihood function is therefore given by

$$\mathcal{L}^d(\gamma_d^{hp}, \gamma_d^{\text{dist}}, \gamma_d^{\text{dist2}}, \boldsymbol{\xi_d}) = \sum_{i=1}^{N^d} \sum_{j=1}^{J} \mathbb{I}_{ij} \log(P_{ij}^d), \tag{14}$$

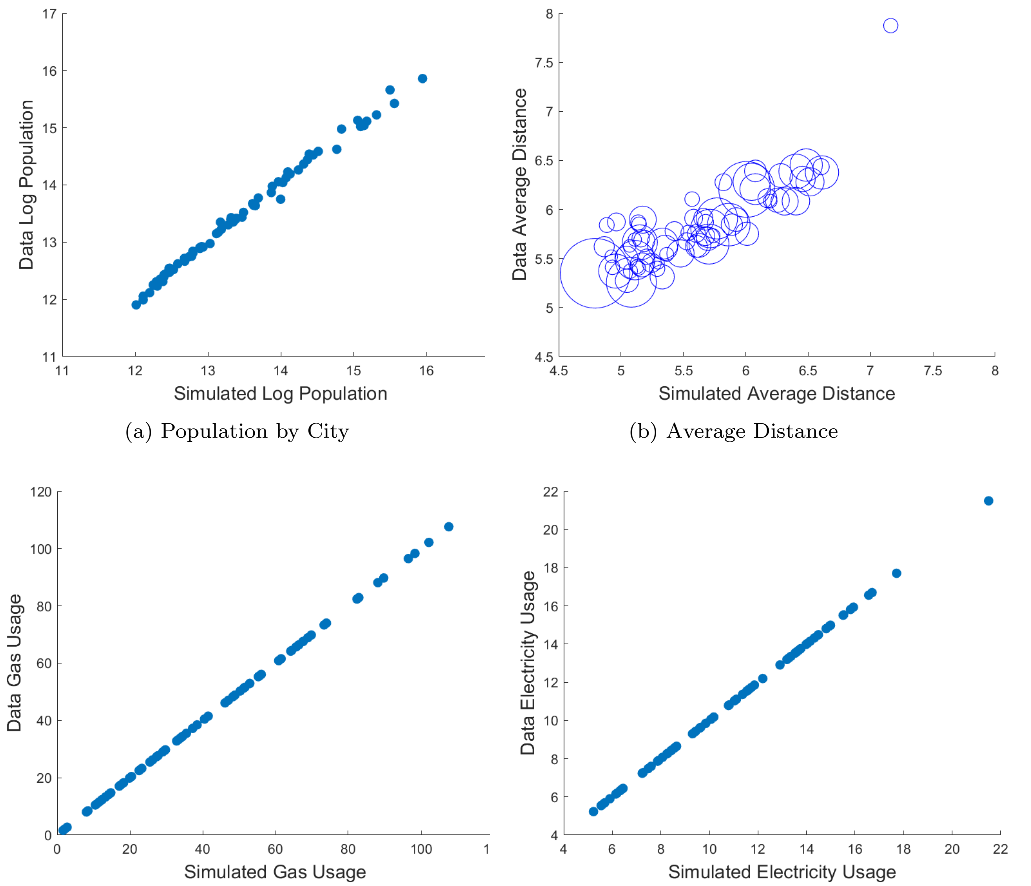
where $\mathbb{I}_{ij}$ is an indicator equal to one if individual i lives in location j and zero otherwise.[26] Our estimates of these parameters are displayed in Section B.3.

6 Model Validation

Model Fit We begin by assessing our model fit. The results are summarized in Figure 2. Panel (a) shows the log number of households in each city in the data and in the baseline simulation. Each circle represents a CBSA. Given that we estimate a separate unobserved amenity value for each demographic group and each city (ξ_{jd}), we are able to match these moments exactly, except for simulation noise. Next, we plot the simulated and observed log average distance between an agent's birth state and chosen city for each CBSA. The results are displayed in panel (b) of Figure 2. Each circle represents a CBSA, and the size of the circle is proportional to population. The model fits this aspect of the data fairly well. Honolulu is the outlier in the upper-right corner of the graph.

Panels (c) and (d) of Figure 2 show the predicted and actual average usage of natural gas and electricity in each city. As we allow the benefit of energy usage (α_{jd}^m) to vary by city and demographic group, we are able to match these moments exactly.

[26] Computationally, we invert the choice probabilities using the contraction mapping in Berry (1994) to obtain the unique mean utility associated with every guess of the parameter vector $[\gamma_d^{hp} \;\; \gamma_d^{\text{dist}} \;\; \gamma_d^{\text{dist2}}]$.



(a) Population by City

(b) Average Distance

(c) Natural Gas

(d) Electricity

Figure 2: Model fit results. Each circle represents a CBSA. Panel (a) shows the log number of households in each city in the data and in the baseline simulation. Panel (b) plots the simulated and observed log average distance between an agent's birth state and chosen city for each city. The size of the circle is proportional to city population. Honolulu is the outlier in the upper-right. Panels (c) and (d) show the predicted and actual average usage of natural gas and electricity in each city.

External Validation: Comparison to Hsieh and Moretti (2019) Hsieh and Moretti (2019) (HM) simulate the effects of relaxing land use restrictions in San Francisco, New York, and San Jose in a model with imperfectly mobile homogeneous workers. To further understand worker sorting in our model, we simulate this same experiment by setting the housing supply elasticity parameter (ψ_j^{WRI}) in these three cities to the level of the median city in the country.

The household sorting component of our model has important differences compared to HM. Workers in HM are homogeneous except for an idiosyncratic preference draw, whereas our model incorporates several dimensions of household heterogeneity. First, households are differentiated by a demographic group, which consists of their education level, age group, marital status, race, and number of children. Therefore, we can analyze the effects of changes in land use restrictions in the composition of households within a city, in addition to the total population of a city. Furthermore, conditional on demographics, individual agents also differ in their birth state. The birth-state premium breaks the independence from irrelevant alternatives restriction within demographic groups and plays an important role in dictating household substitution patterns. For example, a strong birthplace premium implies that if a city becomes more attractive, households born within the state and near the state would be more likely to substitute towards this city than workers living far away. Concretely, this implies that if San Francisco experiences an increase in wages or a decrease in rents, households born in California would be more likely to move to San Francisco than households born in New York. Therefore, households currently living in San Jose or Sacramento are much more likely to substitute to San Francisco compared to households currently living in New York City.

The results are displayed in Table 2. The first row shows the change in population in the three treated cities from HM.[27] In their simulation, relaxing land use restrictions in these three cities leads to a 169%, 140% and 82% increase in population in New York, San Francisco, and San Jose, respectively, and a 151% increase in these three cities collectively.

Panel II shows the results from our simulations. The first row of panel II shows the percent change in population. In our model we predict that these three cities collectively will experience an increase in population of 161%, which is close to the amount predicted in HM. The next three reveal columns key differences. Most notably, our model predicts a *decrease* in the population of San Jose, while HM predict a substantial increase. As emphasized above, the inclusion of birth state premia in our model has important implications for substitution patterns across cities. In our model, when San Francisco becomes more attractive because of the relaxation of land use regulations, households currently living in California are

[27]Note that these results are not reported directly in HM, who instead report changes in the growth rates of population from 1964 to 2009. We converted their results to changes from current population relates to make them easier to compare to our results.

	All 3 Cities	New York	San Francisco	San Jose
I. From Hsieh and Moretti:				
% Change Population	151	169	140	82
II. From Our Simulations				
% Change Population	161	193	93	-2
Change in College Share	4.11	4.78	2.20	-2.75
Change in Married Share	0.58	0.67	-0.05	-0.31

Table 2: Comparison to mobility responses in Hsieh and Moretti (2019). The first row shows the change in population in the three treated cities from HM. The second panel shows the results from our simulations.

much more likely to change locations to San Francisco compared to agents living outside of California. Therefore, relaxing land use regulations in San Francisco leads to many agents moving from San Jose to San Francisco. This implies a decrease in San Jose's population, despite the moderate relaxation of San Jose's land use regulations.[28]

Panel II of 2 show the percentage point change in college share and married share within the three cities. The relaxation of land use restrictions leads to increases in the college share in New York and San Francisco and the share of households that are married. Therefore, while in aggregate our predictions are similar to those in HM, our model predicts additional composition and substitution patterns that may have important implications for national carbon output.

7 Counterfactuals

In this section, we use the estimated model to simulate changes in land use restrictions and imposing a carbon tax. The results of the counterfactuals are summarized in Table 3. The first column shows fuel usage, emissions, income and population distribution in the baseline specification, with all parameters set at their baseline levels.

[28]In the data, land use restrictions are much stricter in San Francisco compared to San Jose. We find that average wages in our simulation increase by 3%, similar in magnitude to the 3.7% increase in total production predicted in HM.

	Baseline	Relax CA	Relax All	Carbon Tax
I. Percent Total Population				
California Cities	9.82	16.50	11.93	9.90
Other West	13.14	11.46	14.87	13.23
Midwest	21.83	20.38	12.50	21.67
South	36.73	34.18	24.82	36.64
Northeast	18.48	17.48	35.87	18.57
II. Mean Usage				
Gas (1000 cubic feet)	53.18	52.58	53.96	45.50
Electricity (MW h)	13.27	13.04	12.08	11.85
Fuel Oil (gallons)	28.47	26.84	45.66	25.37
III. Mean Emissions (lbs of CO_2)				
Gas	6228	6157	6318	5328
Electricity	12804	12465	10651	11351
Fuel Oil	765	721	1226	681
Total	19796	19343	18196	17360
(%)	(100)	(97.7)	(91.9)	(87.7)
IV. Mean Log Income				
Skilled	10.89	10.91	10.99	10.89
Unskilled	10.04	10.05	10.11	10.04
All	10.33	10.34	10.41	10.33

Table 3: Counterfactual results. Each panel shows the simulated percent of total population living in various geographic areas, mean energy usage, mean emissions and mean log income in each specification. See text for details on each individual simulation.

	California Cities	Other West	Midwest	South	Northeast
% Change Population	67.97	-12.78	-6.63	-6.93	-5.43
Change in College Share	3.85	-1.21	-1.14	-1.15	-0.83
Change in Married Share	1.58	-0.22	-0.56	-0.50	-0.38

Table 4: Composition changes of relaxing land use regulations in California cities.

7.1 Relaxing Land Use Restrictions in California

California Senate Bill 50, a bill that would override strict land use restrictions in California cities, is currently being debated. In this section, we examine the effects of California adopting such a policy and relaxing local land use restrictions. As shown in Section 2, California cities are among the greenest in the country. However, they also have very strict land use restrictions—San Francisco and Los Angeles are in the 86th and 78th percentiles in the strictness of land use restrictions, respectively. Intuitively, relaxing land use restrictions in California will lead to increases in California's population and decreases in overall carbon emissions. However, the magnitude of the decrease is an empirical and quantitative question.

Specifically, we simulate setting the land use restrictions, ψ^{WRI}, in California cities to the national median. We display the results in the second column of Tables 3 and in Table 4. Table 4 shows the change in population across regions as a result of the policy change. Setting land use restrictions in California to the national median leads to a 68% increase in the total population in California cities, a 13% drop in the population of other locations in the West, and roughly 5% to 7% drops in the Midwest, South, and Northeast. The following rows of Table 4 show the change in demographic composition of the regions. The change in land use regulations leads to increases in the college share and married share in California. As these groups are relatively higher usage groups, this composition effect leads to slightly larger decreases in carbon emissions than the population change alone.

Panels II and III of Table 3 show how these changes in the distribution of workers translate to average usage and emissions. Panel II shows changes in average usage of natural gas, electricity and fuel oil. The relaxation of land use restrictions leads to decreases in usage of all three types of fuel, as households move to the temperate California climate. Specifically, natural gas usage drop by 1.1%, electricity by 1.7% and fuel oil usage drops by 5.6%. Panel III of Table 3 displays average emissions resulting from each type of fuel. Electricity emissions drop by nearly 2.6% despite only a 1.7% decrease in usage. As power plants utilized in California are relatively carbon efficient, the drop in emissions from electricity is larger than the drop in emissions.

In addition to low emissions, cities in California are very productive. Panel IV of Table 3 shows the effects on average log income. Average income of skilled workers increases by roughly 2% while income of unskilled workers increases slightly. This leads to an increase in income of 1% across all workers. Therefore, relaxing land use restrictions in California leads to increases in average income of both skilled and unskilled workers in addition to a substantial decrease in total carbon emissions.

7.2 Removing the Correlation Between Land Use Restrictions and Emissions

The negative correlation between land use restrictions and city level emissions has important implications for national carbon emissions. To further explore the implications of land use restrictions on carbon output, we simulate setting land use regulations to the national median in all cities.

The results are displayed in the third column of Table 3. From panel I, we can see that changing land use restriction in all cities leads to a dramatic relocation from the South and Midwest to the West and Northeast. Specifically, the population in Northeast region increases from 18% of total population to 36% while the population in the Midwest and the South decrease by roughly one third.

Panel II and III show usage and emissions from each energy type. Demand for natural gas and fuel oil are high while demand for electricity is low in the cold Northeast. As a result, natural gas usage increases by 1.5%, fuel oil by 60%, while electricity usage decreases by 9%. As a result of this decrease in electricity usage and relocation towards areas with more efficient power plants, emissions from electricity decrease by nearly 17%. Overall, this leads to an 8.1% decrease in national carbon output.

7.3 Carbon Taxes

We simulate the effects of imposing a carbon tax in our model. With a carbon tax, the price of energy type m faced by households living in city j is given by $P_j^m + \tau\delta_j^m$, where τ is the tax per unit of carbon emissions. In our model, this change in the price of energy can reduce carbon emissions through two channels. First, conditional on location, households will consume less energy. Second, the carbon tax will lower the utility associated with higher polluting cities, thus shifting households away from these areas. In this section, we use our model to understand the importance of these two channels in carbon abatement, and to measure the burden of a carbon tax.[29]

We implement a carbon tax of $31 per ton, based on the estimates of the social cost of carbon in Nordhaus (2017). The effects on energy usage, emissions, income, and the distribution of households across space are shown in column 5 of Table 3. Overall, the tax leads to a 12.3% decrease in national residential carbon emissions.

Panel I of Table 3 shows the estimates of the effects of carbon tax on the distribution of workers across cities. Compared to the baseline case, the populations in the Western and Northeast increase while populations in the South and Midwest decrease. However, these changes in the distribution of workers are relatively minor, implying the reduction in emissions resulting from geographic redistribution is small in relation to the total reduction from the carbon tax.

Next we explore the welfare implications of the carbon tax in Table 5. To calculate the incidence of carbon tax, we calculate each household's equivalent variation: starting in an equilibrium with no taxes, the lump-sum tax that would give the household the same utility as the equilibrium with a carbon tax. Panel I shows the average equivalent variation of households based on their location choice in the baseline counterfactual and the average equivalent variation of all households. We assume that agents do not value carbon abatement; thus, the equivalent variation captures the tax burden of moving from the baseline equilibrium with no carbon taxes to an equilibrium with carbon taxes. Overall, the average household across all regions experiences an average tax burden of $305.

[29]One shortcoming of the approach is that the elasticity of energy demand with respect to energy prices relies strongly on the Cobb-Douglas utility assumption.

The carbon tax implies an average tax burden equal to $362 and $318 in the carbon intensive Midwest and South, respectively, compared to $251 and $280 in the greener West and Northeast, respectively. Table 14 in the Appendix displays the average equivalent variation for all demographic groups in our analysis. The tax burden is larger for households with children, married households, more educated households, and minority households. Overall, these results suggest that a carbon tax may have significant distribution effects.

The second panel of Table 5 shows that carbon tax raises a revenue of $266 per household. We remain agnostic on how the tax revenue is redistributed and simply display the change in tax revenue and equivalent variation.

Panel III shows the decrease in the social cost of carbon per household. The carbon decrease is equivalent to a decrease in the social cost of carbon of $38 per household. Therefore, the total social benefit of the carbon tax, given by the sum of the of tax revenue and decrease in the social cost of carbon, outweigh the cost of the tax burden on households.[30]

	Carbon Tax
I. Average Equivalent Variation	
West	-251
Midwest	-362
South	-318
Northeast	-280
All	-305
II. Tax Revenue per Household	269
III. Reduction Social Cost of Carbon per Household	38

Table 5: Welfare Effects of Carbon Tax. All measures in dollars per person.

[30] The tax also leads to a minor decrease in land owner profits.

8 Robustness and Extensions

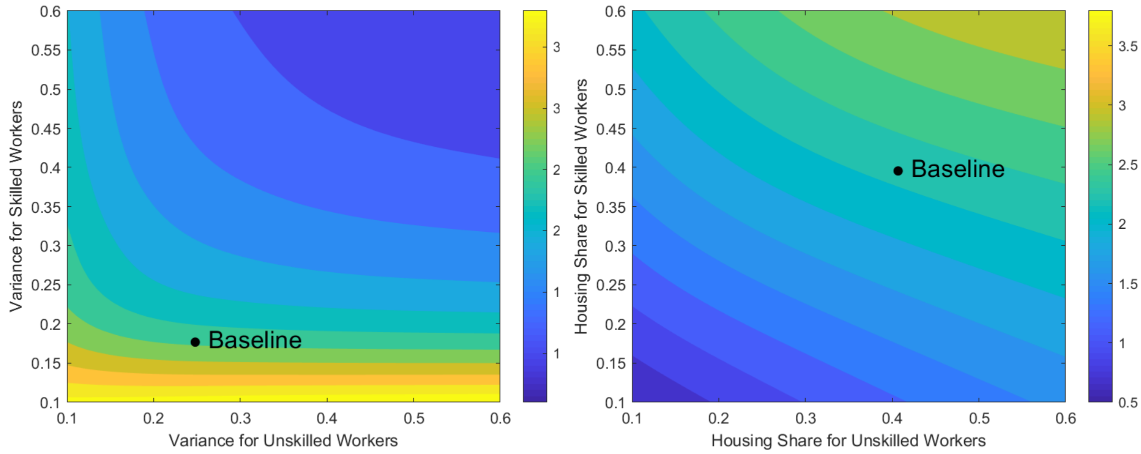
8.1 Sensitivity to Alternative Parameters

In this section, we examine the robustness of our main results to alternative values of key parameters. In particular, we recalculate the reduction in national carbon output resulting from relaxing land use regulations in California cities for a range of parameter values. First, we examine model sensitivity to the scale parameter of the idiosyncratic preference draw, σ_d. Lower values of σ_d imply that household location choice is more elastic with respect to wages and rents.[31] Therefore, households will be more likely to change their location decisions in response to changes in land use regulations.

The reduction in carbon output for a range of values of $\frac{1}{\sigma^d}$ for skilled and unskilled workers is shown in Panel A of Figure 3. Recall in our baseline specification that we calibrate $\sigma_d = \frac{1}{4.15}$ for unskilled workers and $\sigma_d = \frac{1}{5.52}$ for skilled workers and we found a decrease in carbon emissions of 2.3%. In the figure, σ_d for skilled workers is displayed on the vertical axis and σ_d for unskilled workers is displayed on the horizontal axis. Darker colors imply smaller changes in carbon emissions while lighter colors imply larger changes. Figure 3 illustrates that the change in carbon emissions is generally decreasing in σ_d for both types of workers. In the extreme case when $\sigma_d = .1$ for both types of workers, workers are very responsive to changes in rents. As a result, carbon emissions drop by 4% when we relax carbon emissions in California. When $\sigma_d = .6$ for both types of workers, carbon emissions drop by roughly 1%. Overall, it seems like the variance of skilled workers plays a more important role than the variance for unskilled workers in dictating the change in carbon emissions in our counterfactuals.

Next, we examine our model's sensitivity to the budget share of housing parameter, α_d^H. Recall that we calibrate $\alpha_d^H = .4$ for all workers in the baseline counterfactual. Higher values of α_d^H imply households spend a larger fraction of their income on housing and therefore will be more sensitive to housing prices in

[31] For each counterfactual in which we change σ_d, we recalculate the amenity values ξ_j^d such as to keep the mean utility of each demographic group in each city equal to its baseline level. Therefore, the distribution of workers of each demographic group given the observed tax function will be equal to the baseline distribution with the original values of σ_d.



(a) Variance of Preference Draw (b) Housing Expenditure Share

Figure 3: Change in national emissions from relaxing land use restriction in California for various parameter values. In panel (a), we display σ_d for skilled workers on the Y (vertical) axis, and σ_d for unskilled workers on the X (horizontal) axis. Panel (b) shows percent reduction in carbon emissions as a function of α_d^H for both types of workers.

their choice of where to live. The results are displayed in Panel B of Figure 3. The vertical axis shows values of α_d^H for skilled workers and the horizonal axis shows α_d^H for unskilled workers. Again, darker colors imply smaller changes in carbon emissions while lighter colors imply larger changes. Larger values of α_d^H of both types of workers imply larger decreases in carbon emissions. When $\alpha_d^H = .1$ for both type of workers carbon emissions drop by .65% when we relax carbon emissions in California. If we set $\alpha_d^H = .6$ for both types of workers, carbon emissions drop by roughly 3%.

8.2 Power Plant Substitution

One potential issue with our current counterfactual is that new power plants built in order to accommodate increases in demand for electricity may be cleaner or dirtier than the current stock of power plants in that region. Therefore, the carbon emissions factors we use in our analysis will change in response to increases in electricity demand. For example, our main counterfactual of relaxing land use regulations in California led to a substantial increase in population and energy usage in California. As a result, new power plants may be constructed in the corresponding WECC NERC region which may be cleaner or dirtier than the current power plants in the region. If these new power plants are cleaner (dirtier) than the current stock of power plants, we will underestimate (overestimate) the reduction in carbon emissions.

To investigate how endogenous changes in the composition of power plants might affect our results, we compare power plants built before and after 2000. We find power plants built after 2000 emit considerably less CO_2 per MwH than plants built prior. Specifically, for the WECC NERC region we find that power plants built prior to 2000 emit 858 lbs of CO_2 per MwH of electricity, whereas plants built after 2000 emit only 597 lbs of CO_2 per MwH.[32] These results suggest that if new power plants were built in response to increases in California's population, these new plants would be more carbon efficient than the current stock of plants.

8.3 Endogenous Electricity Pricing

In our baseline specification, we assume that electricity is produced at constant marginal cost; therefore, the supply curve of electricity is perfectly elastic. In this section we consider an extension in which the price of electricity is determined endogenously.

Specifically, we assume that electricity producers in each NERC region form an upward sloping long-run electricity supply curve, reflecting differences in costs of productivity of potential electricity production opportunities within a region. For low quantities, electricity can be produced at low cost. As electricity production increases, increasingly less productive resources must be utilized, which therefore implies higher costs of production.

A number of papers examine the short run supply curves of electricity. The short run electricity supply curve is often modeled as a "dispatch curve" with constant or linear marginal costs, to reflect the unique way in which electricity is allocated in the very short term.[33] Essentially, power plants are ranked in terms of their marginal cost of producing electricity. As demand increases, plants are dispatched to produce power in increasing order of marginal cost. However, this type of modeling approach is likely not a good representation of the long run

[32]Section A.9 in the data appendix has further information on the full distribution of emissions from power plants built before and after 2000.

[33]For an example, see Ma, Sun, and Cheung (1999).

energy supply curve which we consider here. In the long run, energy producers may respond to changes in energy demand by opening new reactors and new plants. We therefore posit a more parsimonious long run electricity supply curve as:

$$C_{\mathcal{R}} = \upsilon_{\mathcal{R}} X_{\mathcal{R}}^{\kappa}$$

where $X_{\mathcal{R}}$ is the total quantity of energy produced in region $\mathcal{R}$, κ is a parameter equal to the inverse elasticity of the energy supply curve, and $\upsilon_{\mathcal{R}}$ is a region specific cost shifter.

Electricity is then transmitted to specific local labor markets at an additive transmission cost, ϕ_j.[34] Given the assumption of perfectly competitive generation companies, we can write the inverse energy supply curve to city j as

$$P_j^{\text{elec}} = b_j + \kappa \log \left(X_{\mathcal{R}(j)} \right)$$

where $b_j = \phi_j + \log \left(\upsilon_{\mathcal{R}(j)} \right)$.

To calibrate this model extension, we first calibrate the inverse elasticity of the electricity supply curve as $\kappa = \frac{1}{1.27}$, based on the estimates in Dahl and Duggan (1996). We then choose the parameters b_j to match state level electricity prices.

The main counterfactual results with endogenous electricity pricing are summarized in Table 6. Overall, the population distribution across all counterfactuals are quite similar to the counterfactuals with perfectly elastic electricity supply. Households spend a relatively small fraction of their income on electricity and therefore changes in electricity prices have little impact on their location choices. Natural gas and fuel oil emissions are also nearly identical to the case with perfectly elastic electricity supply. However, the reductions in electricity usage and therefore overall carbon emissions are smaller in the case with endogenous electricity prices. Overall this leads to a 1.6% reduction in carbon emissions from relaxing land use restrictions in California, a 4.9% reduction from setting all cities to the median land use restrictions, and a 9.4% reduction from implementing a carbon tax.[35]

[34] This cost may directly reflect costs of transmissions or network congestion costs.

[35] With perfectly elastic electricity supply, relaxing land use restrictions in California leads to a 2.3% reduction in carbon emissions, setting all cities to the median land use restrictions results in a 8.1% decrease in emissions, and a carbon tax leads to a 12.3% reduction.

	Baseline	Relax CA	Relax All	Carbon Tax
I. Percent Total Population				
California Cities	9.82	16.39	11.53	9.87
Other West	13.12	11.30	14.74	13.18
Midwest	21.84	20.46	13.46	21.69
South	36.80	34.40	26.82	36.80
Northeast	18.42	17.45	33.45	18.46
II. Usage				
Gas (1000 cubic feet)	53.16	52.57	53.73	45.47
Electricity (MW h)	13.29	13.15	12.23	12.43
Fuel Oil (gallons)	28.41	26.82	43.75	25.27
III. Emissions (lbs of CO_2)				
Gas	6225	6156	6291	5324
Electricity	12859	12655	11410	11972
Fuel Oil	763	720	1175	679
Total	19847	19531	18877	17975
(%)	(100)	(98.4)	(95.1)	(90.6)
IV. Average Log Income				
Skilled	10.89	10.91	10.98	10.89
Unskilled	10.04	10.05	10.09	10.04
All	10.33	10.34	10.40	10.33

Table 6: Counterfactual results with endogenous electricity pricing. Each panel shows the simulated total energy usage, total emissions, average log income and fraction of total population living in various geographic areas in each specification. See text for details on each individual simulation.

9 Conclusion

Household carbon emissions vary considerably across cities. Land use restrictions, which are set by local governments, tend to be stricter in green cities and therefore encourage workers to live in cities with less moderate climates and higher polluting power plants.

We began by updating the findings in Glaeser and Kahn (2010) and documented tremendous spatial variation in both the greenness of power plants and energy consumption. Cities with more temperate climates (such as San Francisco) tend to emit substantially less carbon than other cities. Furthermore, these cities also have very high land use regulations.

To examine the effects of land use restrictions on national carbon emissions, we then estimated a model of worker sorting, energy demand, and locations that vary by power plant technology. The model incorporates heterogeneous workers, endogenous income and rents, and energy demand and power plant technology which vary geographically across the United States. To take the model to the data, we employed a combination of calibration and estimation techniques using datasets on household sorting and energy demand, power plants, and energy prices across the US.

We found that relaxing land use restrictions in California leads to a decrease in national carbon output of over 2% while leading to significant increases for average income of both skilled and unskilled workers. A carbon tax lead to a large reduction in carbon emissions but also implied significant distribution consequences. Our main conclusion is that the positive correlation between strict land use restrictions and greenness of cities has large implications for national carbon output.

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A Data Appendix: For Online Publication Only

A.1 Demographic Groups

We restrict the individual choice data to individuals that identify themselves as the decision maker. A demographic group in our model consists of level of education, marital status, minority status, and whether or not the individual has children. We split education by those that have a college degree. Marital status is defined as either being married or single. Minority status is characterized by whether the individual is white or not. Lastly, very few single individuals in our sample have children. Thus, we make the assumption that only married individuals have children. In total this gives us 24 distinct demographic groups.

Table 7 shows average carbon emissions for each demographic group using data on homeowners in single family homes.

		Unskilled	Skilled			Unskilled	Skilled
White				**Nonwhite**			
Young				Young			
Single		22,122	18,421	Single		20,909	18,216
Married	w/o Children	20,223	17,736	Married	w/o Children	19,818	19,060
Married	w/ Children	22,633	21,850	Married	w/ Children	23,299	23,344
Old				Old			
Single		23,364	21,702	Single		20,891	20,475
Married	w/o Children	24,284	23,270	Married	w/o Children	23,348	24,298
Married	w/ Children	25,052	25,204	Married	w/ Children	26,434	27,836

Table 7: Average Emissions by Demographic Group.

A.2 Average Emissions by Family Structure

Table 8 gives average emissions for single households, married households with no children, and married households with children. The first column shows the raw means while the second column controls for cbsa fixed effects. The New England Division is the omitted category.

	(1)	(2)
Married w/ Children	26,099	30,171
	(18.76)	(199.3)
Married w/o Children	23,326	27,167
	(20.54)	(199.4)
Single	20,990	24,824
	(19.44)	(199.2)
Observations	2,742,021	2,742,021
CBSA FE	NO	YES

Table 8: Average emissions by family structure. The first column does not include CBSA fixed effects, the second column does. Results from regression of individual level emissions for for non-renters in single family homes. Robust standard errors in parentheses.

A.3 Hedonic Rents

A major concern about producing a measure of housing costs across CBSA's is that it reflects user cost of housing. To accommodate this, we only use data on renters as home prices reflect both the current cost and expected future costs. Secondly, it is difficult to compare housing units across CBSA's. Thus, we estimate hedonic regressions of log gross rent on a set of housing characteristics and CBSA fixed effects. Specifically, we control for number of units in the structure containing the household, number of bedrooms, number of total rooms, and household members per room. To generate the rent index, we utilize the predicted values from the hedonic regressions, holding constant the set of housing characteristics and CBSA fixed effects.

A.4 NERC Regions

We calculate the emissions factor for each region as a weighted average of the average CO_2 emissions rate in each NERC region. We weight the average by each plants total yearly MwH generation as a fraction of the total MwH generation in the region. Figure 4 gives the emissions factors for each region as well as the percent of total energy generated by renewable sources in each region.

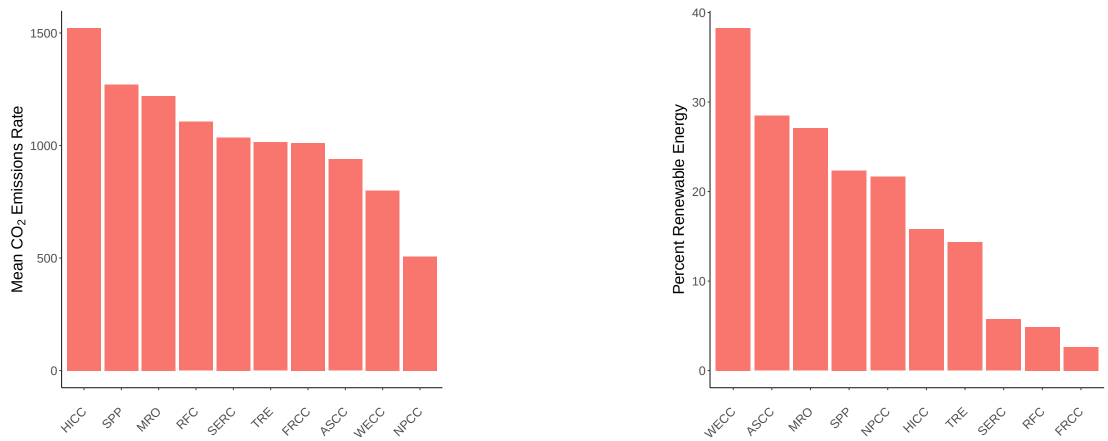

Figure 4: Figure on left: Weighted Average CO_2 emissions rates by NERC region. Figure on right: Percent of total energy generated by renewable sources

The following table summarizes the information in Figure 4.

NERC Region	**Mean Emissions**	**Percent Renewables**
ASCC	939.40	28.47
FRCC	1011.67	2.64
HICC	1522.10	15.79
MRO	1220.49	27.08
NPCC	506.56	21.66
RFC	1105.27	4.86
SERC	1035.40	5.73
SPP	1271.17	22.34
TRE	1014.71	14.34
WECC	799.92	38.26

Table 9: Mean CO_2 emissions rate and percent renewable emissions from power plants in the US. Emissions rate and percent renewables are weighted by output of each plant in the region.

A.5 Energy Usage and Correction

Let x_i^m give household i's usage of energy type m. We then estimate the following household level regression to calculate predicted energy usage by CBSA, controlling for income, household size and age of the household head:

$$x_i^m = \gamma_{\text{CBSA}(i)} + \beta_1 \log(\text{Income}_i) + \beta_2 \text{HHsize}_i + \beta_3 \text{Agehead}_i + \varepsilon_i \tag{15}$$

where $\gamma_{\text{CBSA}(i)}$ is a fixed effect for the CBSA in which household i is located, and β_1, β_2 and β_3 control for a household's log income, household size, and age of the household head. We use the estimated coefficients from this model to predict the median household usage of each energy source.

One concern is that rented homes and multi-family homes are less likely to pay for energy themselves and the proportion of renters and multi-family homes varies across cities. The ACS data has flags for whether the individual owns or rents the house, as well as whether they live in a single family or multi family home. Similar to Glaeser and Kahn (2010), we correct for this by reweighting predicted emissions by the fraction of each of the four groups in each city.

A.6 Emissions and Population

We assume that the marginal benefit of electricity consumption is exogenous to the local population of a given city. As a simple test of the relationship between population and energy consumption, we estimate:

$$\log(\tilde{x}_j^m) = \alpha^m + \alpha_1^m \log(\text{Population}_j) + \varepsilon_j \tag{16}$$

where $m \in \{Elec, Gas, Fuel\}$ and $\tilde{x}_j^m$ is the predicted per capita energy consumption of type m in city j from the regression estimated in Equation 15. Table 10 provides estimates for Equation 16.

	Dependent variable:		
	Electricity Consumption (MwH)	**Gas Consumption** (1000 ft^3)	**Fuel Consumption** (gal)
Population	0.036	−0.014	−0.187
	(0.035)	(0.080)	(0.173)
Constant	2.025***	3.985***	4.992**
	(0.473)	(1.089)	(2.341)
Observations	79	79	79
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 10: Robust standard errors in parenthesis. All variables are measured in logs. Each observation is a CBSA.

The coefficients on all of the regressions for the energy consumption variables are close to zero with relatively small standard errors. This suggests population increases do not lead to significant changes in the benefits of energy usage.

A.7 Emissions and Climate

Figure 5 shows a scatterplot between average August temperature in each CBSA and predicted electricity usage and average January temperature and predicted natural gas usage. Similar to Glaeser and Kahn (2010), we find strong relationships between temperature and consumption of different fuel sources:

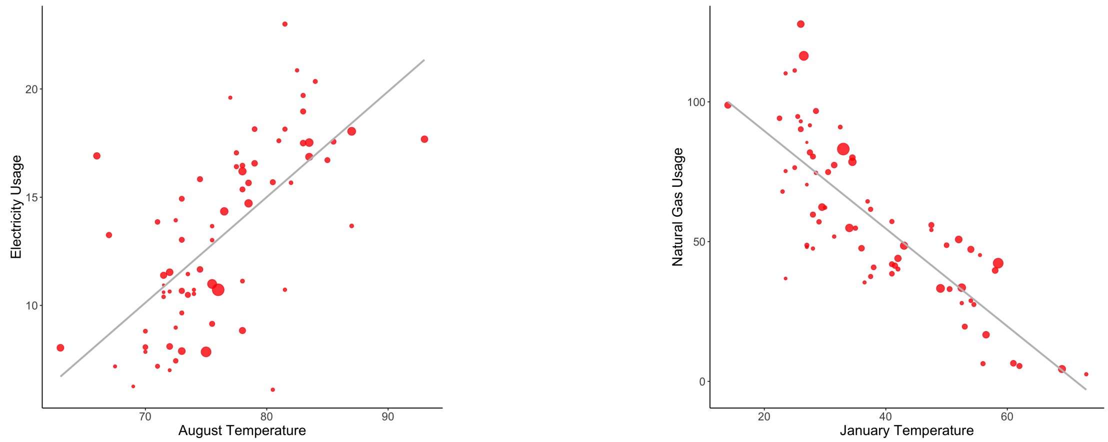

Figure 5: Temperature data was obtained from weather.com. Each point is a CBSA. Temperature corresponds to the midpoint of the average minimum and maximum daily temperature recorded in the month of interest. Size of each point reflects the population of the CBSA. Electricity usage is measured in MwH and natural gas usage is measured in 1000 ft^3.

From Figure 5 we can see that electricity usage has a strong positive relationship with August temperature. Similarly, as January temperature increases, natural gas use decreases.

A.8 Demographics and Emissions

We document variation in mean income, WRLURI, and proportions of demographic groups across cities based on how much CO_2 households emit in Table 11 below.

Sample	WRLURI	Mean Income (in 10,000 $'s)	Mean Population (in 10,000's)	College share	Married share	White share	Under 35 share	Has Children share
USA	0.22	5.50	77.23	0.37	0.51	0.74	0.27	0.31
CA	0.52	6.29	104.19	0.38	0.55	0.65	0.26	0.37
Emissions Percentile								
$< 25\%$	0.75	5.84	67.93	0.38	0.52	0.72	0.26	0.33
$25\% - 75\%$	0.08	5.49	83.94	0.37	0.51	0.75	0.27	0.31
$> 75\%$	-0.07	5.17	73.85	0.36	0.50	0.73	0.28	0.30

Table 11: Demographic information for various subsets of our sample. Emissions percentiles are calculated using the conversion factors for each energy type multiplied by the predicted usage yielded from regression 15.

A.9 New Power Plant Development

Table 12 gives the full distribution of emissions and percent of plants that are renewables, split on whether they were constructed before or after 2000.

NERC	Pre-2000's	Post-2000's	Pre-2000's	Post 2000's
	Mean Emissions		Percent Renewables	
ASCC	935.55	842.37	37.38	15.50
FRCC	935.66	857.27	3.65	2.90
HICC	1649.43	461.88	9.22	70.62
MRO	1566.42	188.09	9.49	80.18
NPCC	410.31	747.15	24.42	14.71
RFC	1176.69	850.51	2.18	14.75
SERC	1055.78	941.07	6.16	5.25
SPP	1741.86	521.45	5.93	46.90
TRE	1135.47	620.07	1.18	29.53
WECC	858.24	597.01	40.48	36.47

Table 12: NERC region mean carbon emissions from plants built before 2000 and after 2000. Emissions rates are measured in lbs/mwh

B Estimation and Simulation Appendix: For Online Publication Only

B.1 Estimation: Production Parameters

Let $x \in \{s, u\}$ index worker skill levels. Income for workers of demographic d living in location j is $I_j^d = W_{jx}\ell^d$, where ℓ^d is the amount of efficiency units supplied by workers from demographic group d.

We specify units as the demographic specific probability of being employed multiplied by the productivity conditional on being employed. We therefore write

$$\ell^d = E^d \hat{\ell}^d$$

where E^d is the national employment-to-population ratio of workers in demographic group d.

We parameterize $\hat{\ell}^d$ as

$$\log(\hat{\ell}^d) = \beta_x^1 \text{White}\,(d) + \beta_x^2 \text{Over35}\,(d)$$

where White (d) is an indicator variable indicating workers of demographic group d are white and Over35 (d) indicates workers of demographic d are over age 35. Therefore $\hat{\ell}^d$ of nonwhite workers below age 35 is normalized to one.

Conditional on working, log income of workers of demographic group d and skill level x living in city j is given by

$$\log\left(I_j^d\right) = \log\left(W_{jx}\right) + \beta_x^1 \text{White}\,(d) + \beta_x^2 \text{Over35}\,(d)\,.$$

We therefore estimate the city level wage rates and parameters of the efficiency unit parameters using the following individual level income regression of individuals conditional on working:

$$\log I_{ij}^d = \gamma_j^x + \hat{\beta}_x^1 \text{White}\,(d) + \hat{\beta}_x^2 \text{Over35}\,(d) + \varepsilon_{ij}$$

where I_{ij}^d is the income level of individual i, γ_j^x is a city fixed effect which is an estimate of $\log\left(W_{jx}\right)$, and ε_{ij} is an individual level error term.

The remaining unknown parameters of the production function are the elasticity of substitution, σ, the vector of city level total factor productivities, A_j, and the vector of factor intensities, θ_j. We calibrate the elasticity of substitution, $\sigma = 2$.

Note that the log wage ratio in a given city j is given by

$$\log\left(\frac{W_{js}}{W_{us}}\right) = -\frac{1}{\sigma}\log\left(\frac{S_j}{U_j}\right) + \log\left(\frac{\theta_j}{1-\theta_j}\right).$$

As wage levels, labor quantities and the elasiticity of substitution, σ, are already known, the factor intensities θ_j can be solved for using the above equation.

The final set of parameters are the total factor productivity, A_j. These are chosen so that wage levels are equal to those in the data.

B.2 Estimation: Housing Supply

We know that total demand for housing in city j is given by:

$$H_j = \sum_d N_{jd} \frac{\alpha_d^H I_{jd}}{R_j \boldsymbol{\alpha}_{jd}}, \tag{17}$$

where N_{jd} is the total number of workers of demographic d living in city j. Plugging this equation for housing demand into the housing supply curve and rearranging yields the following reduced-form relationship:

$$\log(R_j) = k_j \log(\sum_d N_{jd} I_{jd})) + \hat{\zeta}_j, \tag{18}$$

where

$$\hat{\zeta}_j = \zeta_j + k_j \log\left(\sum_d \frac{\alpha_d^H}{\boldsymbol{\alpha}_{jd}}\right)$$

Saiz (2010) estimates the role of physical and regulatory constraints in the determining the role of local housing supply elasticities by using labor demand shocks and instruments for housing demand. As in this paper, we set ψ_j^{WRI} to the log of the Wharton Regulation Index plus 3, and use Saiz's measure of the unavailable land share (due to geography) for ψ_j^{GEO}. We calibrate ν_1, ν_2 and ν_3 based on the estimates in Saiz (2010).[36]

B.3 Parameter Estimates

Household Sorting Table 13 gives the estimates of birth state premium, distance and distance squared of the household's indirect utility function. For all demographic groups, agents receive a large utility premium for choosing a location in their home state. The amenity value of location is decreasing and convex in distance from birth state for all demographic groups.

The parameters governing the unobserved amenity utility of each city, ξ_{jd}, and the marginal benefit of energy usage in each location, α_{jd}^m, all vary by city and

[36] Specifically, we use the estimates from Column (4) of Table III in Saiz (2010), as it is the closest to our specification. As the estimate of the interaction between housing supply constraints is quite similar across specifications in Saiz (2010), we do not suspect that our results will be sensitive to the specific estimates we choose.

demographic group. These are available on request.

B.4 Tax Burden of Carbon Tax by Demographic Groups

This table shows the average equivalent variation of a carbon tax for each of the demographic groups.

		Unskilled	Skilled			Unskilled	Skilled
White				**Nonwhite**			
Young				Young			
Single		-234	-197	Single		-229	-200
Marr.	w/o Child	-225	-200	Marr.	w/o Child	-243	-249
Marr.	w/ Child	-284	-282	Marr.	w/ Child	-312	-330
Old				Old			
Single		-277	-288	Single		-267	-288
Marr.	w/o Child	-316	-325	Marr.	w/o Child	-322	-366
Marr.	w/ Child	-353	-378	Marr.	w/ Child	-376	-424

Table 14: Average equivalent variation of various types of households.

B.5 Simulation: Methane Emissions

As an alternative to carbon-dioxide emissions, we also explore the relationship between of land use regulation on methane emissions. Methane is a global issue; while it is odorless and thus not considered a local pollutant, it is considered a greenhouse gas. According to the Bernstein et al. (2008), pound for pound, methane has 25 times the global warming potential over a 100 year period over carbon dioxide.

The relationship between the WRI and methane emissions is quite similar to that of carbon dioxide emissions. Cities with higher land use regulations tend to have lower methane emissions..

	Single	Married w/o Children	Married w/ Children	Single	Married w/o Children	Married w/ Children
Unskilled						
White	Young			Old		
Birthstate Premium	3.10	3.22	3.09	3.24	2.52	3.18
	(0.09)	(0.03)	(0.01)	(0.01)	(0.49)	(0.01)
Distance	-1.05	-1.58	-1.58	-1.06	-1.03	-1.05
	(0.08)	(0.05)	(0.02)	(0.01)	(0.26)	(0.01)
Distance Squared	0.15	0.39	0.42	0.23	0.20	0.21
	(0.01)	(0.01)	(0.00)	(0.00)	(0.02)	(0.00)
Nonwhite	Young			Old		
Birthstate Premium	3.29	2.95	3.39	3.30	3.14	3.01
	(0.02)	(0.20)	(0.06)	(0.02)	(0.07)	(0.07)
Distance	-1.10	-1.15	-1.21	-1.06	-1.03	-0.93
	(0.03)	(0.14)	(0.05)	(0.02)	(0.04)	(0.09)
Distance Squared	0.16	0.21	0.22	0.24	0.16	0.20
	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.02)
Skilled						
White	Young			Old		
Birthstate Premium	2.88	3.01	2.61	2.79	2.70	2.74
	(0.16)	(0.08)	(0.28)	(0.12)	(0.03)	(0.04)
Distance	-1.10	-1.48	-1.04	-1.40	-1.47	-1.34
	(0.11)	(0.13)	(0.15)	(0.14)	(0.04)	(0.04)
Distance Squared	0.16	0.34	0.14	0.36	0.38	0.37
	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.01)
Nonwhite	Young			Old		
Birthstate Premium	2.83	2.68	2.55	2.68	2.41	2.81
	(0.03)	(0.22)	(0.43)	(0.86)	(1.31)	(0.02)
Distance	-1.41	-0.76	-1.10	-1.12	-0.83	-1.33
	(0.03)	(0.12)	(0.28)	(0.57)	(0.63)	(0.03)
Distance Squared	0.39	0.13	0.14	0.17	0.13	0.31
	(0.01)	(0.01)	(0.03)	(0.06)	(0.06)	(0.01)

Table 13: Parameter Estimates. Standard errors in parentheses.

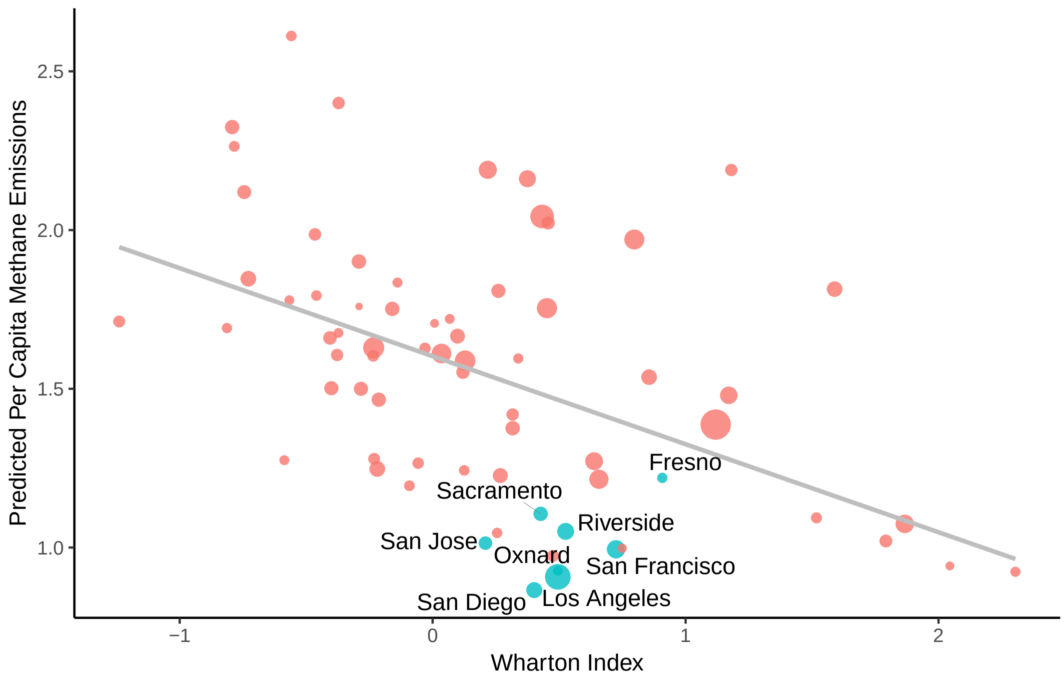

Figure 6: Methane emissions regressed on Wharton Index. Each observation is a CBSA. Size of each observation reflects population of CBSA.

Methane emissions come from two sources: natural gas and electricity generation. Unlike carbon-dioxide, burning natural gas does not emit methane; however, natural gas is composed of 70% methane. Furthermore, natural gas leakages are estimated to be 1.4% according the EPA. To impute the amount of methane emitted from natural gas emissions, we use a conversion factor of 0.7*0.014 = 0.0098. As with carbon dioxide, methane emissions from electricity vary by NERC region. We compute the weighted emissions rate for methane in the same manner as we did with carbon dioxide. Table 15 provides an array of city-level energy consumption, ranked on methane emissions.

CBSA	Rank	Emissions (1000 lbs)	Gas Emissions (1000 lbs)	Electricity Use (MwH)	Electricity Conversion (1000 lbs per MwH)	Electricity Emissions (1000 lbs)
Lowest						
San Diego, CA	1	0.87	0.37	7.35	0.07	0.49
Los Angeles, CA	2	0.91	0.42	7.32	0.07	0.49
Honolulu, HI	3	0.92	0.02	5.76	0.16	0.91
Oxnard, CA	4	0.93	0.46	6.95	0.07	0.47
Worcester, MA	5	0.94	0.44	8.77	0.06	0.50
Hartford, CT	6	0.97	0.47	8.75	0.06	0.50
Middle						
Denver, CO	33	1.54	0.79	11.06	0.07	0.74
Virginia Beach, VA-NC	34	1.55	0.38	15.77	0.07	1.17
Houston TX	35	1.59	0.32	16.40	0.08	1.27
Allentown, PA-NJ	36	1.60	0.46	12.94	0.09	1.13
Birmingham, AL	37	1.60	0.39	16.36	0.07	1.22
Richmond, VA	38	1.61	0.39	16.38	0.07	1.22
Highest						
Memphis, TN-MS-AR	65	2.19	0.57	21.81	0.07	1.62
Detroit, MI	66	2.19	1.26	10.59	0.09	0.93
Tulsa, OK	67	2.26	0.64	15.11	0.11	1.63
Kansas City, MO-KS	68	2.32	0.74	14.76	0.11	1.59
Oklahoma City, OK	69	2.40	0.59	16.80	0.11	1.81
Omaha, NE	70	2.61	1.11	13.44	0.11	1.50

Table 15: Predicted CBSA level **methane** emissions by fuel type for the six lowest emissions cities, the six median cities, and the six highest emissions cities. The third column ("Emissions") shows the sum of predicted **methane** emissions from natural gas, fuel oil and electricity for the CBSA. The next two columns show emissions from gas and fuel oil respectively, which are equal to predicted usage multiplied by the appropriate emissions factor. The last three columns show predicted electricity usage, the electricity emissions factor, and predicted electricity emissions, equal to predicted electricity usage multiplied by the emissions factor. Use is measured in 1000 pounds per megawatt hour.

Our main counterfactual was to relax land use regulations in California cities to the national median. To do this, we simulated how demand for energy services changed as a result of the changes in rental prices from relaxing the land use regulations. To estimate average CBSA level emissions, we multiplied the respective usages by the local emissions factors for each type for carbon-dioxide. We can use the same simulation to examine the changes in methane emissions by using conversion factors for methane emissions. Table 16 demonstrates how methane emissions change as a result of our simulation.

	Baseline	Relax Cali	Relax All	Carbon Tax
II. Emissions (lbs of Methane)				
Gas	0.56	0.55	0.57	0.48
Electricity	1.04	1.01	0.90	0.92
Fuel Oil	0.00	0.00	0.00	0.00
Total	1.60	1.56	1.47	1.40

Table 16: Counterfactual results for methane emissions. Each column shows the amount of methane emitted from each energy source under various counterfactual scenarios.