Supplement to "The environmental cost of land-use restrictions"

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This supplement contains two Appendices. Appendix A contains additional details on the data and on the theoretical details of the model. Appendix B contains additional empirical and simulated results.

Appendix A: Data and theory appendix: For online publication only

A.1 *Demographic groups*

We drop households living in group quarters and whose household head is over age 65. A demographic group in our model is defined by the household head's level of education, marital status, age, minority status, and whether or not there are children in the household. 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. Therefore, we do not differentiate between single households with and without children. In total, this gives us 24 distinct demographic groups.

To better understand which demographic characteristics play the most important role in determining household level emissions, we run the following regression of household level emissions on the demographics of a household using data from the 2017 aggregated ACS:

$$\text{Emissions}_{ij} = \beta X_i + \gamma_j + \varepsilon_i, \tag{A.1}$$

where X_i is the vector of demographic variables, and γ_j is a CBSA level fixed effect.

The results are displayed in Table A.1. Being married, having children, and having an older household head are associated with large values of emissions, while the other demographic variables only play a small role in dictating a household's carbon emissions.

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TABLE A.1. Regression estimates of (A.1).

White	−183.4
	(24.23)
College plus	423.3
	(18.27)
Old	3487
	(24.92)
Married	2286
	(23.30)
Has children	3378
	(22.06)
Constant	19,347
	(33.21)
Observations	2,709,529
R-squared	0.126
CBSA FE	YES

Note: Standard errors in parentheses.

A.2 *Energy prices*

We obtain data on average residential electricity, natural gas, and fuel oil prices by state for 1990, 2000, 2010, and 2017 from the Energy Information Association. For each energy type and year, we assign the average residential price to all CBSAs within a state. Furthermore, for electricity prices, we use the prices given from "full-service providers." Fuel oil prices are reported at a weekly level. We average across weeks to obtain yearly average fuel oil prices. Additionally, as fuel oil is used primarily in the Northeast, many states do not report average prices. For states that do not have fuel oil prices in the EIA's dataset, we assign the yearly average of all states that do have prices.

A.3 *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 plant's total yearly MWh generation as a fraction of the total MWh generation in the region. Figure A.1 is a map of the NERC regions for the contiguous United States with the conversion factors.

A.4 *Correction for rented homes and multifamily homes*

One concern is that rented homes and multifamily homes are less likely to pay for energy themselves and the proportion of renters and multifamily homes varies across cities. As the ACS and Census only contain information on energy costs, not energy usage, this may lead us to understate under usage in cities with high amounts of renters of residents in multifamily homes. Similar to Glaeser and Kahn (2010), we correct for this using data from the 2015 Residential Energy Consumption Survey (RECS), which contains data on energy *usage* for a sample of over 5,0000 households.

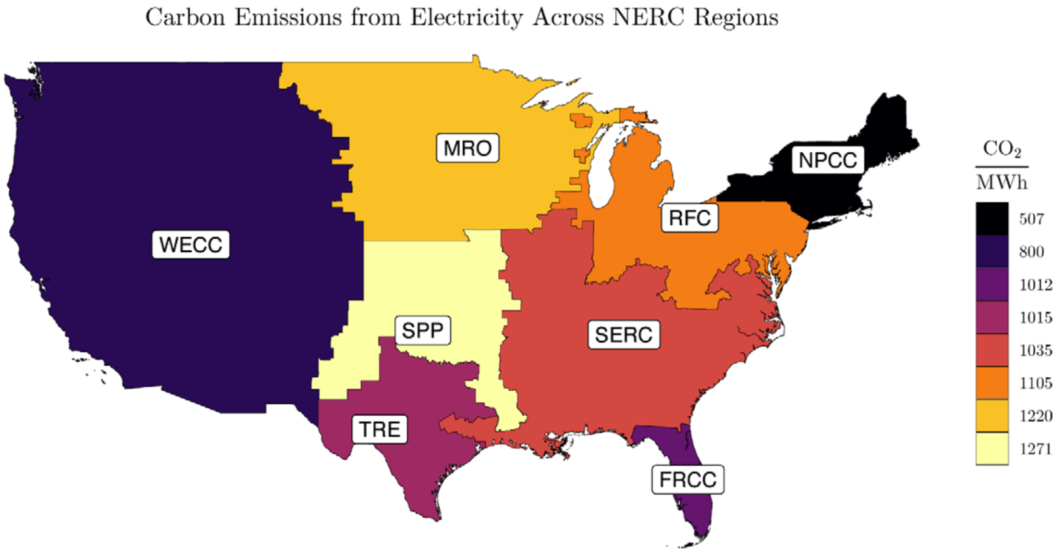

FIGURE A.1. Map of NERC region with regional conversion factors. In the model, there is an additional NERC region for Hawaii—HICC—with an emissions factor of 1522.10.

We use these data to estimate the following regression, which compares the energy usage of renters and those who live in multifamily homes to owners of single-family homes:

$$\log\left(E_i^m\right) = \beta_{\text{MF}}^m \text{MultiFamily}_i + \beta_{\text{Rent}}^m \text{Rent}_i + \text{controls} + e_i^m, \tag{A.2}$$

where controls include controls for household size, number of children, age of household head, whether the household head is white, and division dummies. We then use the coefficients β_{MF}^m and β_{Rent}^m to impute energy usage for households who are renters and who live in multifamily homes. For example, if we estimate that owners of single-family homes in San Francisco use 8 MWh of electricity and estimate $\beta_{\text{MF}}^m = 0.1$, we would impute that owners of multifamily homes use $8 \times 1.1 = 8.8$ MWh of electricity. Finally, we estimate the fraction of renters of single-family homes, renters of multifamily homes, owners of single-family homes, and owners of multifamily homes using data from the ACS and Census, and calculate the predicted usage as the weighted average of the estimated predicted usage of owners of single-family homes, and the imputed usage of the other three groups.

A.5 *Fuel consumption and population*

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

$$\log\left(\hat{E}_j^m + 1\right) = \alpha^m + \alpha_1^m \log(\text{Population}_j) + \varepsilon_j, \tag{A.3}$$

TABLE A.2. Heteroskedastic robust standard errors are in parenthesis. As the selection-correction usages predict zero fuel consumption in certain CBSAs, we use $\log(\hat{E}_j^m + 1)$. Each observation is a CBSA.

	Dependent variable:		
	Electricity Consumption (MwH)	Gas Consumption (1000 ft^3)	Fuel Consumption (gal)
log(Population)	−0.012	−0.413	0.049
	(0.136)	(0.310)	(0.036)
Constant	4.276	8.428	2.232
	(1.809)	(4.088)	(0.484)
Observations	70	70	70

where $m \in \{\text{Elec, Gas, Fuel}\}$ and $\hat{E}_j^m$ is the predicted per-household, selection-corrected energy consumption of type m in city j. Since the selection-correction usages predict zero fuel consumption in certain CBSAs, we use $\log(\hat{E}_j^m + 1)$. The results presented here are not sensitive to this choice. Table A.2 provides estimates for (A.3).

The coefficients on all of the regressions for the energy consumption variables are statistically insignificant. This suggests population increases do not lead to significant changes in the benefits of energy usage.

A.6 *Equilibrium definition*

In this environment, an equilibrium is characterized by household and firm optimization, and market clearing in the housing and labor markets.[1]

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

$$H_j^D = \sum_d N_{jd} \frac{\alpha_d^H I_{jd}}{R_j \boldsymbol{\alpha}_{jd}}, \tag{A.4}$$

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:

$$X_j^{mD} = \sum_d N_{jd} \frac{\alpha_{jd}^m I_{jd}}{P_j^m \boldsymbol{\alpha}_{jd}}. \tag{A.5}$$

[1] In Section 8.2, 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.

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

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

for skilled workers and

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

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

Labor demand for skilled and unskilled workers are implicitly defined by the first-order conditions of the production firms.

Housing supply is given by the marginal cost curve of housing.

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

1. Housing market clearing: $H_j^S = H_j^D$, for all cities, j.
2. Labor market clearing: $S_j^S = S_j^D$ for skilled workers and $U_j^S = U_j^D$ for unskilled workers in all cities.

A.7 *Hedonic rents*

A major concern about producing a measure of housing costs across CBSAs 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. Second, it is difficult to compare housing units across CBSAs. Thus, we estimate hedonic regressions of log gross rent on a set of housing characteristics and CBSA fixed effects. Specifically, we control for the 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.8 *Estimation: Production parameters*

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

We specify efficiency 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, the log income of workers of demographic group d and skill level x living in city j is given by

$$\log(I_{jd}) = \log(W_{jx}) + \beta_x^1 \text{White}(d) + \beta_x^2 \text{Over35}(d).$$

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:

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

where I_{ijd} is the income level of individual i, γ_j^x is a city by skill level fixed effect which is an estimate of $\log(W_{jx})$, 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, $\varsigma = 2$.

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

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

As wage levels, labor quantities, and the elasticity of substitution, ς, are already known, the factor intensities θ_j can be solved by 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.

A.9 *Calibration: Housing supply*

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

$$H_j = \sum_d N_{jd} \frac{\alpha_d^H I_{jd}}{R_j \boldsymbol{\alpha}_{jd}}, \tag{A.6}$$

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:

$$\log(R_j) = \frac{k_j}{1+k_j}\log\left(\sum_d N_{jd}\frac{\alpha_d^H I_{jd}}{\boldsymbol{\alpha}_{jd}}\right) + \zeta_j, \tag{A.7}$$

where $\zeta_j = \frac{\log z_j}{1-k_j}$.

Saiz (2010) estimated the role of physical and regulatory constraints in 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).[2] We then choose the values of ζ_j to match the rent levels observed in the data.

A.10 *InMAP and derivation of the SR matrix*

In this section, we provide a broad overview of InMAP and our process for deriving our pollution-transfer matrix that maps electricity generation in a given NERC region to ambient concentration in a given CBSA.

InMAP and ISRM The Intervention Model for Air Pollution (InMAP, Tessum, Hill, and Marshall (2017)), is a reduced-complexity air transport model that allows users to estimate how changes in emissions impact concentration nationally. InMAP takes into account atmospheric chemistry, local meteorological conditions (i.e., wind), and variables regarding the point of emission—such as stack height and velocity at which the particle was emitted. To estimate particulate matter concentration, InMAP uses data on emissions of primary $PM_{2.5}$ and secondary pollutants that react with gasses in the air and form $PM_{2.5}$. The secondary pollutants InMAP uses are Volatile Organic Compounds (VOC), Nitrogen Oxides (NOx), Ammonia, (NH3), and Sulfur Oxides (SOx). InMAP estimates concentrations for grid cells that vary by population; for urban areas, the grid cells are small, and for rural areas, they are large—making the model computationally expedient.

In Goodkind, Tessum, Coggins, Hill, and Marshall (2019) InMAP is run over 150,000 times to obtain average transfer coefficients for each grid cell—resulting in the InMAP SR matrix (ISRM). Furthermore, ISRM has 3 "height" layers for each of the grid cell; 0 to 57 m, 57–379 m, and $>$379 m. The Python code provided by Goodkind et al. (2019) uses information about a plant's stack height and the velocity at which the particle is emitted to estimate which of these three height layers the plume of the emissions at any given point fall into.

Derivation of the pollution transfer matrix Let $\delta_{R,j}^{\mathrm{PM}_{2.5}}$ be the conversion factor of electricity produced in region R to concentrations of $PM_{2.5}$ in city j. We calculate $\delta_{R,j}^{\mathrm{PM}_{2.5}}$ as an emissions weighted average of conversion factors for each individual power plant in region R. Let s index an individual source (power plant) and $S(R)$ be the set of all sources within NERC region R. Let $\delta_{s,j}^{\mathrm{PM}_{2.5}}$ be source s's conversion factor between electricity production and $PM_{2.5}$ concentration in city j. This is given by

$$\delta_{s,j}^{\mathrm{PM}_{2.5}} = \frac{\mathrm{PM}_{2.5,s,j}}{x_s^{\mathrm{elec}}}, \tag{A.8}$$

[2]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.

where $PM_{2.5,s,j}$ is the ambient air pollution in city j originating form source s (in NERC region R) and x_s^{elec} is the total electricity produced by source s. Then we compute $\delta_{R,j}^{PM_{2.5}}$ as the emissions weighted average of these source-level conversion factors:

$$\delta_{s,j}^{PM_{2.5}} = \frac{\sum_{s \in S(R)} x_s^{elec} \delta_{s,j}^{PM_{2.5}}}{\sum_{s \in S(R)} x_s^{elec}}. \tag{A.9}$$

Plugging (A.8) into (A.9) yields

$$\delta_{s,j}^{PM_{2.5}} = \frac{\sum_{s \in S(R)} PM_{2.5,s,j}}{\sum_{s \in S(R)} x_s^{elec}}, \tag{A.10}$$

where $\sum_{s \in S(R)} PM_{2.5,s,j}$ is the average ambient $PM_{2.5}$ concentration in city j, originating from region R and x_s^{elec} is total electricity production in region R.[3] $\sum_{s \in S(R)} PM_{2.5,s,j}$ is estimated via ISRM by setting pollutant emissions in all regions $R' \neq R$ to zero, and computing the resulting ambient concentration in all cities for emissions from just region R. We note that ISRM only has coefficients for the contiguous United States; thus for Hawaii, we set all transfer coefficients to zero. In the model, this means that the level of particulate matter in Honolulu is fixed and no particulate matter from Honolulu is transferred to the rest of the United States.

A.11 *Derivation of mean utility estimating equation*

Mean utility is given by

$$\mu_{jdt} = \frac{\left(1 + \alpha_d^H + \sum_m \alpha_{jd}^m\right)}{\sigma_d} \log I_{jdt} - \frac{\alpha_d^H}{\sigma_d} \log R_{jt} - \sum_m \frac{\alpha_{jd}^m}{\sigma_d} \log P_{jt}^m + \hat{\xi}_{jdt}.$$

Recall that we have defined $\tilde{\alpha}_{jd}^m = \frac{\alpha_{jd}^m}{1+\alpha_d^H+\sum_m \alpha_{jd}^m}$. Therefore, it is fairly straightforward to show that

$$\sum_{m'} \alpha_{jd}^{m'} = \frac{\sum_{m'} \tilde{\alpha}_{jd}^{m'} (1 + \alpha_d^H)}{1 - \sum_{m'} \tilde{\alpha}_{jd}^{m'}}$$

and, therefore, that

$$\alpha_{jd}^m = \frac{\tilde{\alpha}_{jd}^m (1 + \alpha_d^H)}{1 - \sum_{m'} \tilde{\alpha}_{jd}^{m'}}.$$

[3] In practice, we calculate $PM_{2.5,s,j}$ as population-weighted averages within a CBSA.

Plugging these identities into the mean utility expression yields

$$\mu_{jdt} = \frac{\left(1+\alpha_d^H + \frac{\sum_m \tilde{\alpha}_{jd}^m (1+\alpha_d^H)}{1-\sum_m \tilde{\alpha}_{jd}^m}\right)}{\sigma_d} \log I_{jdt} - \frac{\alpha_d^H}{\sigma_d} \log R_{jt} - \frac{(1+\alpha_d^H)}{1-\sum_{m'} \tilde{\alpha}_{jd}^{m'}} \sum_m \frac{\tilde{\alpha}_{jd}^m}{\sigma_d} \log P_{jt}^m + \hat{\xi}_{jdt}.$$

We can rearrange this to yield

$$\mu_{jdt} = \frac{(1+\alpha_d^H)}{\sigma_d} \frac{\log I_{jdt} - \sum_m \tilde{\alpha}_{jd}^m \log P_{jt}^m}{1-\sum_m \tilde{\alpha}_{jd}^m} - \frac{(\alpha_d^H)}{\sigma_d} \log R_{jt} + \xi_{jdt}.$$

Defining $\tilde{I}_{jdt} = \frac{\log I_{jdt} - \sum_m (\tilde{\alpha}_{jd}^m \log P_{jt}^m)}{1-\sum_m \tilde{\alpha}_{jd}^m}$, $\beta_d^w = \frac{(1+\alpha_d^H)}{\sigma_d}$ and $\beta_d^r = \frac{(\alpha_d^H)}{\sigma_d}$, we arrive at the estimating equation:

$$\mu_{jdt} = \beta_d^w \tilde{I}_{jdt} + \beta_d^r \log R_{jt} + \xi_{jdt}.$$

Appendix B: Results appendix: For online publication only

B.1 *Comparisons of specification of control function*

Table B.1 compares various specifications of the selection control function in estimating (3), which we use to generate selection-corrected predicted emissions. For each specification, we estimate the predicted emissions in each CBSA. Then we calculate the population-weighted mean, standard deviation, and correlation with the Wharton Regulation Index across CBSAs.

Panel I gives the predicted emissions without any selection correction. Row I(a) simply gives the mean emissions without including any demographic controls and I(b) estimates (3) without any selection correction but with demographics controls.

Panel II includes the results with different specification of the control function $M(\cdot)$. Subpanel II(a) present estimates in which $M(\cdot)$ is a function of the probability of choosing the state in question, and the probabilities of choosing the three largest states. Row II(a.i) present our preferred specification, where the selection controls function consists of the probability of choosing the state in question entering linearly, the probabilities of choosing the three largest states entering linearly, and the interactions between the probability of choosing the state in question and each of the three largest state choice probabilities.

The following rows give alternative specifications in which state choice probabilities enter as a quadratic, in which the probability of choosing the state in question also enters as a quadratic, and in which the interaction terms are omitted. Subpanel

TABLE B.1. Comparisons of various specifications of selection control function. See text for details.

	Mean	Standard Deviation	Correlation w/ Land Use Restrictions
I. No selection correction			
a. Raw means	24,946	5729	−0.18
b. OLS	23,711	5526	−0.21
II. Selection correction			
a. Choice location and 3 biggest states			
i. Linear choice, linear states, choice × state interactions	25,518	5740	−0.28
ii. Linear choice, quadratic states, choice × state interactions	26,815	6622	−0.22
iii. Linear choice, linear states, no interactions	23,934	5652	−0.28
iv. Linear choice, quadratic states, no interactions	24,107	5488	−0.28
v. Quadratic choice, linear states, choice × state interactions	33,185	12,114	−0.21
vi. Quadratic choice, quadratic states, choice × state interactions	32,300	11,747	−0.24
vii. Quadratic choice, linear states, no interactions	32,581	11,328	−0.27
viii. Quadratic choice, quadratic states, no interactions	31,199	10,508	−0.23
b. Choice location and 5 biggest states			
i. Linear choice, linear states, choice × state interactions	27,635	6801	−0.17
ii. Linear choice, quadratic states, choice × state interactions	27,339	7073	−0.19
iii. Linear choice, linear states, no interactions	23,940	5654	−0.28
iv. Linear choice, quadratic states, no interactions	24,203	5483	−0.26
v. Quadratic choice, linear states, choice × state interactions	32,277	11,283	−0.17
vi. Quadratic choice, quadratic states, choice × state interactions	30,837	11,252	−0.20
vii. Quadratic choice, linear states, no interactions	32,679	11,563	−0.28
viii. Quadratic choice, quadratic states, no interactions	31,150	10,662	−0.23
c. Choice location and birth states			
i. Linear choice, linear birth state	25,327	6147	−0.32
ii. Linear choice, quadratic birth state	25,467	6202	−0.32
iii. Quadratic choice, linear birth state	30,878	9608	−0.22
iv. Quadratic choice, quadratic birth state	30,416	9308	−0.23
d. Controls for climate in birth state			
i. Linear choice, linear states, choice × state interactions	23,418	5667	−0.12
ii. Linear choice, quadratic states, choice × state interactions	25,281	6524	−0.19
iii. Linear choice, linear states, no interactions	20,369	6609	−0.15
iv. Linear choice, quadratic states, no interactions	22,764	6262	−0.25

II(b) considers the same specification except where we include the probabilities of choosing the 5 largest states. Finally, Subpanel II(c) consider a control function written as a function of choosing the state in question and choosing the individual's birth state.

Subpanel II(d) compare estimates when we also include controls for the average yearly temperature in the state of birth. The specifications are otherwise identical to those in Subpanel II(a.i) through II(a.iv), in which we include controls for the three largest states by population, and the probably of choosing the state in question.

In general, the estimates are relatively similar across specifications. The exception is when the choice probability of the state in question enters as quadratic. In these cases, the standard deviation of the predicted emissions increases. As mentioned before, estimating the intercept of the energy usage equation relies on extrapolating the control function to $P_{\mathrm{is}(j)} = 1$. For smaller states, the probability of choosing the state in question is further from one, so this extrapolation becomes more sensitive to the choice of the control function.

B.2 *Additional summary statistics: No selection correction*

In this section, we replicate our Table 1 and our main descriptive scatterplots without demographic controls and the selection correction.

Table B.2 gives estimates of energy usage and emissions by CBSA, where estimates of energy use are simply given by the unconditional mean for households living in the CBSA. There are no controls for demographic and no selection-correction is implemented.

The next figures are replicates of Figures 1 and 2 without selection-corrected energy usage. Figure B.1 plots household carbon emissions against the Wharton Index. In the scatterplot on the left, we predict household energy use with a simple OLS regression that controls for demographic groups. In the scatterplot on the right, we predict household energy use with CBSA-level means. Overall, the pattern is qualitatively quite similar regardless of the specification; California cities have low household carbon emissions and relatively tight land-use restrictions.

Figure B.2 plots household natural gas usage against January temperature and electricity usage against August temperature. In the two scatterplots in the top row, we predict household energy use with a simple OLS regression that controls for demographic groups. In the scatterplots on the bottom row, we predict household energy use with CBSA-level means.

B.3 $PM_{2.5}$*: Additional results*

This section provides additional summary information about $PM_{2.5}$. Figure B.3 plots the distribution of *total* $PM_{2.5}$ concentrations across cities and Figure B.4 the estimated contribution of household electricity to total $PM_{2.5}$.

From Figure B.3, there are a few key takeaways. First, the histogram demonstrates considerable variation across CBSAs in terms of total $PM_{2.5}$. Second, California cities are relatively dispersed throughout the distribution—some are relatively clean, while others have high concentrations of $PM_{2.5}$.

Next, Figure B.4 with the city-level ratios of household electricity contribution to total $PM_{2.5}$ illustrates two things. Overall, household electricity contributes fairly little to overall $PM_{2.5}$. Second, the amount by which household electricity use contributes to total $PM_{2.5}$ varies across cities; Portland gets near zero percent of its particulate matter emissions from electricity, while Dallas gets roughly 6.5%.

TABLE B.2. 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 in 2017. The third column ("Emissions") shows the *unconditional mean* 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.

CBSA	Rank	Emissions (1000 lbs)	Gas Emissions (1000 lbs)	Fuel Emissions (1000 lbs)	Electricity Use (MwH)	Electricity Conversion (1000 lbs/MwH)	Electricity Emissions (1000 lbs)
Lowest							
Honolulu, HI	1	12.83	0.47	0.07	8.08	1.52	12.29
Oxnard, CA	2	12.85	5.80	0.17	8.61	0.80	6.89
Riverside, CA	3	13.64	5.59	0.17	9.85	0.80	7.88
Los Angeles, CA	4	14.41	6.06	0.09	10.32	0.80	8.26
San Diego, CA	5	14.87	6.42	0.23	10.27	0.80	8.22
Sacramento, CA	6	15.84	7.28	0.40	10.20	0.80	8.16
Middle							
Atlanta, GA	33	25.24	6.46	0.17	17.97	1.04	18.61
Pittsburgh, PA	34	25.77	11.43	1.35	11.74	1.11	12.98
Akron, OH	35	25.85	12.05	0.58	11.95	1.11	13.21
Birmingham, AL	36	26.10	5.42	0.17	19.81	1.04	20.51
Virginia Beach, VA	37	26.19	6.12	0.71	18.70	1.04	19.36
Houston, TX	38	26.37	4.62	0.08	21.35	1.01	21.67
Highest							
Oklahoma City, OK	65	32.29	8.26	0.20	18.76	1.27	23.84
Detroit, MI	66	32.48	18.72	0.36	12.12	1.11	13.40
Philadelphia, PA	67	33.32	11.39	3.12	17.02	1.11	18.81
Memphis, TN	68	34.45	8.37	0.19	25.01	1.04	25.89
Milwaukee, WI	69	35.22	16.71	0.52	16.28	1.11	17.99
Omaha, NE	70	35.98	15.79	0.28	16.31	1.22	19.91

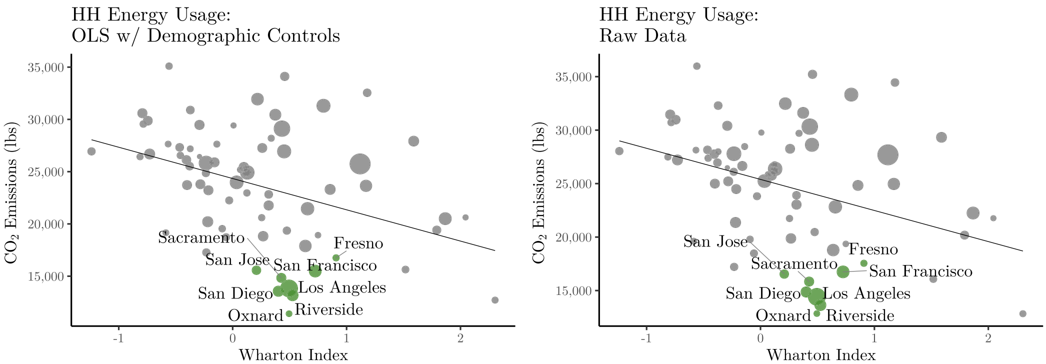

FIGURE B.1. Additional scatterplots in which CO_2 emissions are plotted against the Wharton Index. An observation is a CBSA; a larger circle represents a larger population.

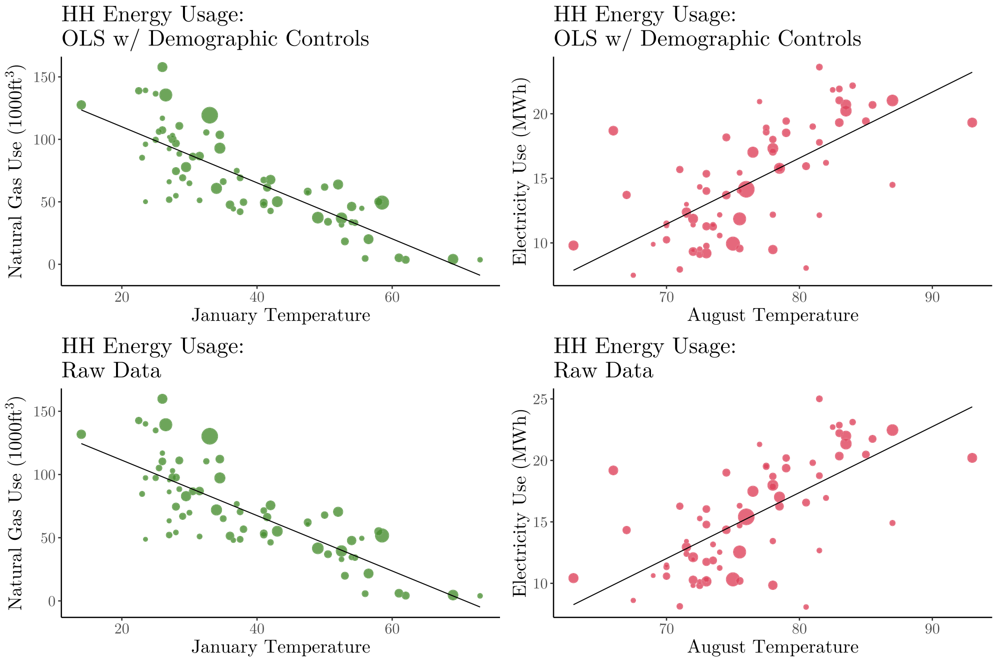

FIGURE B.2. Additional scatterplots in which natural gas and electricity use are plotted against January and August temperatures, respectively. January and August temperature refers to the midpoint between average daily highs and lows for the given month. An observation is a CBSA; a larger circle represents a larger population.

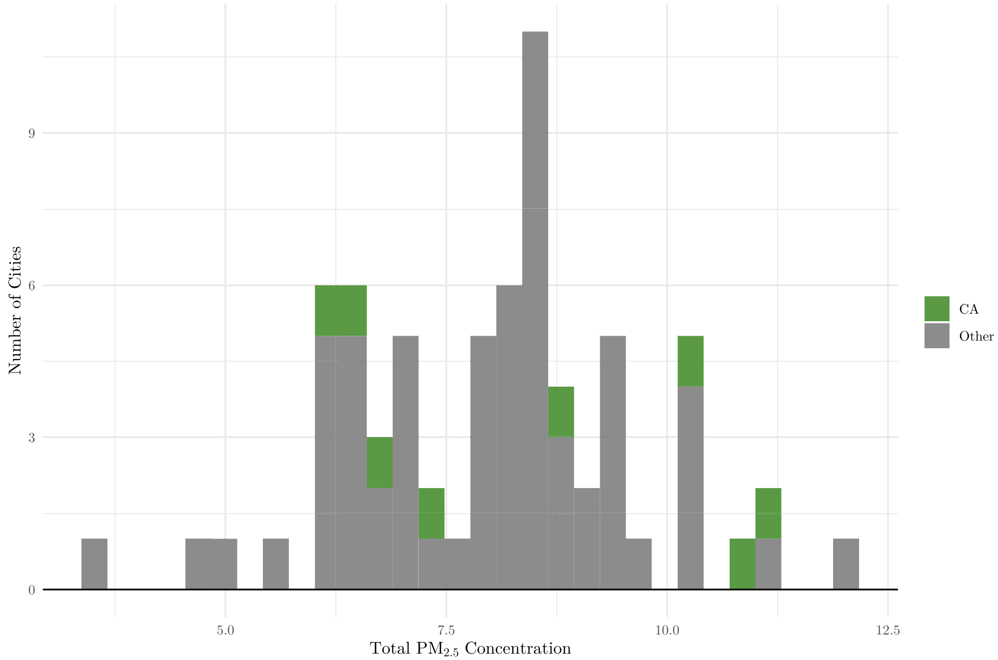

FIGURE B.3. The distribution of 2017 mean $PM_{2.5}$ across CBSAs in our sample.

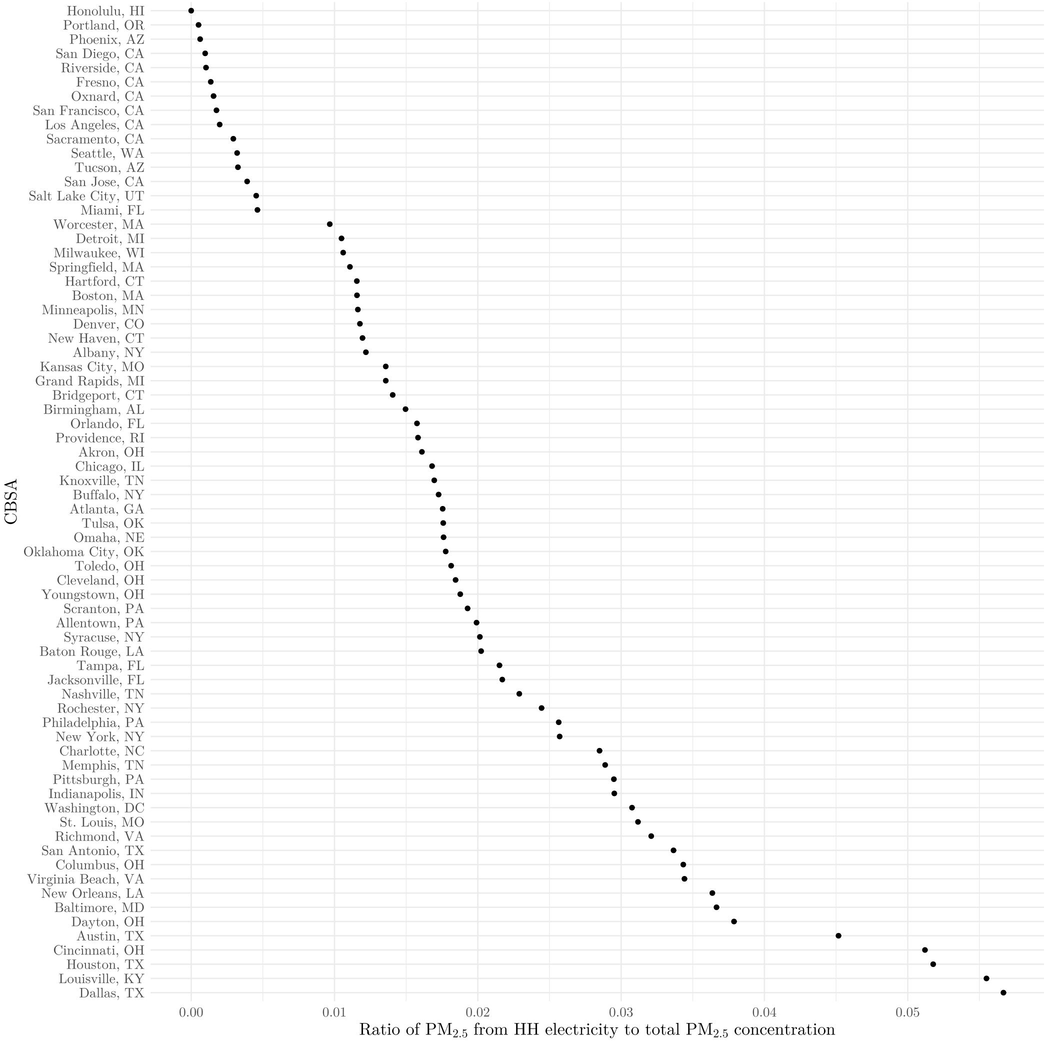

FIGURE B.4. This figure plots the ratio of $PM_{2.5}$ coming from electricity to total $PM_{2.5}$ as measured by the EPA.

Next, Figure B.5 plots a histogram of $PM_{2.5}$ changes from the baseline when we set land-use restrictions to the level faced by the median urban household in all cities.

B.4 *Robustness of main parameter estimates*

Table B.3 gives estimates that vary by age of the household head. The first three columns give estimates for single households, married households without children, and married households with children for which the head of the households is under 35 years old. The next three columns present estimates for single households, married households without children, and married households with children for which the head of the households is over 35 years old. The estimates of β^w and β^r are slightly larger in magni-

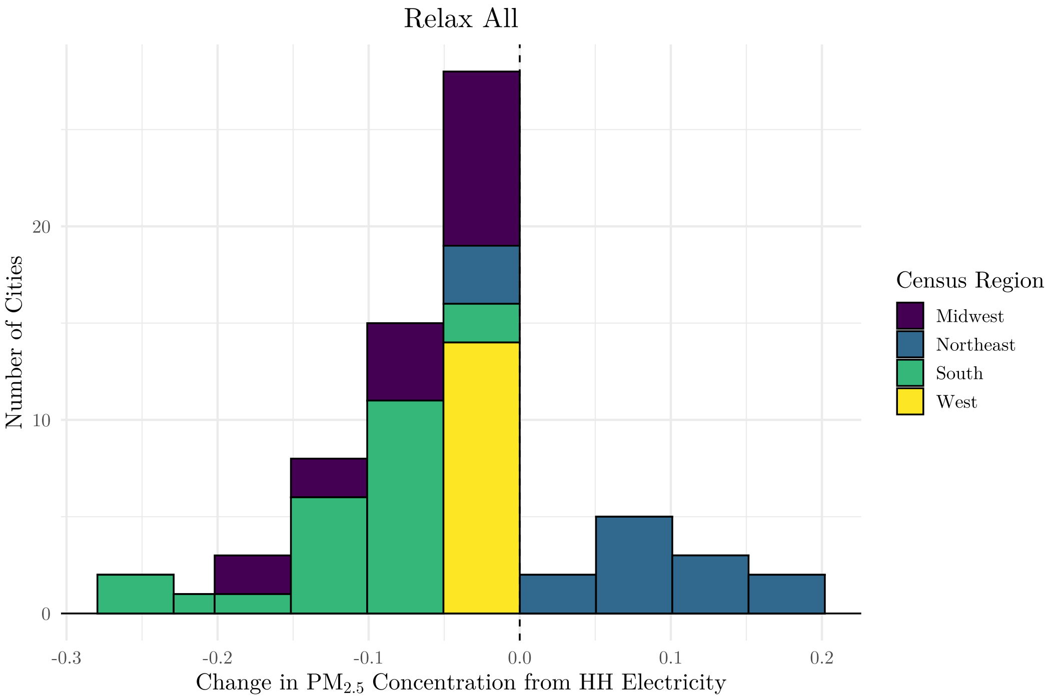

FIGURE B.5. Histogram of CBSA level differences in particulate matter concentration from electricity relative when land-use restrictions in all cities are relaxed relative to the baseline.

tude for households with older household heads conditional on marital status and the presence of children.

Table B.4 gives estimates using alternative instrumental variables. The first panel presents our baseline estimates. Panel II uses estimates where we use the measure of land-use availability from Saiz (2010) in place or the Wharton Land Use Index. Panel III presents estimates when we use both measures as instruments.

TABLE B.3. Parameter estimates. Standard errors in parentheses.

	Head under 35 years experience			Head over 35 years experience		
		Married			Married	
	Single	No children	With children	Single	No children	With children
β^w: Adjusted income	13.37	9.96	7.35	16.81	13.45	7.37
	(3.48)	(2.62)	(2.16)	(4.45)	(3.58)	(2.01)
β^r: Rent	−7.27	−5.02	−5.13	−10.77	−8.76	−4.56
	(2.99)	(2.27)	(1.92)	(3.79)	(3.09)	(1.74)
σ: Idiosyncratic component	0.16	0.20	0.45	0.17	0.21	0.36
	(0.04)	(0.05)	(0.20)	(0.06)	(0.07)	(0.12)
α^H: Housing parameter	1.19	1.02	2.30	1.79	1.87	1.62
	(0.56)	(0.51)	(1.37)	(0.83)	(0.90)	(0.79)
Cragg–Donald Wald F Statistic	3.92	4.04	4.27	4.16	4.24	4.29

TABLE B.4. Parameter estimates. Standard errors in parentheses.

		Married	
	Single	No children	With children
I. Baseline estimates			
β^w: Adjusted income	15.09	11.72	7.33
	(2.80)	(2.19)	(1.47)
β^r: Rent	−9.03	−6.90	−4.82
	(2.40)	(1.89)	(1.29)
σ: Idiosyncratic component	0.17	0.21	0.40
	(0.03)	(0.04)	(0.11)
α^H: Housing parameter	1.49	1.44	1.92
	(0.48)	(0.48)	(0.73)
Cragg–Donald Wald F Statistic	8.09	8.28	8.57
II. Available land instrument			
β^w: Adjusted income	19.39	18.36	16.14
	(4.66)	(4.52)	(4.07)
β^r: Rent	−9.99	−9.06	−9.22
	(3.00)	(2.88)	(2.62)
σ: Idiosyncratic component	0.11	0.11	0.14
	(0.03)	(0.03)	(0.04)
α^H: Housing parameter	1.06	0.98	1.33
	(0.28)	(0.26)	(0.36)
Cragg-Donald Wald F Statistic	5.41	5.14	5.05
III. Both instruments			
β^w: Adjusted income	15.42	12.40	9.08
	(2.36)	(1.90)	(1.46)
β^r: Rent	−8.43	−6.46	−5.61
	(1.73)	(1.39)	(1.09)
σ: Idiosyncratic component	0.14	0.17	0.29
	(0.02)	(0.03)	(0.06)
α^H: Housing parameter	1.20	1.09	1.61
	(0.26)	(0.24)	(0.38)
Cragg–Donald Wald F Statistic	7.91	8.10	8.21

B.5 *New power plant development*

Table B.5 gives the full distribution of emissions and percent of plants that are renewables, split on whether they were constructed before or after 2000.

B.6 *Counterfactual results with model extensions*

Endogenous electricity pricing Table B.6 displays the counterfactual results when electricity pricing is endogenous.

TABLE B.5. NERC regional mean carbon emissions from plants built before 2000 and after 2000. Emissions rates are measured in lbs/MWh.

	Mean emissions		Percent renewables	
NERC	Pre-2000s	Post-2000s	Pre-2000s	Post 2000s
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 B.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 simulation.

	Baseline	Relax Cali	Relax All
I. Percent total population			
California cities	9.1	10.9	7.3
Other West	13.6	13.1	17.1
Midwest	22.2	21.8	10.0
South	37.3	36.6	25.3
Northeast	17.9	17.6	40.3
II. Mean usage			
Gas (1000 cubic feet)	74.4	74.2	75.1
Electricity (MW h)	17.1	17.0	15.5
Fuel oil (gallons)	60.4	59.5	133.0
III. Mean emissions (lbs of CO2)			
Gas	8711	8688	8792
Electricity	16,331	16,267	14,030
Fuel oil	1622	1599	3572
Total	26,664	26,553	26,394
(%)	100.00	99.6	99.0
IV. Average log income			
Skilled	100.0	100.5	112.3
Unskilled	100.0	100.0	100.1
All	100.0	100.2	104.4

Table B.7. Counterfactual results with pollution in the utility function. 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 Section 8.3 for details.

	Baseline	Relax Cali	Relax All
I. Percent total population			
California cities	9.1	11.0	7.2
Other West	13.6	13.1	17.8
Midwest	22.2	21.7	9.3
South	37.3	36.6	23.1
Northeast	17.9	17.6	42.6
II. Mean usage			
Gas (1000 cubic feet)	74.4	74.2	74.9
Electricity (MW h)	17.1	17.0	15.8
Fuel oil (gallons)	60.4	59.5	138.6
III. Mean emissions (lbs of CO2)			
Gas	8711	8686	8771
Electricity	16,331	16,211	13,246
Fuel oil	1622	1598	3722
Total	26,664	26,495	25,738
(%)	100.0	99.4	96.5
IV. Average log income			
Skilled	100.0	100.5	113.0
Unskilled	100.0	100.0	100.4
All	100.0	100.2	104.8

Local pollutants in utility Next, Table B.7 presents counterfactual results in the case where $PM_{2.5}$ enters the utility function. As noted in the text, the results are very similar to the baseline specification, as changes in household electricity are the only component of the model that changes $PM_{2.5}$—and electricity contributes little to overall $PM_{2.5}$.

B.7 *Birth state premium parameters*

Tables B.8 through B.11 display parameters governing the birth state premium for each of the years we use in estimation. In all years, households receive a large utility premium for choosing a location in their home state and the amenity value of a location is decreasing and convex in distance from the household head's birth state.

B.8 *Demographic group city ranks*

Table B.12 provides selected estimated of ξ_{jdt}, the shared unobservable component of amenities, for the year 2017 for households with heads over the age of 35.

TABLE B.8. Parameter estimates for 1990 data. Standard errors multiplied by 1000 in parentheses.

	Young			Old		
		Married			Married	
	Single	w/o children	w/ children	Single	w/o children	w/ children
			Unskilled, Nonwhite			
Birthstate premium	3.14	2.77	2.77	2.94	2.52	2.85
	(0.08)	(0.6)	(0.14)	(0.07)	(0.27)	(0.1)
Distance	−1.78	−1.22	−1.71	−1.78	−1.75	−1.71
	(0.07)	(0.31)	(0.09)	(0.07)	(0.21)	(0.08)
Distance squared	0.3	0.21	0.29	0.2	0.21	0.19
	(0.01)	(0.03)	(0.01)	(0.01)	(0.03)	(0.01)
			Unskilled, White			
Birthstate premium	3.15	3.03	2.94	3.15	3.08	3.13
	(0.02)	(0.06)	(0.02)	(0.01)	(0.02)	(0.01)
Distance	−1.03	−1.41	−2.05	−1.06	−1.03	−1.38
	(0.02)	(0.06)	(0.02)	(0.01)	(0.02)	(0.01)
Distance squared	0.21	0.31	0.54	0.17	0.09	0.25
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
			Skilled, Nonwhite			
Birthstate premium	2.3	2.17	2.43	2.38	2.16	2.37
	(0.47)	(1.99)	(1.1)	(0.4)	(1.21)	(0.46)
Distance	−1.19	−1.04	−1.11	−1.48	−1.09	−1.12
	(0.27)	(0.93)	(0.63)	(0.24)	(0.56)	(0.25)
Distance squared	0.16	0.12	0.14	0.2	0.11	0.09
	(0.03)	(0.08)	(0.06)	(0.02)	(0.05)	(0.02)
			Skilled, White			
Birthstate premium	2.02	2.04	2.1	2.13	1.92	2.11
	(0.05)	(0.1)	(0.06)	(0.04)	(0.05)	(0.02)
Distance	−2.17	−2.16	−2.35	−1.96	−2.05	−2.11
	(0.04)	(0.08)	(0.06)	(0.03)	(0.04)	(0.02)
Distance squared	0.62	0.6	0.64	0.52	0.5	0.54
	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.00)

TABLE B.9. Parameter estimates for 2000 data. Standard errors multiplied by 1000 in parentheses.

	Young			Old		
		Married			Married	
	Single	w/o children	w/ children	Single	w/o children	w/ children
			Unskilled, Nonwhite			
Birthstate premium	3.11	2.62	2.69	2.89	2.66	2.73
	(0.06)	(0.52)	(0.13)	(0.04)	(0.14)	(0.07)
Distance	−1.59	−1.3	−1.55	−1.75	−1.34	−1.71
	(0.05)	(0.29)	(0.09)	(0.03)	(0.11)	(0.05)
Distance squared	0.27	0.23	0.26	0.27	0.16	0.24
	(0.01)	(0.03)	(0.01)	(0.00)	(0.01)	(0.01)
			Unskilled, White			
Birthstate premium	3	3.03	3.16	2.8	2.67	2.9
	(0.02)	(0.08)	(0.03)	(0.01)	(0.01)	(0.01)
Distance	−1.34	−1.37	−1.05	−1.84	−2.07	−1.92
	(0.02)	(0.08)	(0.03)	(0.01)	(0.02)	(0.01)
Distance squared	0.29	0.32	0.19	0.45	0.49	0.47
	(0.00)	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)
			Skilled, Nonwhite			
Birthstate premium	2.22	2.02	2.33	2.37	2.15	2.33
	(0.25)	(1.27)	(0.81)	(0.18)	(0.54)	(0.28)
Distance	−1.13	−1.12	−1.19	−1.37	−1.06	−1.02
	(0.14)	(0.65)	(0.45)	(0.11)	(0.27)	(0.15)
Distance squared	0.17	0.15	0.18	0.2	0.12	0.09
	(0.01)	(0.06)	(0.04)	(0.01)	(0.02)	(0.01)
			Skilled, White			
Birthstate premium	2.08	2.15	2.2	2.21	2.01	2.13
	(0.04)	(0.1)	(0.07)	(0.03)	(0.03)	(0.02)
Distance	−2.04	−2.01	−2.3	−1.73	−1.96	−2
	(0.03)	(0.08)	(0.07)	(0.02)	(0.03)	(0.02)
Distance squared	0.59	0.55	0.63	0.46	0.51	0.53
	(0.01)	(0.02)	(0.01)	(0.00)	(0.01)	(0.00)

TABLE B.10. Parameter estimates for 2010 data. Standard errors multiplied by 1000 in parentheses.

	Young			Old		
		Married			Married	
	Single	w/o children	w/ children	Single	w/o children	w/ children
			Unskilled, Nonwhite			
Birthstate Premium	3.09	2.57	2.57	2.87	2.76	2.85
	(0.07)	(0.75)	(0.2)	(0.03)	(0.11)	(0.09)
Distance	−1.61	−1.19	−1.49	−1.65	−1.3	−1.27
	(0.06)	(0.41)	(0.13)	(0.03)	(0.09)	(0.06)
Distance Squared	0.28	0.22	0.25	0.25	0.16	0.15
	(0.01)	(0.04)	(0.01)	(0.00)	(0.01)	(0.01)
			Unskilled, White			
Birthstate Premium	2.83	2.85	2.72	2.77	2.63	2.74
	(0.02)	(0.1)	(0.04)	(0.01)	(0.01)	(0.01)
Distance	−1.79	−1.36	−2.12	−1.8	−2.17	−2.02
	(0.02)	(0.09)	(0.04)	(0.01)	(0.01)	(0.01)
Distance Squared	0.41	0.31	0.5	0.45	0.57	0.49
	(0.01)	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)
			Skilled, Nonwhite			
Birthstate premium	2.31	1.99	2.16	2.44	2.18	2.21
	(0.19)	(0.95)	(0.58)	(0.12)	(0.31)	(0.2)
Distance	−1.03	−1.06	−1.51	−1.25	−1.13	−1.1
	(0.11)	(0.48)	(0.35)	(0.07)	(0.17)	(0.1)
Distance squared	0.15	0.15	0.24	0.18	0.13	0.11
	(0.01)	(0.05)	(0.03)	(0.01)	(0.02)	(0.01)
			Skilled, White			
Birthstate premium	2.15	2.19	2.37	2.2	2.02	2.09
	(0.04)	(0.08)	(0.06)	(0.02)	(0.02)	(0.01)
Distance	−2.04	−2.03	−2.02	−1.8	−1.89	−2.16
	(0.03)	(0.07)	(0.06)	(0.01)	(0.02)	(0.01)
Distance squared	0.57	0.55	0.51	0.48	0.49	0.6
	(0.01)	(0.02)	(0.02)	(0.00)	(0.00)	(0.00)

TABLE B.11. Parameter estimates for 2017 data. Standard errors multiplied by 1000 in parentheses.

	Young			Old		
		Married			Married	
	Single	w/o children	w/ children	Single	w/o children	w/ children
Less than College, Nonwhite						
Birthstate premium	3.14	2.34	2.68	2.98	2.75	2.94
	(0.07)	(0.68)	(0.25)	(0.03)	(0.11)	(0.09)
Distance	−1.58	−1.22	−1.31	−1.62	−1.54	−1.17
	(0.06)	(0.33)	(0.16)	(0.03)	(0.09)	(0.06)
Distance squared	0.27	0.22	0.21	0.24	0.22	0.12
	(0.01)	(0.03)	(0.02)	(0.00)	(0.01)	(0.01)
Less than College, White						
Birthstate premium	2.89	2.84	2.84	2.7	2.66	2.82
	(0.02)	(0.11)	(0.04)	(0.01)	(0.01)	(0.01)
Distance	−1.8	−1.42	−1.6	−2.04	−2.16	−1.87
	(0.03)	(0.11)	(0.04)	(0.01)	(0.01)	(0.01)
Distance squared	0.43	0.34	0.34	0.52	0.56	0.43
	(0.01)	(0.04)	(0.01)	(0.00)	(0.00)	(0.00)
College or More, Nonwhite						
Birthstate premium	2.35	2.01	2.38	2.53	2.04	2.26
	(0.15)	(0.74)	(0.54)	(0.09)	(0.24)	(0.16)
Distance	−0.91	−0.91	−1.09	−1.25	−1.38	−1.05
	(0.08)	(0.36)	(0.32)	(0.06)	(0.13)	(0.08)
Distance squared	0.14	0.13	0.15	0.18	0.19	0.11
	(0.01)	(0.04)	(0.03)	(0.01)	(0.01)	(0.01)
College or More, White						
Birthstate premium	2.21	2.23	2.37	2.3	2.02	2.13
	(0.03)	(0.07)	(0.05)	(0.02)	(0.02)	(0.01)
Distance	−1.99	−1.92	−2.3	−1.8	−1.94	−2.2
	(0.02)	(0.06)	(0.06)	(0.01)	(0.02)	(0.01)
Distance squared	0.58	0.52	0.62	0.5	0.51	0.61
	(0.01)	(0.02)	(0.02)	(0.00)	(0.00)	(0.00)

TABLE B.12. Demographic group city ranks according to the shared, unobservable component of amenities for households with older household heads.

	College or more		Less than College	
Rank	Single (no kids)	Married (with kids)	Single (no kids)	Married (with kids)
		Panel (a): White		
1	Miami, FL	Portland, OR	San Diego, CA	Seattle, WA
2	Portland, OR	Miami, FL	Miami, FL	Portland, OR
3	Los Angeles, CA	Seattle, WA	Portland, OR	Los Angeles, CA
4	San Diego, CA	Los Angeles, CA	Seattle, WA	Honolulu, HI
5	Orlando, FL	San Diego, CA	Oxnard, CA	San Diego, CA
66	Youngstown, OH	Memphis, TN	Springfield, MA	Memphis, TN
67	Bridgeport, CT	Worcester, MA	Worcester, MA	Springfield, MA
68	Memphis, TN	Springfield, MA	Albany, NY	Worcester, MA
69	Worcester, MA	Syracuse, NY	Rochester, NY	Albany, NY
70	Syracuse, NY	Youngstown, OH	Syracuse, NY	Syracuse, NY
		Panel (b): Nonwhite		
1	Los Angeles, CA	Los Angeles, CA	Los Angeles, CA	Los Angeles, CA
2	San Francisco, CA	Honolulu, HI	Miami, FL	Honolulu, HI
3	Miami, FL	Miami, FL	San Francisco, CA	Seattle, WA
4	Honolulu, HI	San Francisco, CA	San Diego, CA	San Francisco, CA
5	San Diego, CA	San Diego, CA	Seattle, WA	Portland, OR
66	Albany, NY	Knoxville, TN	Springfield, MA	Springfield, MA
67	Memphis, TN	Syracuse, NY	Syracuse, NY	Albany, NY
68	Syracuse, NY	Springfield, MA	Albany, NY	Syracuse, NY
69	Rochester, NY	Scranton, PA	Milwaukee, WI	Rochester, NY
70	Milwaukee, WI	Youngstown, OH	Rochester, NY	Milwaukee, WI

B.9 *Methane emissions*

As an alternative to carbon-dioxide emissions, we also explore the relationship between 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 compared to carbon dioxide.

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

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 to 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 B.13 provides an array of city-level energy consumption, ranked on methane emis-

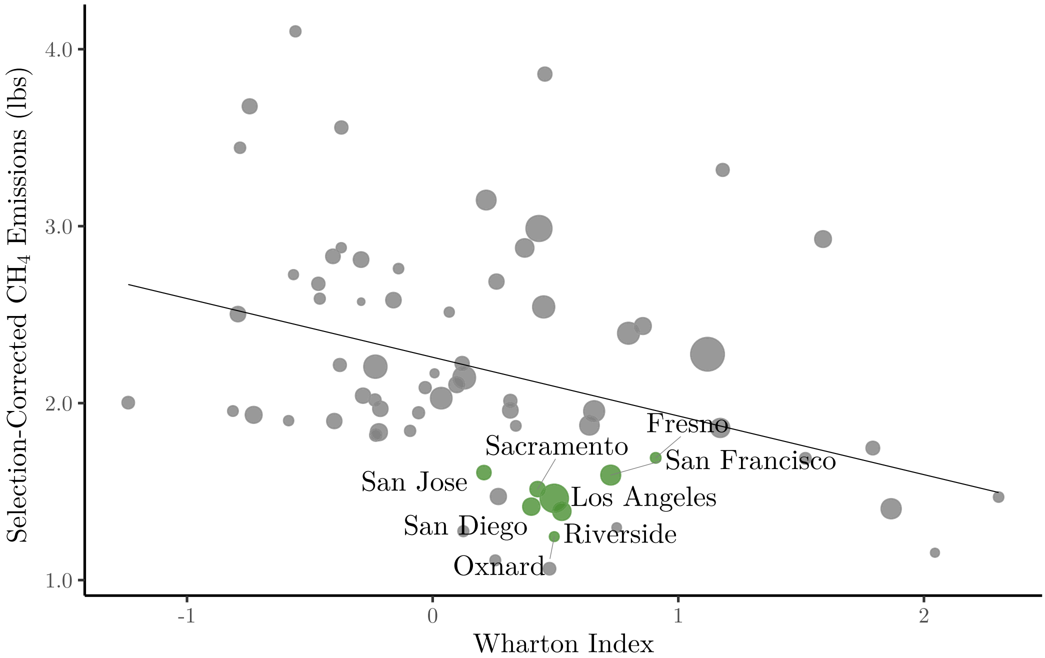

FIGURE B.6. Methane emissions regressed on Wharton Index. Each observation is a CBSA. Size of each observation reflects population of CBSA.

sions. Figure B.6 presents the relation between methane emissions and land-use restrictions. Figure B.7 presents this relationship when we calculate city-level methane usage via OLS and as the raw average methane emissions.

Our main counterfactual was to relax land-use restrictions 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 the relaxation of the land-use restrictions. To estimate average CBSA level emissions, we multiplied the respective usages by the

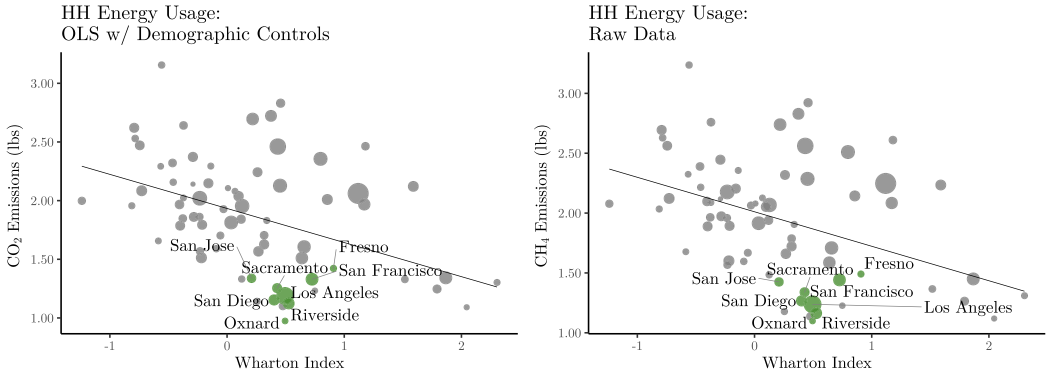

FIGURE B.7. Methane emissions regressed on Wharton Index. Each observation is a CBSA. The size of each observation reflects the population of CBSA.

TABLE B.13. 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 selection-corrected *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.

CBSA	Rank	Emissions (1000 lbs)	Gas Emissions (1000 lbs)	Electricity Use (MwH)	Electricity Conversion (1000 lbs per MwH)	Electricity Emissions (1000 lbs)
Lowest						
Hartford, CT	1	1.06	0.29	13.48	0.06	0.77
New Haven, CT	2	1.11	0.29	14.32	0.06	0.82
Worcester, MA	3	1.15	0.39	13.33	0.06	0.76
Oxnard, CA	4	1.25	0.56	10.26	0.07	0.69
Bridgeport, CT	5	1.28	0.42	15.06	0.06	0.86
Springfield, MA	6	1.30	0.56	12.83	0.06	0.73
Middle						
New Orleans, LA	33	2.00	0.41	21.38	0.07	1.59
Jacksonville, FL	34	2.01	0.06	25.92	0.08	1.96
Birmingham, AL	35	2.02	0.52	20.15	0.07	1.50
Atlanta, GA	36	2.03	0.36	22.45	0.07	1.67
Austin, TX	37	2.04	0.34	22.00	0.08	1.70
Salt Lake City, UT	38	2.09	1.26	12.36	0.07	0.83
Highest						
Memphis, TN	65	3.32	0.95	31.89	0.07	2.37
Tulsa, OK	66	3.44	1.12	21.60	0.11	2.32
Oklahoma City, OK	67	3.56	1.06	23.21	0.11	2.50
Indianapolis, IN	68	3.68	2.08	18.26	0.09	1.60
Milwaukee, WI	69	3.86	1.96	21.72	0.09	1.90
Omaha, NE	70	4.10	1.55	22.84	0.11	2.55

TABLE B.14. Counterfactual results for methane emissions. Each column shows the amount of methane emitted from each energy source under various counterfactual scenarios.

	Baseline	Relax Cali	Relax All
II. Emissions (lbs of Methane)			
Gas	0.78	0.78	0.79
Electricity	1.33	1.32	1.16
Fuel oil	0.00	0.00	0.00
Total	2.11	2.10	1.95

local emissions factors for each type of carbon dioxide. We can use the same simulation to examine the changes in methane emissions by using conversion factors for methane emissions. Table B.14 demonstrates how methane emissions change as a result of our simulation.

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