The Distributional Impacts of Climate Changes across US Local Labor Markets

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Abstract

Climate change has affected households around the globe, but its impacts are not homogenous across space. We first show that disadvantaged demographic groups are disproportionately exposed to climate change in the US and are less responsive in their adaptive behavior. Motivated by these findings, we develop and estimate a spatial equilibrium model of US local labor markets, allowing households to adapt to climate change by choosing where to live and, conditional on that choice, energy and housing consumption. Our results show that climate change to date has caused welfare losses 20% larger for black households relative to white households and twice as large for the lowest income decile relative to the highest income decile. We estimate that these gaps will continue to grow under projections of the future climate. Both the population's ex-ante distribution and differential mobility contribute to the observed disparities. We then evaluate a $3 billion place-based policy from the Inflation Reduction Act, quantifying the tradeoff between subsizing places with high climate damages and the resulting in-migration to climate-exposed areas.

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1 Introduction

Climate change has led to adverse economic outcomes across the globe as households face rising temperatures, sea levels, and natural disaster risks (U. S. Global Change Research Program, 2023). However, there are considerable differences in exposure to climate change across space, both globally and within the United States (Hsiang et al., 2017; Wing et al., 2022; Cruz and Rossi-Hansberg, 2023). For example, climate change has given cold areas like New England milder winters and hot regions like the South East more extreme summers. These changes have significant distributional implications, as the hotter locations within the US are generally poorer and less white than the cold locations.

Assessing the welfare effects of climate change requires accounting not only for exposure but also for households' capacity to adapt. Adaptation may exacerbate disparities in climate-related damages across demographic groups. Economically advantaged households have access to more effective mitigation strategies, while disadvantaged households with limited resources to adapt may experience larger impacts even when facing similar levels of exposure (e.g., Heilmann, Kahn, and Tang, 2021). These differences in exposure and adaptive capacity may deepen the environmental and social inequalities documented in the environmental justice literature (Cain et al., 2023).

In this paper, we use a quantitative spatial equilibrium model of US local labor markets in the spirit of Rosen (1979) and Roback (1982) to quantify heterogeneity in the effects of climate change, allowing for households to adapt through migration and home energy use. In the model, heterogeneous households make static choices over where to live and how much energy and housing to consume. Their location choice is affected by potential wages earned, housing and energy costs, and amenities available in each city. Wages and rents are determined in equilibrium. Firms with varying productivity levels across cities demand labor, using college- and non-college-educated workers as imperfect substitutes. Each city has a housing supply curve, with rents responding endogenously to household location choices.

There are two ways that the climate affects household choices—through home energy demand and amenities. Air conditioning and residential energy use is a critical form of adaptation to climate change (Barreca et al., 2016). We model demand for "comfort," which households produce using electricity, natural gas, and housing as inputs. This notion of comfort production, inspired by Quigley and Rubinfeld (1989), captures the process by which people alter their indoor living space by combining the physical characteristics of a house and the use of appliances such as air conditioners, heaters, or dehumidifiers powered by natural gas or electricity. The climate is also an input into the comfort production function, generating differences in the marginal productivity of electricity, natural gas, and housing. For example, if outdoor temperatures increase, households must use their air conditioner more intensely to maintain the same indoor temperature, thus increasing electricity consumption while holding comfort constant. An energy justice literature suggests that the energy costs associated with climate change will be higher for minority and low-income households (Reames, 2016; Lyubich, 2020). We estimate the parameters driving heterogeneity in household mobility and comfort costs, and critically, allow households to make adaptation decisions endogenously in the model.

Second, climate affects the shared amenities of each location. These amenity values capture how households value the climate when assessing the desirability of a location—for example, households may prefer milder summers. We richly characterize the amenity value of each city's climate using heating and cooling degree days, precipitation patterns, and natural disaster risk. Spatial heterogeneity in exposure to climate change will alter some households' relative rankings of locations—allowing them to mitigate the impact of climate change by moving to a new location (Cruz and Rossi-Hansberg, 2023). There is considerable heterogeneity in household mobility, with the literature consistently finding that lower-income households are less mobile than higher-income households (Kennan and Walker, 2011; Depro, Timmins, and O'Neil, 2015; Piyapromdee, 2021).

We quantify the model with publicly available census data from Ruggles et al. (2022), historical climate data from PRISM (PRISM Climate Group, 2022), and natural disaster risk data from First Street Foundation (First Street Foundation, 2022a,b). We specify the household "comfort" production function and estimate its parameters using relative electricity and gas demand, relative electricity and gas prices, and the climate. The estimated comfort production function allows us to predict energy and housing demand in counterfactual climates. We then estimate the model's key household location choice parameters using the two-step estimator proposed in Berry, Levinsohn, and Pakes (2004), including the amenity value of climate. The first step uses actual household-level location choices to estimate moving costs and the component of city-level utility common among households of the same demographic group, which we call the "mean utilities." The second step uses linear regression to decompose the mean utilities into contributions from wages, rents and energy bills, and climate amenities.

We use our estimated model to simulate the welfare effects from climate change across households in the US, both that have already occurred and that we predict to occur over the next century using state-of-the-art downscaled future climate models shared by Climate Impact Lab (Gergel et al., 2023). We then decompose the contribution of each factor that contributes to the unequal impacts. First, we simulate a counterfactual where we fix household locations, wages, and rents. We call this the "mechanical" effect since it does not allow households to reoptimize across space, thus capturing differences in exposure and comfort costs. However, we can eliminate differences in exposure by comparing welfare within cities, therefore isolating differences in comfort costs. Next, we simulate counterfactuals where households can sort across locations, but we fix wages and rents at their baseline levels. We call this the "sorting" effect as it reflects how differences in mobility impact inequality relative to the "mechanical" effect. We can again condition on location in order to isolate differences in mobility from differences in exposure. Finally, we allow complete flexibility—households can sort across locations, and all prices are determined in equilibrium—to demonstrate the effect of endogenous changes in rents and wages on the welfare effects of climate change.

We find significant distributional consequences of climate change both presently and in the future. Black and low-income households are particularly vulnerable, experiencing negative impacts not only due to their initial exposure to climate change but also due to disparities in their adaptive capacity. Our analysis reveals that, up to this point, black households have suffered 20% greater climate damages compared to white households, and we project this disparity to widen under future emissions scenarios. In the most extreme emissions scenario, we estimate that the gap will increase by over eightfold by the end of the century. Additionally, the welfare losses from climate change accrue disproportionately to lower-income households. The lowest income decile has lost 4% of income from climate change to date, whereas the highest income decile only has losses of 2% of income. The black-white gap remains throughout the income distribution but is larger at lower incomes.

Our model decomposition reveals that the ex-ante distribution of the population is the most significant contributor to these gaps, followed by differences in mobility and, to less of an extent, differences in energy efficiency. When we fix locations, we find that Black households are worse off than white households by 0.8% of income. However, this gap disappears after conditioning on baseline location, suggesting that differences in comfort costs are not contributing to the average gap. When we allow households to sort across locations, the average gap remains at the same level as when fixing locations, while the gap conditional on baseline location increases to 0.5% of income. Thus, Black households are less able to mitigate welfare losses through migration relative to similarly exposed white households.

We then turn to using the model to evaluate the effects of a means-tested, place-based policy inspired by the US Environmental Protection Agency's Community Change Grant program. The Inflation Reduction Act (IRA) allocated $3 billion to the Community Change Grant program, which funds projects in disadvantaged communities with the stated goal of improving climate resiliency (US EPA, 2023). Our results suggest that while the current program helps disadvantaged households generally, it does not help the people most hurt by climate change. We then test alternative spatial distributions of the subsidies. Subsidizing the places most hurt by climate change helps the people most hurt by climate change. However, these subsidies attract marginal households from elsewhere in the country to high-climate-damage cities, thus increasing exposure to climate change. Alternatively, we distribute the subsidies to "climate havens," places where climate amenities have improved. While this distribution of subsidies reduces exposure to climate change, most of the funds go to households that are already relatively well off from a climate perspective. Policymakers must weigh the benefits of spatially targeted of subsidies with their associated effect on the spatial distribution of the population.

Our paper follows a rich literature using spatial equilibrium models to estimate the economic impact of the climate or other environmental goods (Wrenn, 2023; Albouy et al., 2016; Hamilton and Phaneuf, 2015; Bayer, Keohane, and Timmins, 2009). In particular, Albouy et al. (2016) estimates the amenity value of days across the temperature distribution in the US, a methodology we lean heavily on in our own estimation. Wrenn (2023) estimate household MWTP for natural disasters using Rosen-Roback model, but do not run counterfactuals, nor explore the environmental justice considerations. Another set of papers considers migration an adaptation mechanism to climate change in global spatial equilibrium models (Desmet and Rossi-Hansberg, 2015; Desmet et al., 2021; Cruz and Rossi-Hansberg, 2023), but are more focused on quantifying differences in the welfare impacts across space rather than by demographic group. Most similarly, Rudik et al. (2021) estimate a dynamic spatial equilibrium model with daily temperature affecting amenities and firm productivity. They determine that migration is progressive, showing that the benefits of migration correlate with state-level income. We complement their work by formally analyzing the distributional effects of climate change using household-level data on race, education, and income. Meanwhile, their data and estimation strategy, using migration flows between states, limits them to state-level analysis.

We are also related to a set of papers on the effects of climate on energy use (Davis and Gertler, 2015; Rode et al., 2021; Doremus, Jacqz, and Johnston, 2022; Auffhammer, 2022). Their work inspires our strategy for estimating the impact of climate on energy demand. Auffhammer and Mansur (2014) review the literature on the effects of climate change on energy demand. They emphasize a gap in our understanding of climate change's long-run extensive margin effects on energy demand. Notably, our paper addresses two concerns with the existing intensive margin literature: we explicitly deal with sorting across locations and do not assume a constant interior temperature to measure welfare effects.

This paper also contributes to the broad environmental justice literature, recently reviewed in Cain et al. (2023). Several papers study the literature on the interaction between household migration decisions and environmental justice (Bayer, Keohane, and Timmins, 2009; Depro, Timmins, and O'Neil, 2015; Hausman and Stolper, 2021). These analyses focus on how sorting contributes to differences in measured exposure to environmental pollutants, as described in Banzhaf, Ma, and Timmins (2019). We extend this sorting mechanism to climate change.

Methodologically, our model builds on the quantitative spatial equilibrium literature (Diamond, 2016; Piyapromdee, 2021; Colas and Morehouse, 2022). These papers analyze other settings with spatial consequences, allowing rents and wages respond endogenously in general equilibrium to household location choices. Using a similar framework, Morehouse (2022) demonstrates that a first-order concern about enacting serious climate-change regulation (i.e., a carbon tax) is a fear of distributional consequences. Here, we show that there are also significant distributional effects from a lack of climate policy.

2 Data and Descriptive Evidence

We begin by describing the main data sources used throughout the analysis. We break these into three categories: individual household data, climate data, and energy use data. We then show descriptive evidence of the spatial heterogeneity in climate change to-date and how the changes correlate with demographics.

2.1 Data

Household Data. We use repeated cross-sections from the 1990 and 2000 censuses and the 2010 and 2019 5-year aggregated ACS surveys (Ruggles et al., 2022). These give us household demographic information, city, income, employment status, housing, electricity, and natural gas expenditures. We follow standard sample selection and data-cleaning techniques described in Appendix A. From these data, we estimate city-education level wages, city-level rents, and city-demographic group-level energy expenditure for each year. As these indices are standard in the literature, we leave the details in Appendix A.2.

Climate Data We collect historical weather data from the PRISM climate group (PRISM Climate Group, 2022). Specifically, we use the 4-kilometer grid of daily average temperature and precipitation to create a panel of daily temperature and precipitation for each of the CBSAs in our model.[1] We aggregate the gridded data to the CBSA level using the weighted average of grid cells within each CBSA, where we weight by the fraction of the CBSA covered by the grid cell and the 1990 population in the grid cell. Population rasters come from SEDAC (CIESIN, 2017). We then construct various annual summary measures of climate in each city. Following the recent literature, we count the number of days each year in a set of discrete temperature bins (Auffhammer, 2022). We also calculate the percent of days with no rain as those with less than one mm of precipitation. Since in some cases we are interested in the effects of changes in climate, not short-run weather shocks, we take the 5-year moving averages of each of our annual weather variables.

We pair this factual climate data with future climate simulations from the Climate Impact Lab's global downscaled projections for climate impacts research, CIP-GDPCIR (Gergel et al.,

[1] Since the PRISM data only cover the continental US, we collect daily weather station observations from NOAA for stations in Honolulu (Menne et al., 2012), then take the population weighted average of those observations.

2023). These data result from downscaling and debiasing[2] 25 climate models for four emissions scenarios, each with daily precipitation and maximum and minimum surface temperature to 2100. We aggregate these to CBSA-level values by taking a population-weighted average as we do with the PRISM data. We then take the average of the 25 climate models to form an ensemble prediction of daily average temperature and total precipitation. Similarly to the PRISM data, we aggregate the climate model grid to the city level by taking the weighted average of the grid cells within each CBSA, where we weight by 1990 population and the fraction of the CBSA covered by the grid cell.

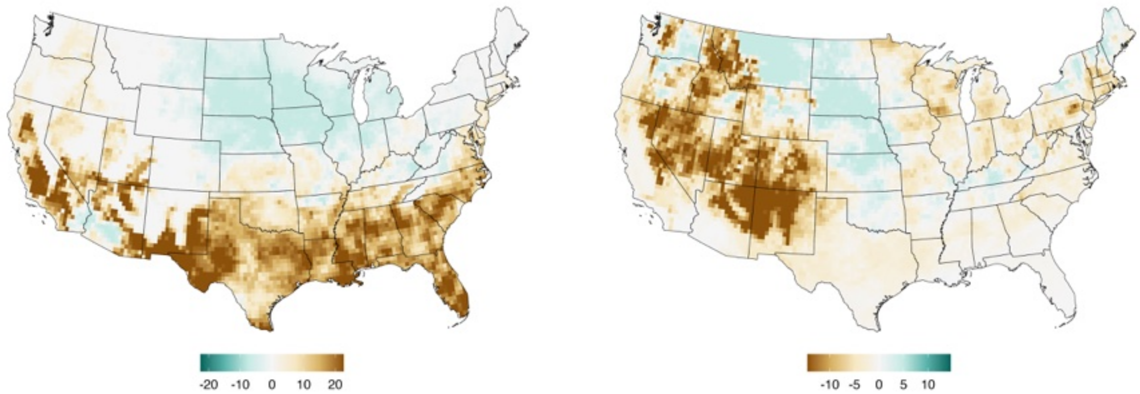
Finally, we use data on natural disaster risks—specifically, First Street Foundation's fire and flood scores aggregated to the zip-code level (First Street Foundation, 2022a,b). They use state-of-the-art fire and flood models to calculate a risk score between 1 and 10 associated with the respective disasters for every property in the US. We calculate various aggregations of the scores for each city—for example, the median score or the percent of properties in specific score ranges. Appendix B has maps of the average risk scores by census tract. While these are presently static, we hope to gain access to time-varying risk scores historically and in the future under different emissions scenarios.

Energy Data. We supplement data on household energy expenditure from the census with state-level annual electricity prices from the EIA. We use these prices to back out energy usage from total expenditures. To address the concern that some households may not report energy expenditures separately from rent,[3] we follow Glaeser and Kahn (2010) in using the Residential Energy Consumption Survey (RECS) to correct for this issue. The details of this estimation are in Appendix A.2.1. We first estimate city-demographic group level energy use for single family homeowners from the Census and ACS data, as those households are most likely to report their expenditures accurately. We then use the RECS to estimate the relationship between energy use for single-family homeowners and multi-family homeowners, single-family renters, and multi-family renters.

2.2 Descriptive Evidence

Geography of climate change Climate change is often talked about as increases in average global temperatures, but this masks significant spatial heterogeneity in the degree and impact of change. Figure 1 shows the change in the number of hot and cold days, above the 90th and below the 10th percentiles of the 1990 temperature distribution, respectively, between 1990 and 2019. The hotter portions of the U.S. have seen significant increases in hot days, while the cold places in the U.S. have seen significant decreases in cold days. Appendix B shows that the

[2] The original models produce output on a 1-degree grid, and the CIP-GDPCIR data downscale this to a 0.25-degree grid.
[3] If their utilities are included as part of rent, for example.



(a) Change in the number of hot days per year **(b)** Change in the number cold days per year

Figure 1: Change in the number of hot and cold days between 1990 and 2019. Hot days are those with an average temperature above the 90th percentile of the temperature distribution, or about 80°F. Cold days are below the 10th percentile, or about 32°F. Difference taken between 5 year moving averages and are censored at the 5th and 95th percentiles of grid cells.

eastern US has generally gotten wetter—higher annual precipitation and fewer days with no rain.

Heterogeneity in the impact of climate change is important because it alters the relative attractiveness of cities. Some cities, such as those in the northeast, may have become more attractive to households as their winters are now milder than previously. Other cities, such as Oklahoma City or Dallas, might have become less attractive now that their already-hot summers have become hotter. These distortions in climate will lead to changes in the share of the population that chooses to live in each city in the long run, with households taking climate into account when considering the utility they would get from choosing a particular city.

Demographics of climate change We are interested in determining whether climate change has differentially affected different demographic groups. Here we look at how variation in demographic makeup between cities in 1990 compare to changes in the climate between 1990 and 2019. By looking at demographics in 1990, we avoid endogenous city-choice sorting that has resulted from changes in the climate.

Figure 2 shows the relationship between the share of a city's population in the lowest income quintile in 1990 and how cold and hot days have changed since 1990. The two have a clear positive association, though the different climate variables require different interpretations. Cities with larger population shares in the lowest income quintile tend to have seen the smallest decrease in cold days. Meanwhile, cities with a higher share of low-income households have seen the largest increase in hot days. Both of these suggest that climate change is regressive – cities with more poor people have had changes in their climate that require spending

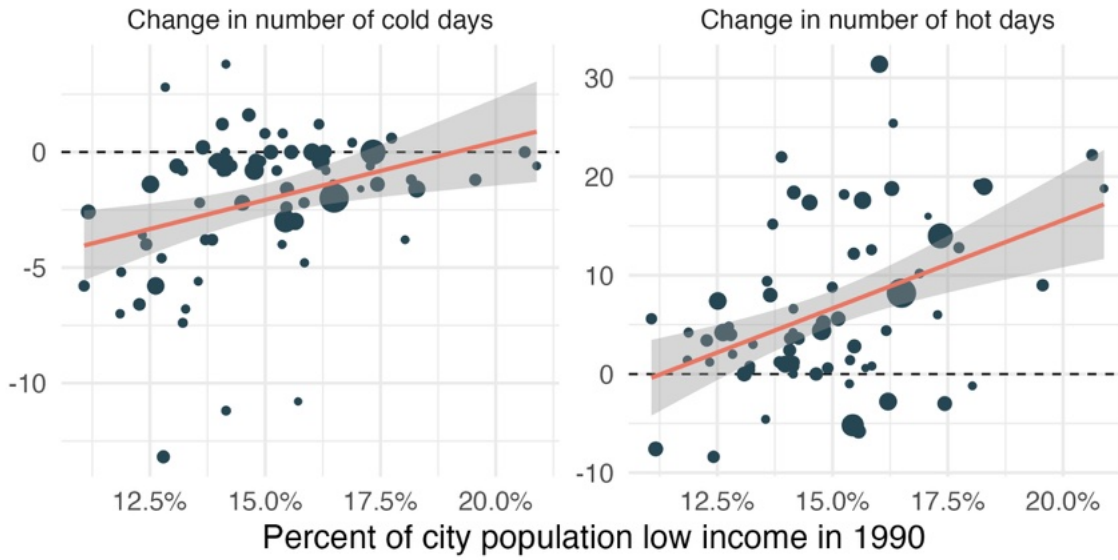


Figure 2: Relationship between income and climate change. Each point is a city, where the size of the point represents the city's 1990 population. Low income defined as households in the bottom quintile of the national income distribution in 1990. Regression lines are weighted by population.

more on heating and cooling to maintain the same indoor temperature relative to cities with fewer poor people. A similar relationship holds for the share of non-white households in cities, as seen in Figure 3. Appendix B has similar figures for precipitation, showing that a similar relationship holds for total precipitation.

We can also summarize the change in climate experienced by the average white and non-white household. The average non-white household experienced 38 (5.1%) more cooling degree days and 303 (12.9%) fewer heating degree days than the average white household in 1990. Between 1990 and 2019, cooling degree days increased by 110 (14.7%) and heating degree days decreased by 126 (5.4%) for white households. Meanwhile, for non-white households, CDDs increased by 124 (15.9%) and HDDs decreased by 125 (6.1%). So the average non-white household experienced an additional 14 (13.5%) cooling degree day increase relative to white households while already having a higher baseline cooling degree day level.

These results suggest that disadvantaged demographic groups have faced disproportionate exposure to the adverse effects of climate change. Lower-income and less white cities have more hot days, while higher-income and more white cities have fewer cold days. However, the welfare effects of climate change may me more or less equitable once we account for adaptation. While the ability to adapt is greater among more economically advantaged households, households

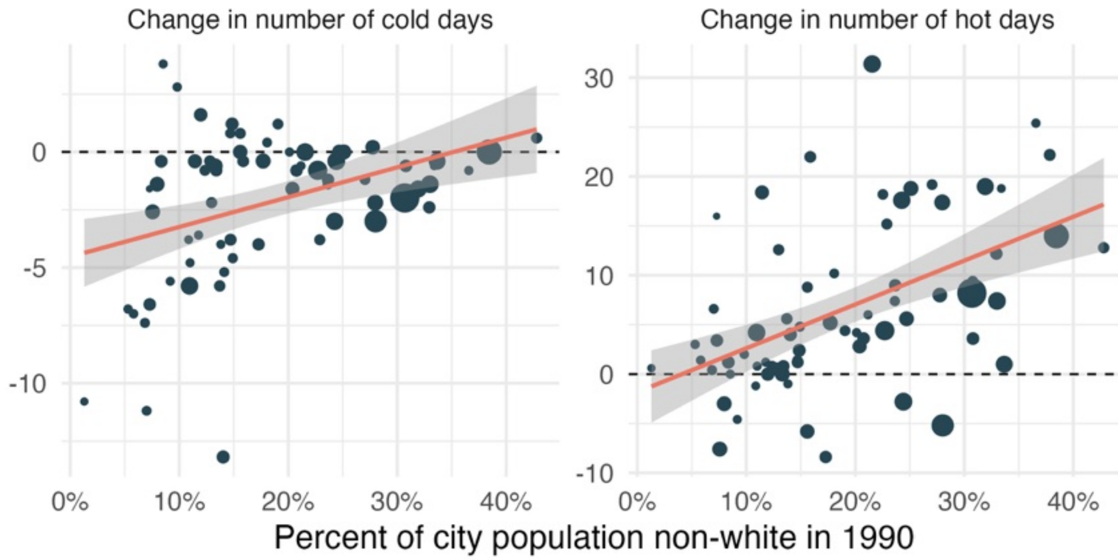


Figure 3: Relationship between share non-white and climate.Each point is a city, where the size of the point represents the city's 1990 population. Low income defined as households in the bottom quintile of the national income distribution in 1990. Regression lines are weighted by population.

that are more exposed have a greater need for adaptation.

Energy use and demographics There is robust evidence from the energy justice literature that black households spend more on energy than observably similar white households (Reames, 2016; Lyubich, 2020). This gap suggests that there may also be differences across demographic groups in the response of household energy demand to climate. We explore this in depth in Appendix B.1. We first replicate the results in Lyubich (2020), finding a conditional energy expenditure gap between black and white households throughout the income distribution. We then find that energy expenditures for black households are more responsive to additional cold weather and less responsive to additional hot weather than white households.

3 Model

In this section, we develop a Rosen (1979) and Roback (1982) style spatial equilibrium model where households make a static, discrete choice of where to live. Conditional on that location, households pick consumption of electricity, natural gas, housing, and the numeraire. Cities vary in their wages, rents, and amenities. The climate impacts household choices through two mechanisms: the amenities available in each city and the marginal benefits of electricity, gas, and housing consumption.

Amenities in the model reflect non-market characteristics of cities that make them more or less desirable, including the climate. We use a rich characterization of the climate as amenities to capture a broad range of values that households have for the climate, for example, outdoor recreation or the risk of physical damage from natural disasters. Additionally, households have an imperfect ability to transform the outdoor environment into a comfortable indoor environment with housing and heating or cooling appliances. In the model, households use housing, electricity, and natural gas as inputs to produce indoor "comfort".[4] The climate affects the marginal benefits of inputs to the comfort production function. For example, if there are fewer cold days in a year, households require less natural gas to heat their homes, which we capture as a decrease in the marginal benefit of natural gas use.

We allow for rich heterogeneity in the parameters governing household mobility. We specify an individual-level moving cost function to capture the psychic costs of relocating.[5] Additionally, households have a location-specific idiosyncratic preference shock that allows us to relax the spatial indifference condition of traditional Rosen-Roback models.[6] The variance of this preference shock governs the elasticities of household location choices. A higher variance means that households have stronger individual preferences for locations relative to the shared components of utility.

Firms in each city produce the tradable numeraire with imperfectly substitutable skilled and unskilled labor. Each city also has an upward-sloping housing supply curve, the slope of which reflects differences in difficulty in developing new housing. These firms and housing supply curves complete the labor and housing markets that allow wages and rents to respond endogenously to household location choices.[7]

3.1 Households

Let $j \in J$ index cities and $d \in D$ index demographic groups. We omit t subscripts for exposition, but re-introduce them when describing the estimation. Household i living in city j receives utility from a composite numeraire good, X, "comfort in dwelling" C, and location-specific amenities $\mathbb{A}$. We specify this utility in traditional Cobb-Douglas form,

$$U_{ij} = X^{\alpha_d^X} C_{dj}^{\alpha_d^C} \exp(\mathbb{A}_{ij}).$$

Households produce comfort using electricity, gas, and housing, which we specify as a

[4] We use a similar notion of comfort to that found in Quigley and Rubinfeld (1989).

[5] Bayer, Keohane, and Timmins (2009) emphasize the importance of including these moving costs.

[6] The spatial indifference condition requires households to receive the same utility from all cities in equilibrium. Busso, Gregory, and Kline (2013) and Kline and Moretti (2014) demonstrate the importance of relaxing such a constraint.

[7] We define an equilibrium for our model in Appendix C.6.

nested CES production function. This production function captures the utility services provided by electricity, gas, and housing. For example, electricity does not give people utility directly, but an air conditioner can use electricity to provide cool indoor temperatures in a bedroom. Specifically, let comfort C be:

$$C(H, \mathcal{E}|d, j) = A^c_{dj}\left(\theta^H_{dj}H^{\rho_c} + \theta^{\mathcal{E}}_{dj}\mathcal{E}^{\rho_c}\right)^{1/\rho_c}. \tag{1}$$

where H is housing and $\mathcal{E}$ is energy. The measure of housing, H, represents both the quantity and quality of housing—i.e. both an additional room in a house and a more recently built house could be interpreted as higher values of H. $\sigma_C = \frac{1}{1-\rho_C}$ is the elasticity of substitution between housing and energy. This aggregation reflects the imperfect complementarity or substitutability between energy and housing. For example, larger houses may require more energy to heat or cool, or a newer home may be better insulated, requiring less energy to heat or cool, all else equal. $\mathcal{E}(\cdot)$ is the household's energy production function, which we parameterize as

$$\mathcal{E}(E, G|d, j) = \left(\theta^E_{dj}E^{\rho_{\mathcal{E}}}_{dj} + \theta^G_{dj}G^{\rho_{\mathcal{E}}}_{dj}\right)^{1/\rho_{\mathcal{E}}}, \tag{2}$$

where $\sigma_{\mathcal{E}} = \frac{1}{1-\rho_{\mathcal{E}}}$ is the elasticity of substitution between electricity, E, and natural gas, G. Climate impacts the production of comfort through θ^m_{dj}, where $\theta^m_{dj} = f(\boldsymbol{Z}_j; \boldsymbol{\kappa}^m_d)$ for $m \in \{E, G\}$, where $\boldsymbol{Z}_j$ is a vector of local climate variables and $\boldsymbol{\kappa}^m_d$ is a parameter vector governing the potentially non-linear shape of $f(\cdot)$. Since we do not normalize the share parameters to sum to one, we can think of these parameters as affecting the productivity of electricity and gas in both relative and absolute terms. We provide more intuiton on the effect of climate on housing and energy demand in Section 3.1.1.

Finally, we specify amenities as

$$\mathbb{A}_{ij} = \boldsymbol{\alpha}^Z_d \cdot \boldsymbol{Z}_j + \xi_{dj} + g(j, \boldsymbol{b}_i) + \sigma_d \varepsilon_{ij},$$

where $\boldsymbol{\alpha}^Z_d$ is a vector of parameters on a vector of climate variables $\boldsymbol{Z}_j$, ξ_{dj} is a shared, unobservable component of amenities, $g(j, \boldsymbol{b}_i)$ are moving costs as a function of the household's birth state, $\boldsymbol{b}_i$ and location j, and ε_{ij} is an idiosyncratic preference draw with variance σ_d. A higher variance in the idiosyncratic utility parameter reduces household mobility, as larger changes in the other components of utility would be required to overcome the idiosyncratic term. We parameterize moving costs, $g(\cdot)$, as:

$$g(j, \boldsymbol{b}_i) = \gamma^{st}_d \mathbb{I}\left(j \in b^{st}_i\right) + \gamma^{\text{dist}}_d \phi\left(j, b^{st}_i\right) + \gamma^{\text{dist2}}_d \phi^2\left(j, b^{st}_i\right), \tag{3}$$

where $\mathbb{I}\left(j \in b_i^{st}\right)$ is an indicator for j being in household i's birth state, $\phi(j, b_i^{st})$ is the Euclidean distance between location j and the agent's birth state b_i^{st}, and $\phi^2(j, b_i^{st})$ is the squared Euclidean distance between j and b_i^{st}.

Conditional on choosing location j, households are subject to their budget constraint,

$$I_{dj} + \Upsilon_d = X + P_j^E E + P_j^G G + P_j^H H,$$

where I_{dj} is earned income for demographic group d in city j, Υ_d is unearned income for demographic group d, P_j^E and P_j^G are prices of electricity and gas, and P_j^H is the price of housing. We normalize the price of the composite to one.

We can find the household's utility maximizing choices of electricity, gas, housing, and the numeraire by first solving the nested cost minimizations associated with comfort production, the details of which are in Appendix C.1. Households choose the cost-minimizing combination of electricity and gas to produce a given amount of energy, which we can then use to solve for a unit cost function for energy. We call this unit cost function the "price of energy",

$$P_{dj}^{\mathcal{E}} = \left(\theta_{dj}^{E\ \sigma_{\mathcal{E}}} P_j^{E\ 1-\sigma_{\mathcal{E}}} + \theta_{dj}^{G\ \sigma_{\mathcal{E}}} P_j^{G\ 1-\sigma_{\mathcal{E}}}\right)^{\frac{1}{1-\sigma_{\mathcal{E}}}}. \tag{4}$$

Given this price of energy, households choose a cost-minimizing combination of housing and energy to produce a given amount of comfort. Similarly, we can use the conditional demand functions for housing and energy to solve for the unit cost function of comfort, which we'll call the "price of comfort,"

$$P_{dj}^{C} = \left(\theta_{dj}^{H\ \sigma_c} P_{dj}^{H\ 1-\sigma_c} + \theta_{dj}^{\mathcal{E}\ \sigma_c} P_{dj}^{\mathcal{E}\ 1-\sigma_c}\right)^{\frac{1}{1-\sigma_c}}. \tag{5}$$

The price of comfort is a useful, and rarely quantified object that reflects the cost of not only housing, but also the energy required to heat or cool that housing.

We can now transform the problem into a simpler form where, conditional on their location choice, households choose comfort and composite good consumption subject to a simplified budget constraint,

$$\max_{X,C} X^{\alpha_d^X} C^{\alpha_d^C} \exp(\mathbb{A}_{ij}) \quad \text{s.t.} \quad I_{dj} + \Upsilon_d = X + P_{dj}^C C_{dj}.$$

This gives us the familiar demand functions for consumption and comfort, $X_{dj}^* = \frac{\alpha_{dj}^X (I_{dj} + \Upsilon_d)}{\boldsymbol{\alpha_{dj}}}$ and

$C^*_{dj} = \frac{\alpha^C_{dj}(I_{dj}+\Upsilon_d)}{\boldsymbol{\alpha_{dj}} P^c_{dj}}$, where we define $\boldsymbol{\alpha_{dj}} = (\alpha^X_{dj} + \alpha^C_{dj})$ to simplify notation. These demand functions yield the following conditional indirect utility function after taking logs,

$$v_{ij} = \boldsymbol{\alpha_{dj}} \log\left(I_{dj} + \Upsilon_d\right) - \alpha^C_{dj} \log(P^C_{dj}) + \boldsymbol{\alpha}^Z_d \cdot \boldsymbol{Z}_j + \xi_{dj} + g(j, \boldsymbol{b}_i) + \sigma_d \varepsilon_{ij}. \tag{6}$$

Assuming ε_d is distributed extreme-value type 1, we can write the probability household i chooses location j as:

$$P_{ij} = \frac{\exp(\tilde{v}_{ij})}{\sum_j \exp(\tilde{v}_{ij})}, \tag{7}$$

where $\tilde{v}_{ij} = v_{ij}\sigma_d^{-1} - \varepsilon_{ij}$.

3.1.1 The impact of climate change on household decisions

In order to clarify the mechanisms through which climate affects household choices in the model, we provide some partial equilibrium derivations here. Consider a change in climate variable $z^l_j \in \boldsymbol{Z}_j$ on household conditional indirect utility holding income, rent, electricity, and gas prices fixed:

$$\frac{\partial v_{ij}}{\partial z^l_j} = \alpha^l_d - \frac{\alpha^C_d}{P^C_{dj}} \times \frac{\partial P^C_{dj}}{\partial z^l_j}. \tag{8}$$

There are two channels through which a change in climate affects utility, the amenity value of a location and the price of producing comfort. The change in amenity value of city j is reflected by $\alpha^l_d \in \boldsymbol{\alpha^Z_d}$. If the change in climate is not desirable, such that α^l_d is negative (i.e., temperatures get hotter in the summer), then the utility households get from living in city j decreases. The second term $\frac{\alpha^C_d}{P^C_{dj}} \times \frac{\partial P^C_{dj}}{\partial z^l_j}$ reflects the effect of the change in the cost of producing comfort inside one's home. Suppose, for simplicity, that the climate variable is one that affects cooling demand (i.e. cooling degree days), where $\partial\theta^E/\partial z^l = \kappa_E$ is the marginal effect on the electricity share parameter and $\partial\theta^G/\partial z^l = 0$. Taking the derivative of the price of comfort given in equation (5), we have

$$\frac{\partial P^C_{dj}}{\partial z^l_j} = \frac{-\kappa_E}{\rho\varepsilon} \frac{P^E_j E_{dj}}{C_{dj}}. \tag{9}$$

The sign of this derivative hinges on the elasticity of substitution between electricity and gas, $\sigma_{\mathcal{E}} = \frac{1}{1-\rho_{\mathcal{E}}}$. If electricity and gas are gross substitutes, such that $\rho_{\mathcal{E}} > 0$ and $\sigma_{\mathcal{E}} > 1$, then $\partial P^C_{dj}/\partial z^l_j < 0$. If electricity and gas are gross complements, such that $\rho_{\mathcal{E}} < 0$ and $\sigma_{\mathcal{E}} < 1$, then $\partial P^C_{dj}/\partial z^l_j > 0$. In the gross complements case, increases in values of θ^E or θ^G caused by changes in the climate lead to a decrease in produced energy for given levels of electricity and gas, thus decreasing the productivity of the household's comfort production function.

Note that this implies that the sign effect of an increase in z^l on indirect utility caused by the change in comfort prices is determined by the sign of κ_E and $\rho_{\mathcal{E}}$. Plugging equation (9) into (10) and simplifying, we get

$$\frac{\partial v_{ij}}{\partial z^l_j} = \alpha^l_d + \frac{\kappa_E}{\rho_{\mathcal{E}}} \frac{P^E_j E_{dj}}{I_{dj} + \Upsilon_d}. \tag{10}$$

We would generally expect both of the terms in Equation (10) to have the same sign, since a change in climate that makes outdoor amenities less desirable typically also makes it more expensive to produce comfort inside. Importantly note that $\partial v_{ij}/\partial z^l_j$ is decreasing in income I_{dj} and increasing in electricity use E_{dj}. Thus, all else equal, households with lower incomes, or higher electricity usage conditional on income will be more affected by changes in the climate. Appendix C.2 has derivations for the marginal effect of climate on electricity, gas, and housing demand.

Now, we consider the effect of the climate variable on a household's city choice probability P_{ij}. Taking the derivative of equation (7), again holding income, rent, electricity, and gas prices constant, we have,

$$\frac{dP_{ij}}{dz^l_j} = \frac{1}{\sigma_d} \frac{\partial v_{ij}}{\partial z^l_j} P_{ij}(1 - P_{ij}). \tag{11}$$

This derivative makes it clear that larger values for variance of the idiosyncratic utility shock, σ_d decrease mobility. Higher values of σ_d mean that the unobserved, idiosyncratic portion of utility an individual has a higher relative weight as compared to wages, rents, and shared amenities. If an individual has a particularly strong affinity for a city, for example due to their social connections or cultural ties, this will make them less sensitive to changes in other aspects of the city, such as wages, rent, or the climate. Note that in general equilibrium, a change in the climate in one city can affect indirect utility in all other cities through endogenous changes in wages and rents. Colas and Saulnier (2023) provide a general derivation for this case—the intuition remains the same, higher values of the variance of idiosyncratic portion of utility decrease responsiveness to the shared components of utility.

3.2 Firms

Firms competing in perfectly competitive markets combine college-educated labor and non-college-educated labor to produce the composite numeraire good. We parameterize the firms' production function as:

$$Y_j = B_j K_j^{\alpha} \mathcal{L}_j^{1-\alpha}, \tag{12}$$

where B_j is city-specific total factor productivity, K_j is capital use, and $\mathcal{L}_j$ is a CES aggregator between the two labor types. More specifically,

$$\mathcal{L}_j = \left(\lambda_j S_j^{\rho_l} + (1-\lambda_j) L_j^{\rho_l}\right)^{\frac{1}{\rho_l}}, \tag{13}$$

where λ_j is the college labor input use intensity in city j, S_j is efficiency units of college labor, L_j is the efficiency units of non-college labor, and $\rho_l = \frac{\sigma_l - 1}{\sigma_l}$ is the elasticity of substitution between college and non-college labor.

Assuming capital supply is perfectly elastic and supplied on an international market (at rate $\bar{r}$), we can write the firm's optimal capital demand as

$$K_j^{\star} = \frac{B_j \alpha Y_j}{\bar{r}}.$$

Plugging this into the firm's production function and then solving for the first order-conditions yields the firm's labor demand curves for college- and non-college educated labor:

$$\begin{aligned} W_j^S &= \tilde{B}_j \mathcal{L}_j^{1-\rho_l} \lambda_j S_j^{\rho_l - 1} \\ W_j^L &= \tilde{B}_j \mathcal{L}_j^{1-\rho_l} (1-\lambda_j) L_j^{\rho_l - 1} \end{aligned} \tag{14}$$

where $\tilde{B}_j = (1-\alpha) B_j^{\frac{1}{1-\alpha}} \left(\frac{\alpha}{\bar{r}}\right)^{\frac{\alpha}{1-\alpha}}$. Appendix C.3 has additional details on the firm's profit maximization problem.

3.3 Rents

Each city is characterized by a long-run, upward sloping rental supply curve, which we parameterize as

$$\log(P_j^h) = a_j + \zeta_j \log(H_j), \tag{15}$$

where P_j^h is the price of housing in city j, a_j is a city-specific intercept capturing construction costs, ζ_j is the inverse elasticity of housing supply, and H_j is the total housing demand in the city. The intercept, a_j, varies across cities due to differences in baseline construction costs, such as the cost of building materials or labor. The elasticity, ζ_j, captures how responsive housing prices are to changes in the quantity of housing demanded. The availability of land for development and local regulatory constraints, such as zoning laws and land-use restrictions, affect the inverse elasticity—more restrictive housing development conditions lead to steeper increases in housing prices.

We assume that rental profit, $\Pi = \sum_j \left(P_j^H H_j - \frac{\exp a_j}{\zeta_j+1} H_j^{\zeta_j+1}\right)$ is distributed back to landowners lump-sum as unearned income, $\Upsilon_d = s_d \Pi$, where s_d is demographic group d's share of investment income.

4 Estimation

In this section, we detail our estimation procedure. We focus our exposition on the estimation of the household demand and labor supply parameters. We use city-level energy, wage, and rent indices in estimating various parts of the model. Details for how we construct these indices can be found in Appendix A.2.

4.1 Energy and Housing Demand

We estimate the parameters of the household's nested CES comfort function in two steps. First, we use the relative demand functions to estimate the elasticity of substitution between electricity and gas, $\sigma_{\mathcal{E}}$, and then the elasticity of substitution between energy and housing, σ_C in first differences. Then, we use the implied values for the θ's to estimate the effect that climate has on comfort production.

We begin by normalizing the energy production function (2) by $\left(\theta_{djt}^G\right)^{1/\rho_{\mathcal{E}}}$ and the comfort production function (1) by $\left(\theta_{djt}^H\right)^{1/\rho_c}$, defining $\tilde{\mathcal{E}}$ and $\tilde{C}$ as

$$\tilde{\mathcal{E}}_t(E, G|d, j) = \left((\theta^E_{djt}/\theta^G_{djt})E^{\rho\varepsilon} + G^{\rho\varepsilon}\right)^{1/\rho\varepsilon} \tag{16}$$

$$\tilde{C}_t(H, \mathcal{E}|d, j) = \left(H^{\rho_c} + \tilde{\theta}^{\mathcal{E}}\tilde{\mathcal{E}}^{\rho_c}_{djt}\right)^{1/\rho\varepsilon}. \tag{17}$$

where $\tilde{\theta}^{\mathcal{E}}_{djt} = \left(\theta^{\mathcal{E}}_{djt}/\theta^H_{djt}\right)\left(\theta^G_{djt}\right)^{\rho c/\rho\varepsilon}$. This normalization allows us to estimate the effect of climate on both θ^E_{djt} and θ^G_{djt}, which is described in further detail below.

4.1.1 Elasticity of substitution estimation

The next step is to derive the first-order conditions from households choosing the cost minimizing combination of electricity and gas to produce a certain quantity of energy. The details of this cost-minimization problem are in Appendix D.1, which yields the following relative demand function for electricity and gas,

$$\log\left(\frac{E_{djt}}{G_{djt}}\right) = \sigma_{\mathcal{E}} \log\left(\frac{\theta^E_{djt}}{\theta^G_{djt}}\right) + \sigma_{\mathcal{E}} \log\left(\frac{P^G_{jt}}{P^E_{jt}}\right). \tag{18}$$

Since we observe quantities demanded and prices for both electricity and gas, we can estimate $\sigma_{\mathcal{E}}$ using linear regression. We take first differences of Equation (18) to arrive at our estimating equation,

$$\Delta \log\left(\frac{E_{djt}}{G_{djt}}\right) = \sigma_{\mathcal{E}} \Delta \log\left(\frac{P^G_{jt}}{P^E_{jt}}\right) + \Delta u_{djt}, \tag{19}$$

As we are concerned with endogeneity when regressing quantities of electricity and gas demanded on the prices of electricity of gas due to the simultaneity of supply and demand, we follow Burke and Abayasekara (2018) and instrument the log ratio of retail electricity and gas prices with the log ratio of lagged commercial electricity and gas prices, where $P^{m,Comm}_{jt}$ for $m \in \{E, G\}$ is the price of electricity or natural gas for commercial customers. Formally, the exclusion restriction is

$$E\left[\Delta \log\left(\frac{P^{G,Comm}_{j,t-1}}{P^{E,Comm}_{j,t-1}}\right) \Delta u_{djt}\right] = 0, \tag{20}$$

where u_{djt} is any other factor affecting the change in the ratio of electricity and gas demand.

Thus, we use variation in energy prices that is driven by supply side factors and not correlated with other factors affecting residential energy demand, including the climate.

With the estimate of $\sigma_{\mathcal{E}}$ in hand, we back out the remaining parameters of the normalized energy function as $\log\left(\theta^E_{djt}/\theta^G_{djt}\right) = \frac{1}{\sigma_{\mathcal{E}}}\log\left(E_{djt}/G_{djt}\right) - \log\left(P^G_{jt}/P^E_{jt}\right)$. This allows us to calculate the quantity and price of normalized energy, using equation (16) and the normalized version of equation (4).

Next, we estimate σ_C, the elasticity of substitution between housing and energy from the comfort production function in the same manner. Agents produce comfort in their dwelling using housing and energy as inputs.[8] Once again, we use the relative conditional demand functions, but now for energy and housing, that result from households choosing the cost-minimizing combination of housing and energy to produce a given amount of comfort,

$$\log\left(\frac{\tilde{\mathcal{E}}_{djt}}{H_{djt}}\right) = \sigma_c \log\tilde{\theta}^{\mathcal{E}}_{djt} + \sigma_c \log\left(\frac{P^H_{jt}}{P^{\mathcal{E}}_{jt}}\right).$$

Taking first differences yields our estimating equation,

$$\Delta\log\left(\frac{\tilde{\mathcal{E}}_{djt}}{H_{djt}}\right) = \sigma_C \Delta\log\left(\frac{P^H_{jt}}{P^{\mathcal{E}}_{jt}}\right) + \Delta\epsilon_{djt}. \tag{21}$$

Note that we do not observe amenities, and many amenities are correlated with both housing demand and rent. For example, consider a city with higher quality restaurants. These restaurants will cause increases in housing prices and housing demand, confounding our parameter estimates. Therefore, we use instrumental variables to isolate exogenous variation in the ratio of rent to energy price. Our instrument interacts labor demand shocks with land availability, where the labor demand shocks are from Katz and Murphy (1992), and the interaction with land availability follows Diamond (2016). We construct the labor demand shocks by multiplying the historical share of workers with the change in the number of workers in the rest of the country. Formally, the labor demand shock is

$$\Delta Z_{djt} = \sum_{\iota\in n} \omega^{1990}_{dj\iota} \times \left(\Delta N_{d,-j,\iota,t}\right), \tag{22}$$

[8] We estimate the quantity of housing, H, by regressing gross rent reported in the data on a set of observable characteristics about the dwelling and a city fixed effect in logs. We interpret the city fixed effect as the cost per unit of housing, and then back out the quantity of housing by dividing gross rent by this per unit cost of housing. Appendix A.2.3 explains this process in detail.

where $\omega_{dj\iota t}^{1990}$ is the share of workers in demographic group d from city j that worked in industry ι in 1990 as a fraction of the total number of workers across all industries in demographic group d in city j. $\Delta N_{d,-j,\iota,t}$ is the change in the number of workers in industry ι between years t and $t-1$ outside of city j. We interact this with the measure of housing supply elasticity from Saiz (2010), which reflects geological and bureaucratic constraints on space to build homes in a city. The exclusion restriction is

$$E\left[\Delta Z_{djt}\Delta\epsilon_{djt}\right] = 0 \tag{23}$$

$$E\left[\text{Elasticity}_j \Delta Z_{djt}\Delta\epsilon_{djt}\right] = 0. \tag{24}$$

Any factors that effect relative energy and housing demand besides the relative prices are included in ϵ_{djt}, this includes climate and other amenities as described above. The instruments—labor demand shocks interacted with a static measure of land availability in the city—are unlikely to be correlated with changes in these other factors. We use our estimate of σ_C from equation (21) to back out $\tilde{\theta}_{djt}^{\mathcal{E}}$.

4.1.2 Effect of climate on comfort production

The next step of our estimation is to measure the effect of climate on the θ_{djt}^{m}'s, capturing how climate effects the productivity of electricity, gas, and housing. Using the normalizations described previously, we have

$$\tilde{\theta}_{djt}^{G} = \left(\theta_{djt}^{\mathcal{E}}/\theta_{djt}^{H}\right)^{\rho_{\mathcal{E}}/\rho_c}\theta_{djt}^{G} \tag{25}$$

$$\tilde{\theta}_{djt}^{E} = \left(\theta_{djt}^{\mathcal{E}}/\theta_{djt}^{H}\right)^{\rho_{\mathcal{E}}/\rho_c}\theta_{djt}^{E}. \tag{26}$$

Since we have already estimated $\log\tilde{\theta}_{djt}^{\mathcal{E}} = \log\left(\theta_{djt}^{\mathcal{E}}/\theta_{djt}^{H}\right) + \frac{\rho_C}{\rho_{\mathcal{E}}}\log\theta_{djt}^{G}$ and $\log\left(\theta_{djt}^{E}/\theta_{djt}^{G}\right)$, we are able to calculate $\log\tilde{\theta}_{djt}^{E}$ and $\log\tilde{\theta}_{djt}^{G}$.[9] In this specification, the share parameters in the energy function are $\tilde{\theta}_{djt}^{E}$ and $\tilde{\theta}_{djt}^{G}$, and the share parameters in the comfort function are both equal to one. We parameterize the effect of climate on these parameters as:

$$\log\tilde{\theta}_{djt}^{E} = \sum_{\tau}\kappa_E(\tau)D_{\tau jt} + \psi_j^E + \psi_d^E + \nu_{djt}^E \tag{27}$$

$$\log\tilde{\theta}_{djt}^{G} = \sum_{\tau}\kappa_G(\tau)D_{\tau jt} + \psi_j^G + \psi_d^G + \nu_{djt}^G, \tag{28}$$

[9] To see this, note that $\log\tilde{\theta}_{djt}^{\mathcal{E}} + \frac{\rho_C}{\rho_{\mathcal{E}}}\log\left(\theta_{djt}^{E}/\theta_{djt}^{G}\right) = \log\tilde{\theta}_{djt}^{G}$, where we have already estimated everything on the left-hand-side, allowing us to calculate $\log\tilde{\theta}_{djt}^{G}$.

where $D_{\tau jt}$ is the number of days at temperature τ in city j and year t, ψ_j are city fixed effects, ψ_d are demographic group fixed effects, and the ν_{djt}'s are random disturbances. $\kappa_m(\tau)$ for $m \in (E, G)$ is the marginal effect of an additional day at temperature τ on electricity or gas. As we have limited data, we choose to allow for flexible non-linearity with relatively few parameters by estimating the $\kappa(\tau)$'s with cubic splines, following Albouy et al. (2016). Specifically, for $m \in \{E, G\}$, let $\kappa_m(\tau) = \sum_s \kappa_s^m S_s(\tau)$, where $S_s(\tau)$ for $s \in \{1, \ldots, S\}$ are the standard basis functions of a cubic B-spline of degree S. Substituting this into the above parameterization of the θ's gives us our two estimating equations,

$$\log \tilde{\theta}^E_{djt} = \sum_s \kappa_s^E \left(\sum_\tau S_s(\tau) D_{\tau jt} \right) + \psi_j^E + \psi_d^E + \nu_{djt}^E \tag{29}$$

$$\log \tilde{\theta}^G_{djt} = \sum_s \kappa_s^G \left(\sum_\tau S_s(\tau) D_{\tau jt} \right) + \psi_j^G + \psi_d^G + \nu_{djt}^G, \tag{30}$$

Thus, we identify the marginal impacts of climate on comfort demand using random deviations of weather outcomes from the long-run average climate within cities. For robustness, we use various degrees for the spline, as well as alternative parameterizations of climate.

4.2 Labor Supply

We use an estimation procedure similar to that of Diamond (2016) to transform the nonlinear discrete choice problem into a linear instrumental variables estimator. We proceed in two steps. First, we define the mean utility associated with each choice as:

$$\delta_{djt} = \beta_e^I \log(I_{djt} + \Upsilon_{dt}) + \beta_e^C \log(P^c_{djt}) + \beta_e^Z \cdot Z_{jt} + \xi_{djt}, \tag{31}$$

where $\beta_e^I = \frac{1}{\sigma_e}$, $\beta_e^C = -\frac{\tilde{\alpha}_e^C}{\sigma_e}$ and $\beta_e^Z = \frac{\alpha_e^Z}{\sigma_e}$. We then write the household's choice probability as:

$$P_{ijt}(\delta_{djt}; \gamma_{dt}) = \frac{\exp\left(\delta_{djt} + \tilde{\gamma}^{st}_{dt} \mathbb{I}\left(j \in b_i^{st}\right) + \tilde{\gamma}^{\text{dist}}_{dt} \phi\left(j, b_i^{st}\right) + \tilde{\gamma}^{\text{dist2}}_{dt} \phi^2\left(j, b_i^{st}\right)\right)}{\sum_{j'} \exp\left(\delta_{dj't} + \tilde{\gamma}^{st}_{dt} \mathbb{I}\left(j' \in b_i^{st}\right) + \tilde{\gamma}^{\text{dist}}_{dt} \phi\left(j', b_i^{st}\right) + \tilde{\gamma}^{\text{dist2}}_{dt} \phi^2\left(j', b_i^{st}\right)\right)}, \tag{32}$$

where the tildes over the parameters indicate they are normalized by the variance of the idiosyncratic preference shock, σ_e. Given these choice probabilities, the likelihood function is:

$$LL(\delta_{djt};\gamma_{dt}) = \sum_{i\in d}\sum_{j} \mathbb{I}_{idjt}\log(P_{ijt}(\delta_{djt};\gamma_{dt})), \tag{33}$$

where $i \in D$ is the set of all households in demographic group d and $\mathbb{I}_{idjt}$ is an indicator equal to one if the household chose city j in the data. We recover the $\delta_{djt};\gamma_{dt}$ using the contraction mapping proposed in Berry, Levinsohn, and Pakes (2004).

We then decompose δ_{djt} from step one to estimate climate amenities. First, we use estimates from Diamond (2016) to calibrate β_e^w to 5.22 for college and 4.15 for non-college. Additionally, we use the observed comfort expenditure shares for each city, demographic group, and year to calibrate β_{djt}^C. With these parameters, we calculate the residual deltas as $\hat{\delta}_{djt} = \delta_{djt} - \left(\beta_e^I \log(I_{djt}) + \beta_{djt}^C \log(P_{djt}^c)\right)$. We then estimate the effects of climate on the mean-utilities using a rich specification of the climate that includes heating and cooling degree days, total precipitation, the number of days without precipitation, and measures of fire and flood risk. Our estimating equation is

$$\hat{\delta}_{djt} = \boldsymbol{\beta}^Z \cdot \boldsymbol{Z_{jt}} + \beta^x X_j + \omega_d + \omega_t + \xi_{djt}, \tag{34}$$

where $\boldsymbol{Z_{jt}} = \{\text{Fire}_j, \text{Flood}_j, \text{CDD}_{jt}, \text{HDD}_{jt}, \text{Precip}_{jt}, \text{NoRain}_{jt}\}$ is a vector of climate variables. Fire_j and Flood_j are median fire and flood risk scores in city j that are static over time. CDD_{jt} and HDD_{jt} are heating and cooling degree days. Precip_{jt} is total precipitation and No Rain_{jt} is the proportion of days with no precipitation. X_{jt} is a vector of geographic and demographic controls including average elevation, average slope, percent of population married, average age, and percent of population Black in each city and year. ω_d and ω_t are demographic group and year fixed effects. This is a parisimonuous, but rich characterization of the climate that allows us to capture the nuanced heterogeneity in the effects of climate change.

5 Parameter Estimates

Comfort Demand. Here, we report our parameter estimation for comfort demand. First, Table 1 shows the results from estimating Equations (19) and (21) with instrumental variables, where the columns of the table have results for alternative fixed effects included in the regressions. While the results are presented together for concision, they were run as two separate regressions. Our preferred specification is in column 1, with demographic group and city fixed effects.

We estimate that electricity and gas are net complements, as we estimate the elasticity of substitution, $\sigma_{\mathcal{E}}$, to be less than one. Intuitively, a house that requires more electricity for cooling also requires more gas to heat. The instrument for the log ratio of electricity and gas

Model:	(1)	(2)	(3)	(4)	(5)
Parameters					
$\sigma_{\mathcal{E}}$	0.501***	0.525***	0.439***	0.432***	0.432***
	(0.063)	(0.066)	(0.070)	(0.086)	(0.087)
σ_C	0.594***	0.463***	0.316***	0.293	0.570
	(0.079)	(0.091)	(0.092)	(0.348)	(0.436)
Fixed-effects					
Dem Group	Yes	Yes			Yes
City	Yes		Yes		
Year				Yes	Yes
Fit statistics					
Observations	1,260	1,260	1,260	1,260	1,260
F-test (1st stage), $\log(P_g/P_e)$	378.82	363.51	392.65	391.88	391.25
F-test (1st stage), $\log(P_h/P_{\mathcal{E}})$	147.47	65.63	143.79	1.78	0.90

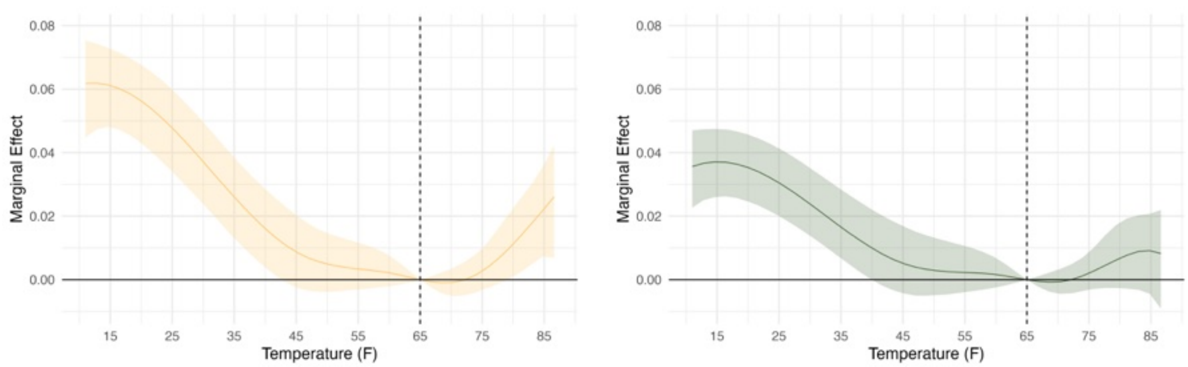
Clustered (City) standard-errors in parentheses
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Coefficients are shown in the same column, but come from separate regressions. Regressions are weighted by 1990 population. We exclude the division aggregation CBSA's in estimation.

Table 1: Estimation results for the elasticity of substitution between electricity and gas, $\sigma_{\mathcal{E}}$, and the elasticity of substitution between energy and housing, σ_C.

prices, which is the log ratio of lagged commercial electricity and gas prices, is strong, with an F-stat of well over 300 in our preferred specification. Housing and energy are net complements as well. Suppose the price of housing goes down relative to energy prices. In that case, the housing quantity demanded will increase, but so will the energy demanded since more energy is required to keep that increased amount of housing comfortable. Here, we instrument the log ratio of rent to energy price with the same instrument from energy estimation, and the Katz-Murphy index interacted with housing supply elasticities from Saiz (2010). Again, our first stage F-stat is very strong.

With the estimated elasticities of substitution in hand, we can calculate values for $\log \tilde{\theta}^E_{djt}$ and $\log \tilde{\theta}^G_{djt}$, which we then regress on climate variables to determine the impact of the climate on the comfort production function. We use cubic B-splines with 7 degrees of freedom to flexibly estimate the marginal effect of an additional day at a given temperature. For electricity, an additional day at either a hotter or colder temperature than 65 degrees leads to additional energy demand, reflecting that households use electricity for both heating and cooling. Additionally, the demand response is stronger further into temperature extremes. Meanwhile, natural gas has coefficients significantly different from zero only when the temperature is colder than 65 degrees. We investigate heterogeneity in the climate's effect on comfort production in appendix D.1, finding differences that are small in magnitude. We then use the above estimates to calculate the marginal effect of climate on comfort prices, finding that the effect is larger for black households than white—though not outside of bootstrapped confidence intervals. Appendix D.1 provides other figures describing patterns in comfort production across cities.



(a) Estimate of $\kappa_E(\tau)$, the marginal effect of temperature on $\log \tilde{\theta}^E$.

(b) Estimate of $\kappa_G(\tau)$, the marginal effect of temperature on $\log \tilde{\theta}^G$.

Figure 4: Estimation results for the effect of climate on comfort production, parameters $\kappa^E(\tau)$ and $\kappa^G(\tau)$ using cubic splines with 7 degrees of freedom. The effect is normalized to a day with an average temperature of 65 degrees F. Standard errors are calculated with clustered bootstrapping using 10,000 draws, clustered by city-year. We have limited the range of temperature to between the 1st and 99th percentile of average daily temperature, weighted by 1990 population.

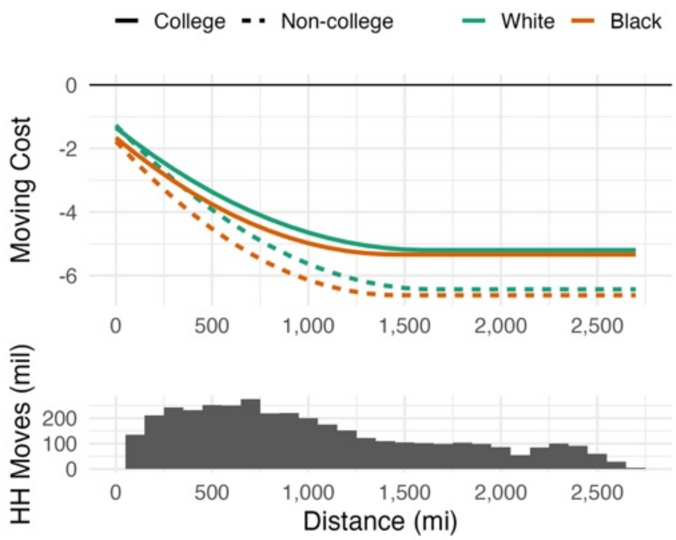


Figure 5: Moving cost estimates for black and white households as a function of distance in 2019. We use estimates from Table A9, but hold moving costs constant at the minimum for distances further than the estimated mininimum. The intercept reflects the parameter estimates of $\tilde{\gamma}^{st}$. The histogram shows the distribution of *potential* moves in 2019, excluding the census divisions—so each household in the model shows up 70 times, once for each of the cities we include in the model. We set moving costs equal to the minimum value of the moving costs function at distances further beyond its estimated minimum.

Labor Supply. Figure 5 plots the estimated moving cost function (3) using parameters for estimated by equation (33). We plot the moving cost estimates over the range of possible distances from a household's birthstate.[10] We find that black households are generally less mobile than other households. The birth-state premium parameter is positive, indicating a utility premium, and larger for black households. Furthermore, the distance parameter is negative, indicating a utility penalty for moving further away from one's birth state, and more negative for black households. We also find that non-college-educated workers are generally less mobile than college-educated workers. Our estimates are quantitatively very close to those in Colas and Morehouse (2022) and Diamond (2016). We include moving cost estimates for all years in Appendix D.4.

Table 2 shows the parameter estimates for climate amenities. We show the robustness of our controls to the inclusion of different geographic and demographic controls. Households dislike both heating and cooling degree days and like days without rain. These estimates are larger in magnitude than Albouy et al. (2016), but smaller than Rudik et al. (2021). Households dislike both fire and flood risk—they are willing to pay 24% of income for a one standard

[10] In both Figure 5 and in our simulations, we set the moving cost function equal to its minimum value for distances beyond its estimated minimum.

deviation decrease in fire risk and 6% of income for a one standard deviation decrease in flood risk. We emphasize that we do not presently have natural disaster risk indices that vary over time or climate scenarios. Appendix D.5 contains estimates for alternative specifications for temperature portion of climate amenities, showing qualitatively similar results to our degree day specification.

Table 2: Estimation results for non-temperature climate amenities.

Dep. Var.	Mean Utility Residual			
Model:	(1)	(2)	(3)	(4)
Variables				
HDD (1000's)	-1.73***	-1.62***	-1.60***	-1.99***
	(0.14)	(0.15)	(0.15)	(0.23)
CDD (1000's)	-1.54***	-1.44***	-1.03***	-1.63***
	(0.28)	(0.30)	(0.28)	(0.43)
Median Fire Risk	-0.75***	-0.60***	-0.55***	-0.62***
	(0.13)	(0.14)	(0.10)	(0.11)
Median Flood Risk	-0.83***	-0.94***	-0.68***	-0.75***
	(0.15)	(0.14)	(0.11)	(0.11)
Annual Precip (m)	-2.81*	-2.30	-2.03	-1.17
	(1.69)	(1.61)	(1.59)	(1.75)
Annual Precip Squared (sq m)	1.55*	1.42*	0.75	0.53
	(0.81)	(0.79)	(0.73)	(0.77)
Pr(No Rain)	7.00**	7.06**	7.10**	7.18**
	(2.99)	(3.03)	(2.86)	(2.86)
Geographic Controls		Yes		Yes
Demographic Controls			Yes	Yes
Fixed-effects				
Dem Group	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,680	1,680	1,680	1,680
R^2	0.94	0.94	0.95	0.95
Within R^2	0.27	0.29	0.33	0.34

Heteroskedasticity-robust standard-errors in parentheses
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Regresions are weighted by population. We exclude the division aggregation CBSA's in estimation. Geographic controls include city's average slope and elevation. Demographic controls include percent married, average age, and percent black.

Table 3 shows the top and bottom ten cities according to their climate amenities in 2019 ($\hat{\beta}^{Z} \cdot \boldsymbol{Z}_{j,2019}$), with category-specific rankings also broken out. These rankings demonstrate our model's ability to richly characterize a city's climate. For example, the top ten has cities from California with mild summers, winters, and risks, as well as San Antonio—which ranks poorly due to its hot summer weather but makes up for it by having very few cold days. Most striking is the inclusion of Baton Rouge in the top ten and nearby New Orleans in the bottom ten. This is due to the difference in flood risk between the two cities—nearly every property in New Orleans has at least moderate flood risk, whereas less than half do in Baton Rouge. Table 4 shows how climate amenities have changed between 1990 and 2019, using 5-year moving averages. Increased hot temperatures have decreased amenities in most cities, while fewer cold days have improved amenities. In already-hot places, the shape of the temerature-amenity curve means that the decrease in amenities from more hot days outweighs the improvement in amenities from fewer cold days. The opposite generally holds for places that are relatively cold.

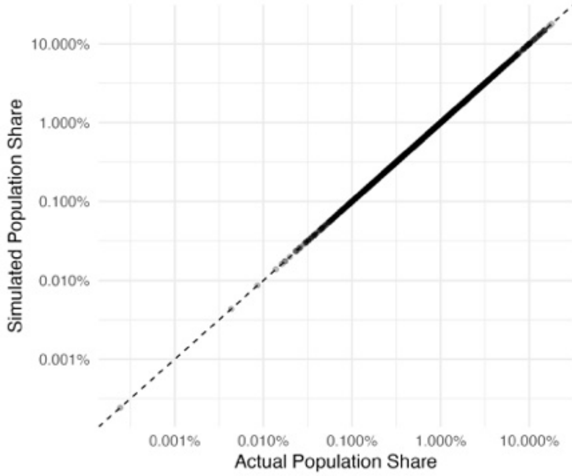
Table 3: Estimated climate amenity rankings by city for 2019. The Hot category is from temperatures over 65F, Cold from temperatures below 65F, Rain from percent no rain days and annual precipitation, and Risks from median fire and flood risk. Full sample degree day specification with geographic and demographic controls.

		Category Rankings			
Rank	City	Hot	Cold	Rain	Risks
Best Cities					
1	San Jose-Sunnyvale-Santa Clara, CA	5	18	7	32
2	Los Angeles-Long Beach-Santa Ana, CA	40	7	2	54
3	San Diego-Carlsbad-San Marcos, CA	30	10	5	65
4	San Francisco-Oakland-Fremont, CA	2	21	10	59
5	Oxnard-Thousand Oaks-Ventura, CA	18	15	1	67
6	Fresno, CA	53	17	6	53
7	Sacramento–Arden-Arcade–Roseville, CA	38	22	9	57
8	Baton Rouge, LA	59	13	61	4
9	San Antonio, TX	61	12	13	58
10	Phoenix-Mesa-Scottsdale, AZ	69	6	3	64
Worst Cities					
61	Grand Rapids-Wyoming, MI	7	67	42	14
62	Buffalo-Cheektowaga-Tonawanda, NY	10	64	58	7
63	Scranton–Wilkes-Barre, PA	12	59	51	43
64	Springfield, MA	16	62	25	44
65	Worcester, MA	8	63	32	48
66	Albany-Schenectady-Troy, NY	14	66	41	37
67	Rochester, NY	9	65	56	42
68	Minneapolis-St. Paul-Bloomington, MN-WI	11	70	20	22
69	New Orleans-Metairie-Kenner, LA	65	8	60	70
70	Syracuse, NY	4	68	67	45

Table 4: Change in climate amenities from 1990 to 2019. Full sample degree day specification with geographic and demographic controls.

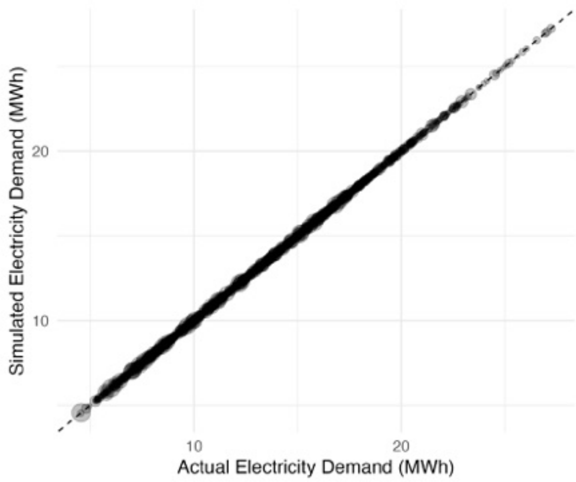
City	Change (%)	Category Change (%)		
		Rain	Hot	Cold
Improving Cities				
Hartford-West Hartford-East Hartford, CT	26.2	7.1	-22.4	41.5
Grand Rapids-Wyoming, MI	25.7	0.3	-2.7	28.1
Honolulu, HI	23.8	17.8	6.0	-0.1
New Haven-Milford, CT	23.1	5.5	-17.7	35.3
Denver-Aurora, CO	21.6	-12.2	-16.0	49.8
San Antonio, TX	19.8	15.3	-14.2	18.7
Worcester, MA	19.2	-11.9	-15.5	46.7
Portland-Vancouver-Beaverton, OR-WA	18.9	-3.0	-11.7	33.6
Buffalo-Cheektowaga-Tonawanda, NY	18.2	10.1	-10.1	18.3
Bridgeport-Stamford-Norwalk, CT	17.1	1.3	-17.3	33.2
Worsening Cities				
St. Louis, MO-IL	-27.6	-34.2	-9.4	16.0
Dayton, OH	-28.3	-40.6	-11.2	23.4
Houston-Baytown-Sugar Land, TX	-31.1	-27.2	-35.0	31.1
Louisville, KY-IN	-32.8	-47.8	-21.4	36.4
Baton Rouge, LA	-35.9	-30.5	-35.5	30.1
Tampa-St. Petersburg-Clearwater, FL	-62.8	-44.6	-28.6	10.4
Jacksonville, FL	-68.6	-55.3	-39.9	26.5
Orlando, FL	-70.4	-41.9	-42.7	14.2
Miami-Fort Lauderdale-Miami Beach, FL	-73.0	-40.3	-39.8	7.1
New Orleans-Metairie-Kenner, LA	-73.4	-54.4	-54.8	35.8

Model Fit We use our estimated parameters to simulate baseline results for each year. Appendix C.7 provides detailed steps to solve the model's equilibrium given climate $\tilde{\mathbf{Z}}$. In summary, we begin with population share and housing price guesses, use those guesses to calculate household energy and housing demand, wages, and comfort prices, and then recalculate population shares given those wages and comfort prices. If the population shares match the original guess, then we have found the equilibrium. If they do not match, we update our initial guess and repeat until they do match. In the baseline simulations, we plug in the actual climate values as $\tilde{\mathbf{Z}}$ to validate the model's predictions against actual data from each of our four years of data. Figure 6 shows the simulated shares of each demographic group that choose to live in a particular city against the actual population shares and simulated housing, electricity, and gas demand relative to actual electricity, housing, and gas demand. Each observation represents a demographic group in a city for the given year.

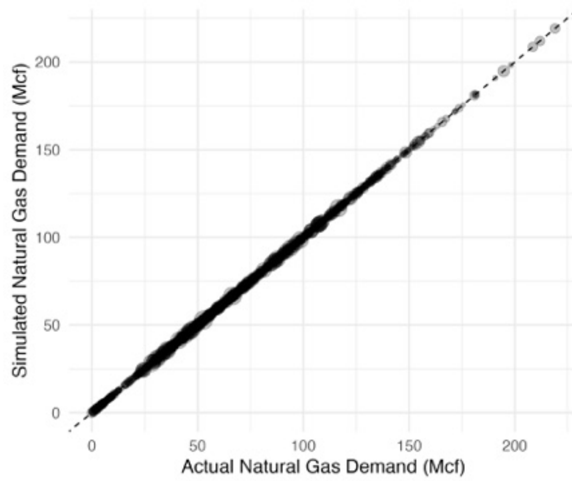


(a) Simulated vs actual population shares.

(b) Simulated vs actual housing demand.



(c) Simulated vs actual electricity demand.



(d) Simulated vs actual natural gas demand.

Figure 6: Simulations use actual climate data across all years. The size of the observations represents the population of that demographic group.

6 The welfare effects of climate change

We calculate the welfare effects from climate change using compensating variation, defined as the percent of baseline income that households would need to receive in order to maintain the same level of utility under the counterfactual climate, $\tilde{\mathbf{Z}}$, as they do under the current climate, $\mathbf{Z}$. Household i's compensating variation is given by:

$$CV_i = \left(\mathbb{E}[V_i(\tilde{\mathbf{Z}})] - \mathbb{E}[V_i(\mathbf{Z})]\right) \times \frac{1}{\beta_e^I}, \tag{35}$$

where $V_i(\mathbf{Z}) = v_{ij^*}(\mathbf{Z})$ is household i's indirect utility with climate $\mathbf{Z}$, evaluated at equilibrium choices j^* and prices. We calculate these equilibrium choices using the same algorithm referenced in the model fit section, which is detailed in Appendix C.7. Taking the expectation of indirect utility over the idiosyncratic shocks gives us

$$\mathbb{E}[V_i(\boldsymbol{Z})] = \bar{\gamma} + \log\left(\sum_{j' \in J} \exp\left(\beta_e^I \log I_{dj'} + \beta_{dj'}^C \log P_d^C(Z_{j'}) + \beta_d^Z \cdot Z_{j'} + \xi_{dj'} + g(j', \boldsymbol{b}_i)\right)\right),$$

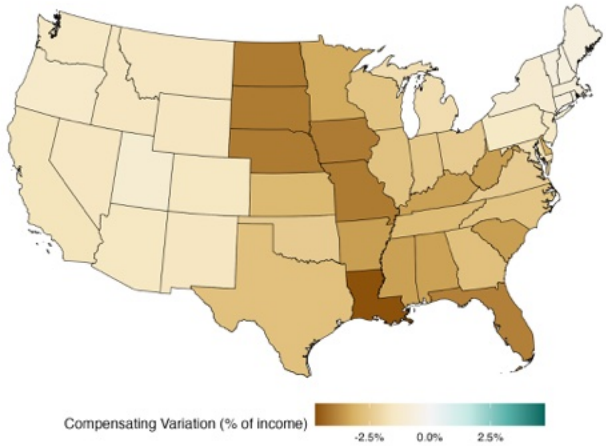
where $\bar{\gamma}$ is Euler's constant. Note that the price of comfort, $P_d^C(Z_j)$, is a function of local climate variables.

6.1 Effect of climate change to-date

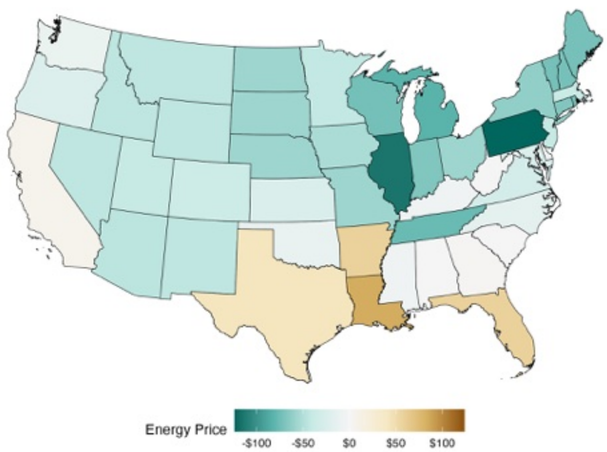
We begin with a simulation where counterfactual climate comes from the average climate between 1986 and 1990, before there was any significant human-caused changes to the climate. Note that we do not yet include changes in natural disaster risk. Before showing results comparing CV across races, we show how climate change to-date has affected the US economy across space. Generally, the South and Midwest are worse off than the Northeast and West, owing to increases in temperature being unpleasant in an already hot location and pleasant in a cool location. Additionally, fewer rain-free days in the Midwest lead to decreased amenities. Figure 7a shows compensating variation by state—showing that already hot places are hurt by more than cool places. The effect of climate on the energy price drives some of this heterogeneity, shown in Figure 7b. Producing comfort has become more expensive in hot places and less expensive in cold places. Figure 7c shows that households would migrate in relatively large numbers away from the South and Midwest and into the Northeast and West.[11] These spatial changes suggest that the baseline distribution of the population is essential in determining differences in welfare effects across demographic groups.

Figure 8 shows the distribution of CV_i, where most households are worse off under the current climate than the 1990 climate. However, there is important heterogeneity in the welfare effects—namely that the mean welfare loss for black households is nearly twenty percent larger than that of white households. In order to precisely characterize heterogeneity in the welfare effects of climate change, we regress compensating variation on dummy variables for race, college, and their interaction, with results shown in Table 5. The first column shows that the average white household is worse off from climate change to-date by 2.74% of income, whereas black households are worse off by an additional half percent, at 3.25% of income. Adding

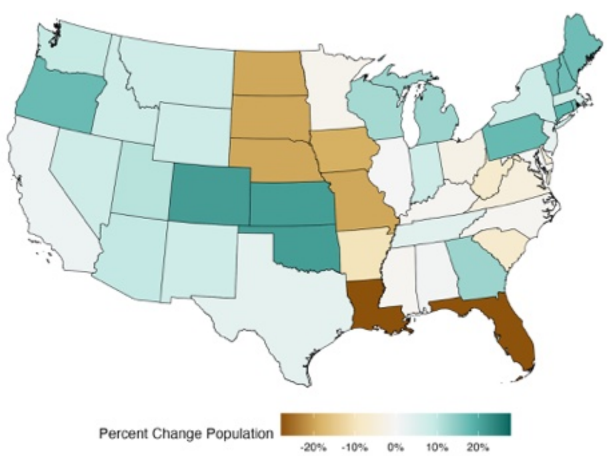
[11] Table A11 has the top and bottom 10 cities by change in population. Maps of rent, wages, and comfort demand are available in Figure A18. Additionally, Figure A19 shows how the skill ratio affects wages in the counterfactual.



(a) Average CV in each state.



(b) Average change in energy price, $P_{\mathcal{E}}$



(c) Average percent change in population.

Figure 7: Change in welfare, energy prices, and population across states. Averages are weighted by population. For states without any CBSAs in them, we use the value for the census division in which the state is located.

fixed effects for baseline city reduces the gap between white and black households by about a third, suggesting that the ex-ante distribution of the population plays an important role in the differences in the welfare effects of climate change across demographic groups. However, the remaining gap is *within cities*, meaning that black households indeed face more difficulties in adapting to climate change beyond differential exposure.

The remaining four columns explore the role of education level on the welfare effects. Column (3) adds city by education fixed effects, thus controlling for differences in the education composition of the race groups. This difference in educational composition further reduces the gap. The final three columns compare welfare within education levels. Non-college households are worse off than college households across all races, however black non-college households are marginally worse off than other races. The black-white gap is 0.3% of income for college households and 0.07% of income for college households. Adding city by education fixed effects again reduces the gap for both education groups, suggesting the importance of both the ex-ante population distribution and the difficulties for black and non-college educated households to adapt to climate change.

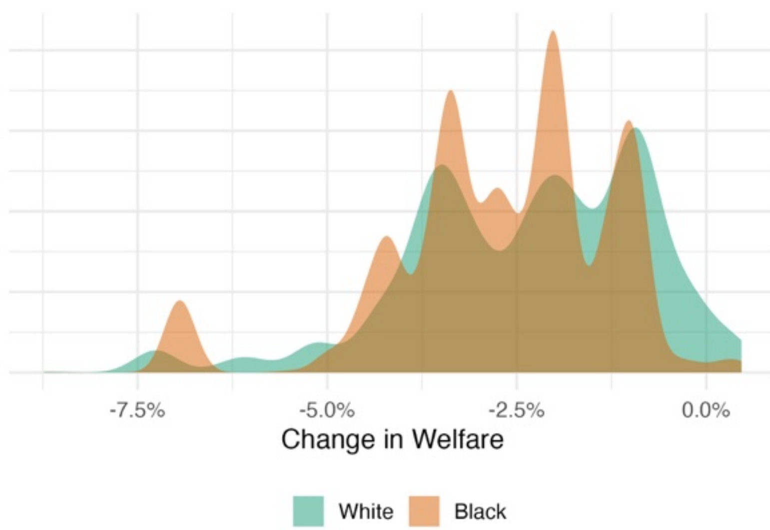


Figure 8: Compensating Variation by race in 2019 if the climate was the same as in 1990.

Next, we attempt to determine which of the proposed mechanisms drives the gap in CV between white and black. We run three simulations in addition to the fully flexible model to do this. First, we fix locations, rent, and wages—reflecting the "mechanical" effect of changing the climate without allowing households to migrate. In this simulation, they still optimally choose their comfort demand. In a second simulation, we continue to fix locations and wages but allow the local housing market to clear since housing demand responds to climate as part of comfort production. In the third simulation, we allow households to sort across locations, keep

Table 5: Differences in Compensating Variation by Demographic Group

Dependent Variable			CV (% of income)			
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Constant	-2.48***			-1.73***		
	(0.18)			(0.10)		
Black	-0.47***	-0.30***	-0.12	-0.28***	-0.09	-0.17***
	(0.15)	(0.09)	(0.09)	(0.08)	(0.06)	(0.05)
Rest	0.81***	0.50***	0.52***	0.49***	0.27***	0.34***
	(0.15)	(0.11)	(0.10)	(0.09)	(0.07)	(0.07)
Non-college				-1.31***	-1.21***	
				(0.13)	(0.11)	
Black × Non-college				-0.05	-0.05	0.08
				(0.12)	(0.10)	(0.07)
Rest × Non-college				0.55***	0.46***	0.33***
				(0.10)	(0.10)	(0.07)
Fixed-effects						
City		Yes			Yes	
City x College			Yes			Yes
Fit statistics						
Observations	18,698	18,698	18,698	18,698	18,698	18,698
R^2	0.03	0.26	0.37	0.14	0.35	0.37
Within R^2		0.02	0.01		0.14	0.02

Clustered (City) standard-errors in parentheses
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1
Regresions are weighted by population.

wages fixed to their original level, and keep rent at the same level as in the second simulation. This "sorting" simulation tells us the effect of allowing households to reoptimize their location choice across space. Additionally, we run each simulation with just climate's effect on comfort, just its effect on amenities, and both effects.

Table 6 has the results, where we calculate the gap in average CV as a percent of income by race unconditionally and conditional on city and city by education fixed effects.[12] Starting with the fixed location results, we see a slightly larger unconditional welfare gap than the full model. The ex-ante distribution of the population entirely explains this gap, as it drops to zero when adding city fixed effects. While allowing for sorting marginally increases the unconditional gap, over two-thirds of the gap remains after controlling for baseline location. Thus, white households can better take advantage of migration as an adaptation mechanism conditional on exposure. Finally, the unconditional welfare gap shrinks slightly when wages and rents are allowed to adjust fully. Households migrating from the South to the West or Northeast depress wages and inflate rents in their new cities, while the opposite happens in the South. These changes reduce the unconditional gap due to the differences in the baseline populations in those regions.

Table 6: Decomposition of welfare effects. Values are the difference between black and white CV a percent of income.

	Climate Effect From		
Fixed Effects	Both	Amenities	Comfort
Fixed Location			
None	-5.61	-5.34	-5.05
City	-4.68	-4.79	-4.59
City x College	-4.36	-4.44	-4.36
Fixed Location, adjust comfort			
None	-0.81	-5.34	-0.25
City	-0.02	-4.79	0.07
City x College	0.05	-4.44	0.05
Sorting, fixed prices			
None	-0.87	-5.35	-0.26
City	-0.58	-5.25	-0.18
City x College	-0.46	-4.83	-0.22
Full Effects			
None	-0.47	-0.35	-0.12
City	-0.30	-0.24	-0.05
City x College	-0.12	-0.02	-0.10

[12] The unconditional results are available in levels in Table A10.

There are also significant differences in the welfare effect of climate chage across the income distribution. We calculate the average compensating variation by income decile and race in figure 9. The welfare effects are generally worse for poorer households among all races. However, the welfare effects for black households are worse for black households relative to white households within every income decile. CV as a percent of income is twice as high for the lowest income decile relative to the highest, or 4% of income.

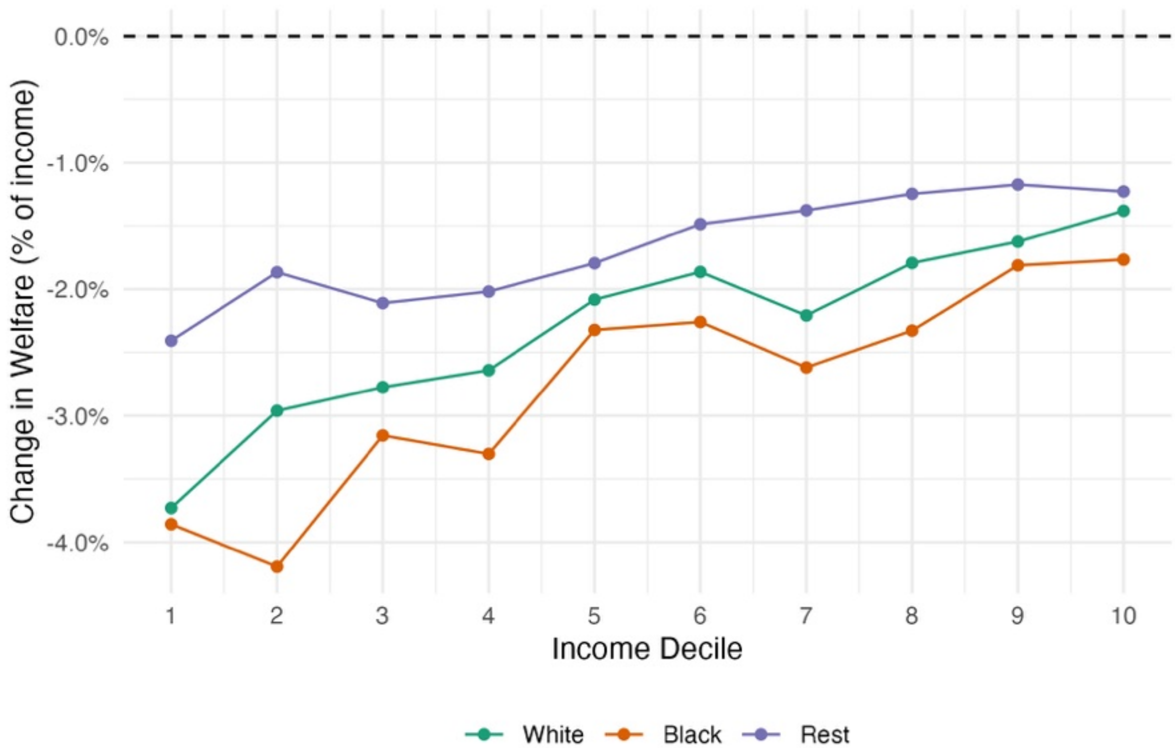


Figure 9: Compensating Variation by income decile and race in 2019 if the climate was the same as in 1990.

6.2 The black-white gap simulated under future emissions scenarios

Next, we simulate the model under different emissions scenarios each year to 2100 using the CIL-GDPCIR data. We then calculate the black-white gap as the change in welfare for black households relative to their baseline welfare minus the change in welfare for white households relative to their baseline welfare. Figure 10 shows the evolution of the black-white welfare gap, which generally grows with more emissions.

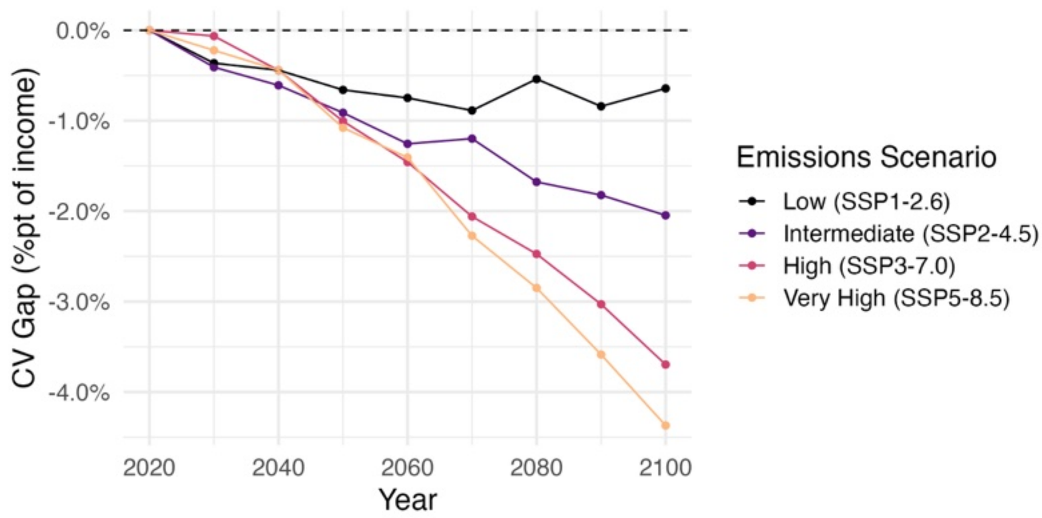


Figure 10: Time series of the black-white welfare gap under different emissions scenarios.

Even under the lowest emissions scenario (SSP1-2.6), which assumes zero emissions by 2050 and 1.8 degrees of warming by the end of the century, climate change is expected to hurt black households by 2% of income relative to white households. Under the more likely, higher emissions scenarios, this gap grows to between 4% to 7% depending on the emissions scenario. This gap highlights the need for equity to be an important part of climate policy in the future.

7 IRA inspired place-based, means-tested subsidies

Given the unequal impacts of climate change discussed previously, we now turn to thinking about how government policy interacts with the effects of climate change. We incorporate a means-tested, place-based subsidy into our main model, the structure and magnitude of which are inspired by the EPA's Community Change Grant program. We compare the effects of climate change to date with and without these subsidies and test alternative ways to distribute the funds.

The Inflation Reduction Act (IRA) contains many programs addressing climate change. Additionally, President Biden's Justice40 initiative seeks to provide 40 percent of the benefits of federal rulemaking on climate, clean energy, affordable housing, and other related categories to disadvantaged communities (Executive Office of the President, 2021).[13]

[13] The administration defines a disadvantaged community as places, "historically marginalized and overburdened by pollution and underinvestment in housing, transportation, water and wastewater infrastructure, and health care" Executive Office of the President (2021). In practice, the Climate and Economic Justice Screening Tool classifies disadvantaged tracts based on eight different categories: climate, energy, health, housing, legacy pollution,

One such IRA program is the EPA's Community Change Grants Program. The IRA allocated nearly \$3 billion for projects in disadvantaged communities related to climate resiliency and adaptation, mitigating climate and health risks, and several other related categories (US EPA, 2023). In describing the program, Brenda Mallory, the Chair for the White House Council on Environmental Quality, said, "As part of the President's Justice40 Initiative, these grants will help disadvantaged communities tackle environmental and climate justice challenges they face by reducing pollution, increasing resilience to impacts from climate change, and building community capacity to see these projects through" (US EPA, 2024). Applications for the primary round of funding are due in November of 2024.[14] There are few restrictions on how the EPA distributes Community Change Grant funds across space. In principle, any disadvantaged community is eligible for a project.[15]

We incorporate the Community Change grants into the model by considering them as means-tested, place-based subsidies. The government decides the total size of the program, G, and the portion of the total given to each city, wt_j, where $\sum_j wt_j = 1$. Households who choose to live in city j and are below the income threshold, I_{thresh}, divide the subsidy equally. $N_j^{disad} = \int_i P_{ij}\mathbb{I}\left(I_{dj} < I_{thresh}\right)di$ gives the total population in city j that lives in a disadvantaged community, where P_{ij} is household i's probability of choosing city j, as defined by Equation (7). We set the income threshold equal to the 41st percentile of income, matching the share of the population living in a disadvantaged community according to the 2020 Decennial Census. We calculate the subsidies for each city and demographic group as $\text{IRA}_{dj} = \frac{Gwt_j}{N_j^{disad}}\mathbb{I}\left(I_{dj} < I_{thresh}\right)$. A flat tax paid by all households funds the subsidy program, $G = \int_i \tau I_{dj} di$. Income in city j for demographic group d is now $(1-\tau)I_{dj} + \Upsilon_d + \text{IRA}_{dj}$.

We consider three policy alternatives that vary the spatial distribution of the subsidies across cities, wt_j. These distributions give subsidies to cities based on (1) the percent of the national disadvantaged population living in each city, (2) the share of losses in climate amenities for cities that experience losses in amenities, or (3) the share of gains in climate amenities for cities that experience gains in amenities. Distributing funds equally based on the disadvantaged population most closely mirrors the current Community Change Grant program.

We design the second and third distributions to capture the tradeoff between helping

transportation, or workforce development. For all but workforce development, communities are disadvantaged if they are above the 65th percentile for the share of low-income households and above a threshold for exposure to various environmental stressors (e.g., above the 90th percentile expected agricultural, building, or population loss, projected flood, or fire risk for the climate change category).

[14] An initial round of \$325 million in funding was awarded in July of 2024. While the specific projects take on a wide array of activities, the most common types are providing weatherization assistance, creating "community resilience hubs", improving public parks, and installing solar panels and energy storage.

[15] Appendix Figure A20 shows the proportion of the population living in a disadvantaged community by state. While there is some variation, all states have a significant portion of their population living in disadvantaged communities. There are several target areas that place spatial restrictions on funds: \$150 million for tribes in Alaska, \$50 million for territories, and \$100 million for southern border communities.

people hurt by climate change and the general equilibrium consequences of place-based subsidies. If households are immobile, then giving subsidies to places that are hurt the most by climate change will also help the people who are hurt the most by climate change. However, since households are mobile, these subsidies will cause marginal households to move into the places harmed by climate change—increasing rents and decreasing wages, thus dampening the intended welfare effects while also increasing exposure to future climate change. Therefore, we also consider giving subsidies to places that have benefited from climate change, which we'll refer to as "climate havens." Distributing funds to climate havens will decrease exposure to climate change but also gives subsidies to many "inframarginal" households who are already better off from climate change relative to other locations since they would have lived in a climate haven regardless of the additional subsidies.

We calculate expected subsidies without allowing households to reoptimize across locations, thus holding locations, wages, and rents fixed to equilibrium choices under the 2019 climate without subsidies. Thus, we are able to determine how important migration and general equilibrium effects are relative to the mechanical effect of introducing subsidies. Each individual's mechanical subsidy is the weighted average of subsidies across cities, weighted by the probability they choose each city in the 2019 climate equilibrium, denoted P^*_{ij},

$$E[\mathrm{IRA}_{dj}|i] = \sum_j P^*_{ij}\mathrm{IRA}_{dj}(P^*_{ij})$$

We then simulate the full model, allowing households to sort across space and for wages and rents to respond to these new choices. We consider the equilibrium with the 2019 climate and no subsidies as the baseline and then quantify changes from that equilibrium when adding the three different distributions of subsidies described above. Since the size of the effects will depend on the total size of the program, we present results per dollar of total subsidies. Appendix E.1 compares results across a wide range of values for G, from \$30 million to \$10 billion.

Figure 11 shows compensating variation from introducing the subsidies relative to our baseline comparison of welfare under the 2019 and 1990 climates. We first calculate each household's decile of CV from our main results comparing the 2019 and 1990 climates. We then calculate CV for each household from adding subsidies under the 2019 climate, both for location choices fixed to the baseline, no-subsidy simulation, and allowing for households to reoptimize across space fully. We split the figure up into three income-based groups—households below the 10th income percentile, households in the 10th-50th income percentile, and households above the 50th income percentile.[16] As expected, the most prominent effects are among the

[16] We calculate these household-level income percentiles by taking the weighted average of incomes the household

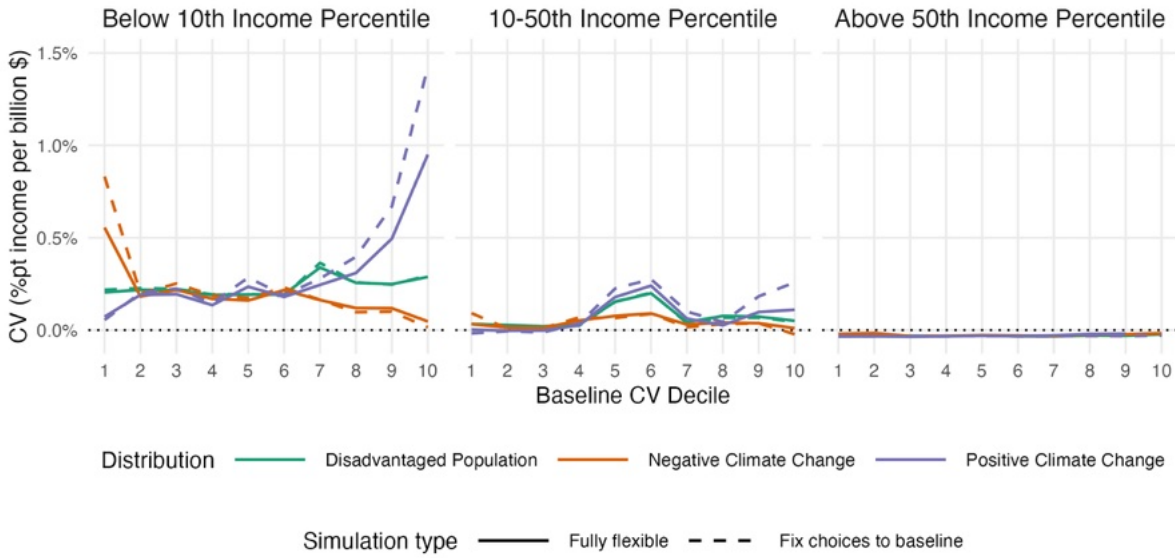


Figure 11: CV from subsidies relative to CV from climate change to date for different spatial distributions of IRA subsidies. The X-axis is a household's decile in CV from the baseline simulation comparing 2019 and 1990 climates. The Y-axis is average CV with subsidies relative to without subsidies under the 2019 climate. We split the figure into three income bins, below 10th percentile, 10th-50th percentile, and above 50th percentile based on household expected income in the baseline simulation. The "Fix choices to baseline" simulation type takes choice probabilities from the baseline simulation and calculates expected subsidies given those choices—which is what would happen if households were not allowed to reoptimize their location choices after the government introduces subsidies. The "Fully flexible" simulations allow for full flexibility in choosing locations. See description in the text on the subsidy distributions

lowest-income decile, for whom the subsidies represent a larger share of income. Meanwhile, Above median income households have a slight welfare loss from paying the flat tax.

Distributing funds to cities based on their share of the disadvantaged population helps low-income households generally, but not proportionately to welfare losses from climate change. The spatial variation in the disadvantaged population would need to be more significant to drive large differences in who benefits from the subsidies across space. The Negative Climate Change distribution does the best job of helping households most hurt by climate change—this is the only distribution where CV from subsidies is decreasing in the baseline CV percentile. In contrast, the Positive Climate Change distribution benefits those who are already relatively well off from climate change. To get a sense for the magnitude of these effects, Figure A22 shows CV for our baseline results comparing 2019 and 1990 climates, as well as the 2019 climate with $3 billion in subsidies relative to the 1990 climate. For almost all households, the effects

would earn in each city, weighting by the probability the household chooses to live there.

from the subsidies are smaller than the effects from climate change to date.

Comparing the dashed and solid lines in Figure 11 demonstrates the effect of households reoptimizing their location choices in response to the subsidies. Under the Negative Climate Change distribution, the benefits to households in the lowest income decile are 20% lower in the fully flexible simulation relative to fixing location choices. The loss is the result of marginal low-income households moving into the cities that are now relatively more attractive due to the subsidies. Not only does this migration result in lower per-capita subsidies, but it also increases rents and decreases non-college wages (See Figures A24, A25, and A26 on the change in population, rents, and wages from the subsidies). Since this simulation distributes subsidies to places that have been hit the hardest by climate change, the observed in-migration results in higher exposure to climate change. In aggregate, losses in climate amentities are 1% higher under the Negative Climate Change subsidy distribution relative to the baseline.

Alternatively, the government could subsidize climate havens in order to decrease climate exposure by making those climate havens relatively more attractive. Aggregate climate exposure decreases under the Positive Climate Change distribution by about the same amount as the increase in the Negative Climate Change distribution. However, since there are many "inframarginal" households—those who would have chosen to live in the climate havens anyways—the Positive Climate Change distribution is primarily a subsidy to people who are relatively well off from a climate perspective. Well over 90% of subsidies in the Positive Climate Change distribution are given to households who would have lived in a city with increases in cliamte amenties absent the subsidies. Our results emphasize that any such program designed to reduce climate exposure must target marginal households in order to be successful.

Since each of the policies we analyze redistribute funds from high- to low-income households, they all reduce the aggregate disparities in welfare effects of climate change across race and income that we quantified in our main results. The Negative Climate Change distribution reduces these gaps the most since a primary mechanism driving the gaps is differential exposure to climate change.

In summary, we find that to help the people most hurt by climate change using place-based subsidies, we must distribute those subsidies to the places most harmed by climate change. However, this comes with the caveat that such a policy could increase exposure to future climate damages. Appendix E.1 demonstrates that these results qualitiatively hold regardless of the magnitude of the subsidy program.

8 Conclusion

We have found that climate change has already had and will continue to have significant distributional consequences. Black and non-college-educated households are worse off under climate change, owing not only to their ex-ante exposure to changes in climate but also due to a differential ability to adapt. Black households are worse off by 0.5% of income relative to white households from climate change to date, and that gap will continue to grow further under various future emissions scenarios. In the worst-case emissions scenario, the gap grows by over 7%pts of income at the end of the century. Low-income households are much worse off than high-income households, with the welfare effect of climate change to date being 2 times larger for the lowest-income decile as compared to the highest-income decile.

We evaluated the effectivenes of a place-based, means-tested subsidy program to address the observed inequalities in the effects of cliamte change. We found that there is a fundamental tradeoff when using such place based policies between targetting the places that are most hurt by climate change and altering aggregate exposure to future climate damages. Policymakers must balance these when designing such place-based programs.

Future work can address other forms of inquality that may arise due to climate change. For example, the urban heat island effect may lead to differential experienced climates within cities that our model is not well suited to analyze. One could allow for households to choose both their city and neighborhood in that city to directly model any within-city sorting.

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Appendix A Data Appendix

A.1 Sample Selection

We use 5% samples of the 1990 and 2000 censuses in addition to the 2010 and 2019 5-year aggregated American Community Survey. In all years, of data, we drop individuals living in group quarters, veterans, and any households younger than 16 and older than 64. We consider the household head the decision maker—unless the head is unemployed and the spouse is employed, in which case the spouse is the decision maker. We consider a household college educated if they have at least four years of college.

A.2 City-Level Indices

In this section, we detail how we construct-city level estimates of energy consumption, wages, and rents. In each section, we use individual data from the Census and American Community Survey.

A.2.1 Energy Use

Our model features electricity and natural gas use in the household utility function. The main concern is that some renters may not pay utility bills separately from rent and thus falsely report zero energy expenditure in the census and ACS data. We follow Glaeser and Kahn (2010) and use the EIA's Residential Energy Consumption Survey (RECS) to correct this feature of the census data. RECS directly reports energy consumption, but we cannot use it as our primary data source since it does not report the location of each household and has a relatively small sample. We proceed in two steps, first estimating city-demographic group-year level energy consumption for single-family homeowners in the census data, then adjusting those estimates by the difference between single-family homeowners and renters in the RECS data.

Specifically, we estimate the following regression for single-family homeowners in the census,

$$e^m_{idjt} = \gamma^m_{djt} + X'_{idjt}\beta^m + \varepsilon_{idjt}, \tag{36}$$

where e^m_{idjt} is use of energy type $m \in \{elec, gas\}$ for household i, in demographic group d, city j, and year t. Our vector of controls, X'_{idjt}, includes the number of people in the household, the number of children, and the age of the household head. We estimate this for single-family homeowners since they are most likely to report accurate energy expenditures in the census. We then take the national average of the controls for each year-demographic group, $\bar{X}'_{dt}$, and use the coefficients estimated in equation (36) to predict energy use for single-family homeowners for each city, demographic group, and year,

$$E^{SFO}_{djt} = \hat{\gamma}^{elec}_{djt} + \bar{X}'_{dt}\hat{\beta}^{elec} \tag{37}$$

$$G^{SFO}_{djt} = \hat{\gamma}^{gas}_{djt} + \bar{X}'_{dt}\hat{\beta}^{gas}. \tag{38}$$

Then, we turn to the RECS, which is administered every three to six years. We match our census years to the closest RECS survey available, using the 1993, 2001, 2009, and 2015 surveys.[17] We estimate the following regression,

$$e^{m}_{it} = \alpha^{1}_{mt} MultiFam_{it} + \alpha^{2}_{mt} Rent_{it} + \alpha^{3}_{mt} MultiFam_{it} \times Rent_{it} + X'_{it}\beta_{mt} + \varepsilon_{it}, \tag{39}$$

where e^{m}_{it} is use of energy type $m \in \{elec, gas\}$, $MultiFam_{it}$ is an indicator for whether household i lives in a multifamily home in year t, $Rent_{it}$ is an indicator for whether household i rents their home, X'_{it} is a vector of controls. The controls include indicators for the census division, number of children, household size, age of the household head, and an indicator for whether the household head is white. To estimate energy usage for each demographic group, we use the estimated coefficients $\hat{\alpha}^{1}_{mt}$, $\hat{\alpha}^{2}_{mt}$, and $\hat{\alpha}^{3}_{mt}$ to adjust the single-family owners estimates, E^{SFO}_{djt} and G^{SFO}_{djt}, weighting by the proportion of single-family and multifamily renters as follows,

$$E_{djt} = \pi^{SFO}_{djt} E^{SFO}_{djt} + \pi^{MFO}_{djt} E^{SFO}_{djt} e^{\hat{\alpha}^{1}_{elec,t}} + \pi^{SFR}_{djt} E^{SFO}_{djt} e^{\hat{\alpha}^{2}_{elec,t}} + \pi^{MFR}_{djt} E^{SFO}_{djt} e^{\sum_k \hat{\alpha}^{k}_{elec,t}} \tag{40}$$

$$G_{djt} = \pi^{SFO}_{djt} G^{SFO}_{djt} + \pi^{MFO}_{djt} G^{SFO}_{djt} e^{\hat{\alpha}^{1}_{gas,t}} + \pi^{SFR}_{djt} G^{SFO}_{djt} e^{\hat{\alpha}^{2}_{gas,t}} + \pi^{MFR}_{djt} G^{SFO}_{djt} e^{\sum_k \hat{\alpha}^{k}_{gas,t}}, \tag{41}$$

where π^{SFO}_{djt}, π^{MFO}_{djt}, π^{SFR}_{djt}, and π^{MFR}_{djt} are the proportion of single/multifamily owners/renters in demographic group d, city j, and year t.

A.2.2 Wages

We can write total income for a household of a demographic group d, in the city j and year t, as $I_{djt} = W_{ejt} \times l_{dt}$, where l_{dt} is the efficiency units of labor supplied by a worker in the demographic group d in year t. Efficiency units account for the probability that a worker is employed, the hours worked, and the productivity of that work conditional on being employed. Specifically,

[17] The 1997 and 2001 RECS surveys did not ask about the education status of surveyed households. We use divison, race, home type, rental status, and household size from 1993 and 2009 to predict the probability of each observation in the 2001 sample being college educated using logistic regression. After predicting the probability of being college educated, we draw actual outcomes according to the predicted probability.

we have $l_{dt} = E_{dt} \times \tilde{l}_{dt}$, where E_{dt} is the probability that a household in the demographic group d is employed in year t, and $\tilde{l}_{dt}$ is productivity conditional on working. We consider a household employed if the household head or their spouse reports they are employed, work at least 48 weeks per year, and at least 35 hours per week.[18] We parameterize the productivity term as $\log \tilde{l}_{dt} = X'_{dt}\beta_{et}$ for a vector of controls X'_{d}, where $e \in$ {No College, College} indexes education level.

We first calculate E_{dt} as the proportion of employed households in the demographic group d and year t. Next, we estimate the following regression for employed households,

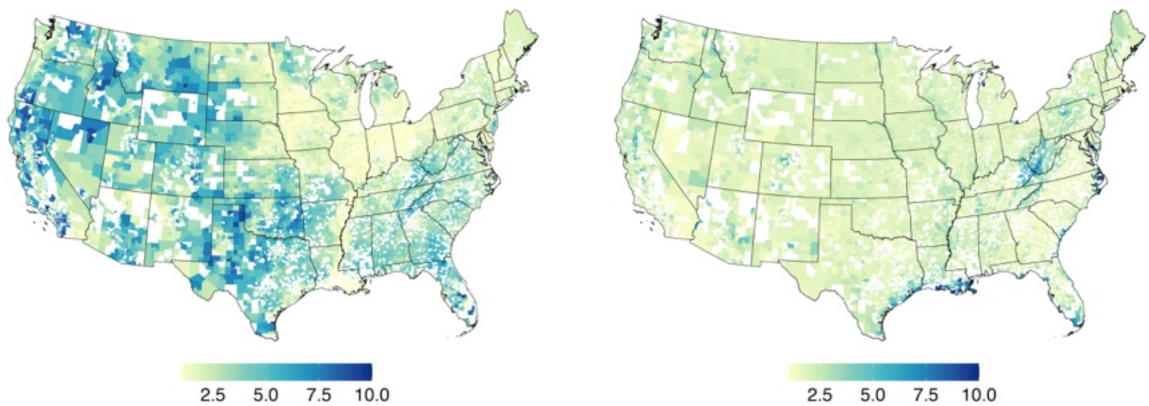
$$\log I_{idjt} = X'_{idjt}\beta_{et} + \nu_{ejt} + \varepsilon_{idjt}, \tag{42}$$

where ν_{ejt} is a education-city-year fixed effect that estimates $\log(W_{ejt})$. Our vector of controls, X'_{idjt} includes whether the household is married, whether the household has over 25 years of potential experience, and whether the household head or spouse is white. We assume that no unobservable factors affect income after adding the vector of controls, X'_{idjt}, and the education-city-year fixed effect. Baum-Snow and Pavan (2012) and Roca and Puga (2017) provide evidence that after conditioning on education, there is little selection on unobservable factors that affect income. We then calculate demographic-city-year income, I_{djt}, using estimates of $\hat{\nu}_{djt}$ and $\hat{\beta}_e$, as $I_{djt} = E_{dt} \times \exp(\hat{\nu}_{ejt} \times \bar{X}'_{dt}\hat{\beta}_{et})$. Here, $\bar{X}_{dt}$ is the demographic group-year average value for each control variable. Using demographic group-year averages holds these observable characteristics constant across all cities.

A.2.3 Housing Quantity and Rent

Our model requires a quantity of housing units, H and the price for those housing units, P^H_j, but our data from the Census reports total housing expenditure. Specifically, the variable *RENT* gives monthly contract rent payments in nominal dollars, which we convert to annual, real dollars. Note that an individuals' housing expenditures can be written as $\mathbb{E}^H_{ijt} = P^H_{jt} H_{ijt}$ where H_{ijt} is the quantity of housing the individual consumes. We parameterize housing quantity as $H_{ijt} = X'_{ijt}\beta_t$, where X'_{ijt} is a vector of observable characteristics, including the number of rooms, the number of units in the building, the number of bedrooms, the number of people living in the house per room, and the decade the house was built. Plugging in our parameterization and taking logs yields our estimating equation:

[18] We assume that the probability of employment within a demographic group does not vary across cities.



(a) Mean fire risk score **(b)** Mean flood risk score

Figure A1: Mean fire and flood risk scores from the First Street Foundation data by census tract. The property-level scores range between 1 and 10, with 10 representing the most at-risk property. White tracts are those not included in the public FSF data.

$$\log(\mathbb{E}^H_{ijt}) = \mu_{jt} + X'_{ijt}\beta_t + \varepsilon_{ijt}. \tag{43}$$

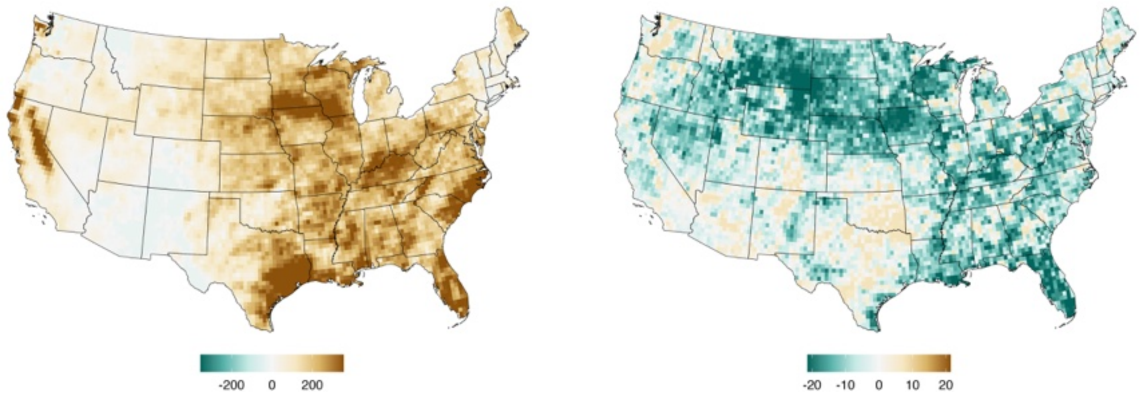
where μ_{jt} is a city-year fixed effect that estimates P^H_{jt}. The coefficients on all of the observable housing characteristics are allowed to vary by year. We then define the per-unit cost of housing using the city-year fixed effect, $P^H_{jt} = e^{\mu_{jt}}$, and quantity of housing as housing expenditure divided by the per-unit cost of housing, $H_{ij} = \mathbb{E}^H_{ijt}/P^H_{jt}$. We limit the sample to renters aged 16 to 64 in this estimation. We refer to the per-unit cost of housing as rent throughout the paper.

Appendix B Additional Descriptive Results

Figure A1 shows mean fire and flood risk scores by census tract from the First Street Foundation data. The arid West generally has the highest fire risk scores, while the gulf coast has the highest flood risk scores.

Figure A2 shows how the number of no-rain days and annual precipitation have changed between 1990 and 2019. Generally, the eastern half of the US has gotten wetter.

Figures A3 and A4 show the relationship between 1990 share of each city's population that is low-income or non-white and changes in precipitation variables between 1990 and 2019. Similar to temperature, there is a positive relationship between the share of a city that is low-income or non-white and increases in total precipitation. There is no clear relationship



(a) Change in total precipitation per year (mm) **(b)** Change in the number of no rain days

Figure A2: Change in the no rain days and annual precipitation. No rain days are days with less than 1mm of precipitation. Difference taken between 5 year moving averages and are censored at the 5th and 95th percentiles of grid cells.

between the number of rain free days and either of the demographic variables.

B.1 Energy demand and climate

A robust energy justice literature explores differences in energy expenditures and demand between demographic groups. For example, Lyubich (2020) demonstrates that black households spend more on energy than observably similar white households. We begin by replicating this result using our census and ACS data. We regress total expenditure on electricity and natural gas on indicators for race interacted with income decile, adding fixed effects for city, year, education, and several other characteristics that may affect energy expenditures.[19] Figure A5 shows the gap in energy expenditures between black and white households throughout the income distribution. Black households spend more on energy than observably similar households throughout the income distribution—aside from the highest income decile, where black households spend slightly less on electricity. These results suggest that either (1) black households have stronger preferences for the services provided by this energy, or (2) black households live in structures with unobservably lower energy efficiency. Research demonstrates that black households have faced, and continue to face, more significant barriers in the housing market than white households (Christensen, Sarmiento-Barbieri, and Timmins, 2021; Christensen and Timmins, 2021).

The gap in expenditures between white and black households does not tell us whether they respond differently to changes in weather. Thus, we run similar regressions but now include

[19] Specifically, these are characteristics of the physical house: number of rooms, kitchen present, plumbing present, decade built, units in the structure, and number of bedrooms, as well as characteristics about the household: the number of children and marital status.

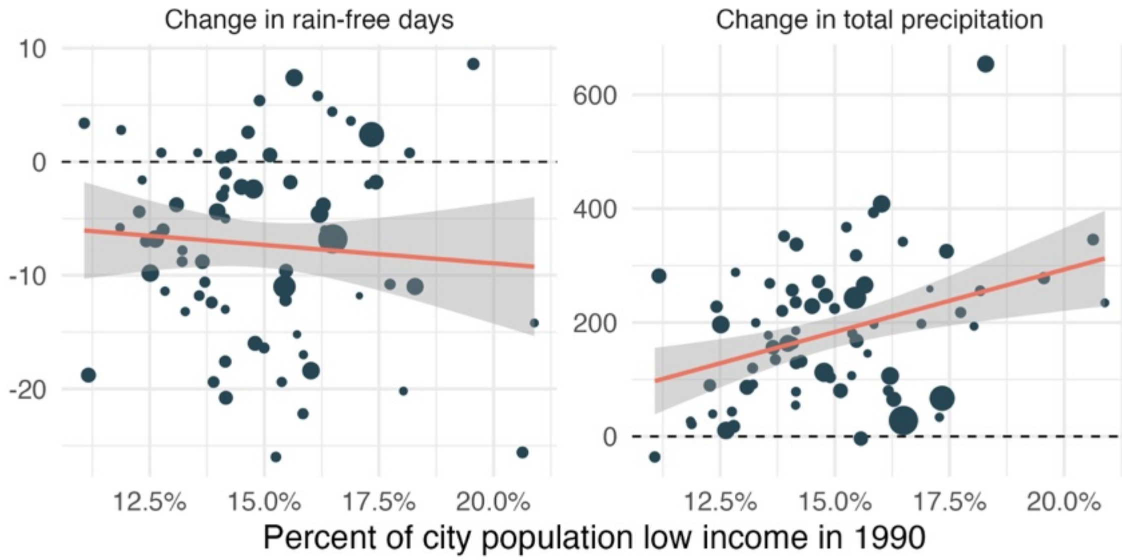


Figure A3: Relationship between share non-white and climate. Each point is a city, where the size of the point represents the city's 1990 population. Low income defined as households in the bottom quintile of the national income distribution in 1990. Regression lines are weighted by population.

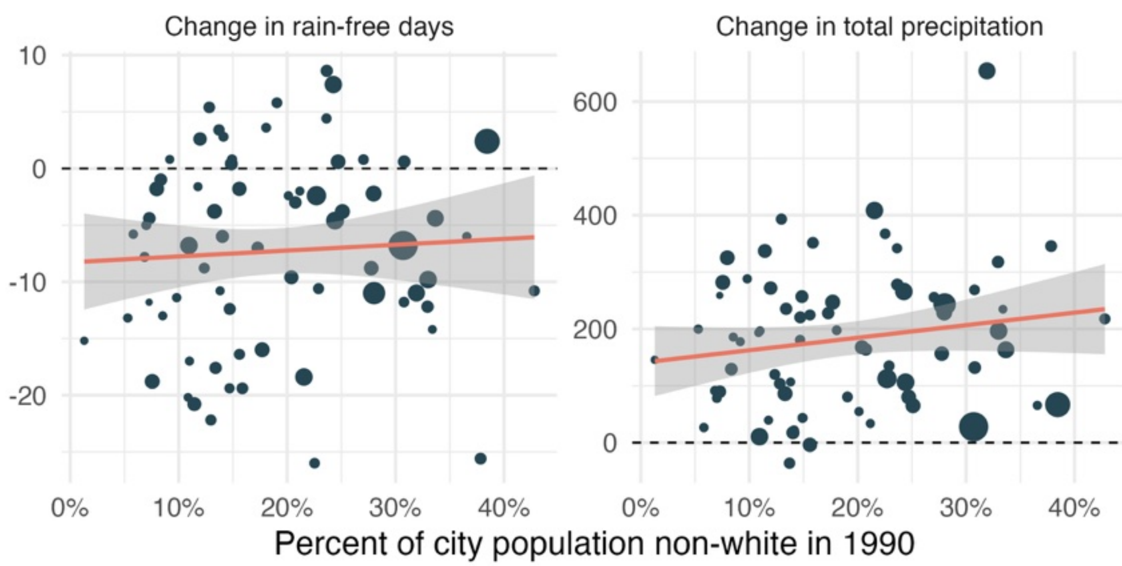


Figure A4: Relationship between share non-white and climate.Each point is a city, where the size of the point represents the city's 1990 population. Low income defined as households in the bottom quintile of the national income distribution in 1990. Regression lines are weighted by population.

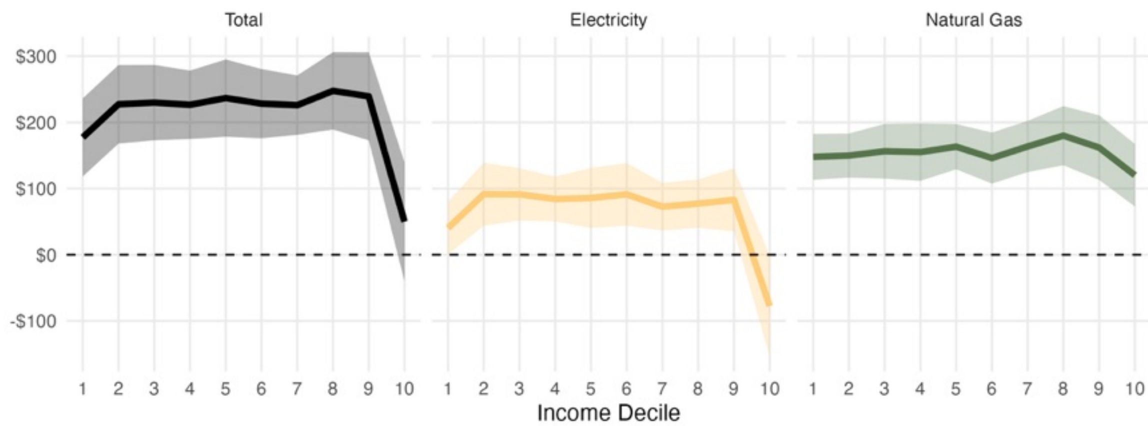


Figure A5: Black-white energy expenditure gap by income decile. The coefficients plotted are those from a regression of energy expenditures on indicator variables for income decile and income decile interacted with whether the household is black, with fixed effects for city, year, education level, number of children, marital status, number of rooms, kitchen present, plumbing present, decade built, units in the structure, and number of bedrooms. We randomly downsampled to 1 million observations to ease computation. Standard errors are clustered by city.

CDD and HDD as regressors and look for heterogeneity in the effects of CDD and HDD on energy expenditure by race and income. We add the same battery of fixed effects as before. Table A1 shows heterogeneity in the effect of degree days by race. Black households increase spending by more than white households for an increase in HDD and by less than white households for an increase in CDD. Differences in the predominant heating fuel may explain this—black households increase electricity expenditure by more than white in response to more HDDs and decrease their natural gas use by less than white households in response to CDDs.

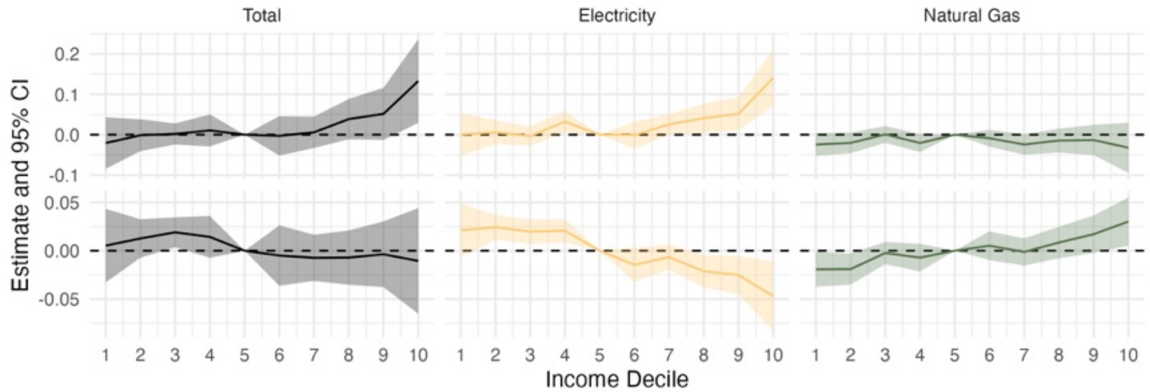
Next, we explore heterogeneity in the effect of degree days across the income distribution. Figure A6 shows how the effect of degree days on energy expenditures differs from the fifth income decile for the rest of the income distribution. The wealthiest households have the strongest increase in electricity expenditure in response to more CDDs and in natural gas expenditure in response to HDDs. Generally, the electricity response to HDDs is decreasing in income—suggesting that low-income households are more likely to use electricity as their heating fuel source. Since the highest income decile is least likely to be income-constrained with respect to their electricity spending, these results may suggest that their stronger response in CDD is the result of always maintaining their preferred indoor temperature. Other households may have a lower expenditure response if they tolerate a higher indoor temperature when it is hotter outside instead of spending more money on electricity to run air conditioning more intensely.

Table A1: Effect of CDD and HDD on Energy Expenditures.

Dep. Var.	Total	Electricity	Natural Gas
Model:	(1)	(2)	(3)
Variables			
Black	155.0*	-27.22	143.3***
	(87.76)	(68.10)	(49.16)
HDD × Black	0.0580**	0.0493**	0.0235
	(0.0251)	(0.0191)	(0.0154)
HDD	0.0434	0.0989*	-0.0569
	(0.0801)	(0.0503)	(0.0500)
CDD × Black	-0.0740	-0.0126	-0.0440*
	(0.0519)	(0.0400)	(0.0255)
CDD	0.3588**	0.1204	0.2531**
	(0.1370)	(0.1295)	(0.1263)
Fit statistics			
Observations	820,930	872,960	829,054
R^2	0.30894	0.31055	0.18668
Within R^2	0.00411	0.00117	0.00528

Clustered (City) standard-errors in parentheses
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Regresions include city, year, education, number of children, marital status, kitchen, number of rooms, plumbing, decade built, units in structure, number of bedroom fixed effects. Data from downsampled census and ACS data from 1990, 2000, 2010, and 2019 matched to PRISM data from that year.



Effect of CDD on total expenditures for 5th decile of 0.33. Effect of HDD on total expenditures for 5th decile of 0.06. Effect of CDD on electricity expenditures for 5th decile of 0.09. Effect of HDD on electricity expenditures for 5th decile of 0.11. Effect of CDD on natural gas expenditures for 5th decile of 0.27. Effect of HDD on natural gas expenditures for 5th decile of -0.05

Figure A6: Heterogeneity in the effect of degree days on energy expenditures by income decile. The coefficients plotted are those from a regression of energy expenditures on CDD and HDD interacted with indicator variables for income decile, with fixed effects for city, year, education level, number of children, marital status, number of rooms, kitchen present, plumbing present, decade built, units in the structure, and number of bedrooms. Thus, the estimates are difference in effects of degree days for an income decile relative to the fifth income decile. We randomly downsampled to 1 million observations to ease computation. Standard errors are clustered by city.

Figure A7 shows heterogeneity in degree days' effect by race and income decile. All estimates are relative to white households in the fifth income decile. Black and white households respond similarly in electricity expenditure to CDDs, except for the highest income decile—where white households have a much stronger response. Black households tend to have stronger responses to HDDs, though these differences are generally not statistically significant.

We can also use the Residential Energy Use Survey (RECS) to evaluate how households respond to climate. Though the surveys here do not report the respondents' exact locations, the EIA does report HDD and CDD for those locations.[20] We are interested in heterogeneity in household energy responses to changes in climate. We regress electricity and natural gas usage on HDD and CDD, as well as interactions between climate variables and race. We add year, census division, and race fixed effects. The results, shown in Table A2, are descriptive rather than causal—demonstrating differences in energy demand responses to climate by race. Households increase their electricity usage in response to higher HDD and CDDs. Black households are less responsive than white households on average, though the coefficients are not statistically significant. The results for natural gas usage are surprising—the coefficient on HDD is not significant, and the coefficient on CDD is negative and significant. This unintuitive result

[20] The EIA adds noise to this measure to prevent identifying the respondent's exact location. This noise will slightly attenuate the results presented here.

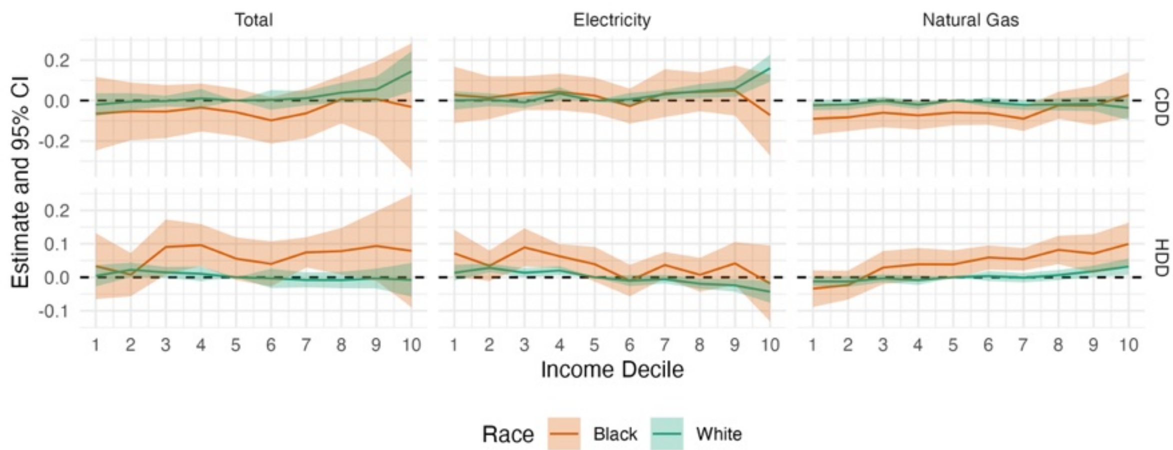


Figure A7: Heterogeneity in the effect of degree days on energy expenditures by income decile and race. The coefficients plotted are those from a regression of energy expenditures on CDD and HDD interacted with indicator variables for income decile and race, with fixed effects for city, year, education level, number of children, marital status, number of rooms, kitchen present, plumbing present, decade built, units in the structure, and number of bedrooms. Thus, the estimates are difference in effects of degree days for an income decile relative to white households in the fifth income decile. We randomly downsampled to 1 million observations to ease computation. Standard errors are clustered by city.

may be because households in warmer climates (high CDDs and low HDDs) are less likely to have natural gas heaters. We find that black households have a stronger demand response for natural gas to HDDs.

Appendix C Model

C.1 Derivation of Comfort and Energy Prices

We can solve the households utility maximization problem conditional on choosing city j in three steps. First, households will consume gas and electricity in a cost-minimizing manner to produce a given amount of energy. The first-order conditions from minimizing the cost of energy using equation (2) give us the following conditional demand functions for electricity and gas.

$$E^*(\mathcal{E}|d,j) = M^{\mathcal{E}}_{dj}\left(P^G_j\theta^E_{dj}\right)^{\sigma\varepsilon}\mathcal{E}, \tag{44}$$
$$G^*(\mathcal{E}|d,j) = M^{\mathcal{E}}_{dj}\left(P^E_j\theta^G_{dj}\right)^{\sigma\varepsilon}\mathcal{E} \tag{45}$$

Table A2: Effect of CDD and HDD on Energy Demand.

Dep. Var. Model:	Electricity Usage (kWh) (1)	Natural Gas Usage (cu ft) (2)
Variables		
HDD	0.6920***	0.5345
	(0.0644)	(0.7423)
CDD	1.274**	-5.781**
	(0.2925)	(1.760)
HDD × Race = Black	-0.1726	7.200**
	(0.1237)	(2.134)
HDD × Race = Rest	0.1121	0.9732
	(0.0809)	(0.8979)
CDD × Race = Black	-0.1448	3.088
	(0.3853)	(1.452)
CDD × Race = Rest	-0.0347	-0.2569
	(0.0833)	(0.9812)
Fit statistics		
Observations	29,702	29,702
R^2	0.15988	0.18400
Within R^2	0.01079	0.02157

Clustered (year) standard-errors in parentheses
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Regresions include year, census division, and race fixed effects. Data from the 1993, 2001, 2009, and 2015 RECS surveys.

where $M^{\mathcal{E}}_{dj} = \left(\theta^{E}_{dj}{}^{\sigma_{\mathcal{E}}} P^{G}_{dj}{}^{\sigma_{\mathcal{E}}-1} + \theta^{G}_{dj}{}^{\sigma_{\mathcal{E}}} P^{E}_{dj}{}^{\sigma_{\mathcal{E}}-1}\right)^{\frac{\sigma_{\mathcal{E}}}{1-\sigma_{\mathcal{E}}}}$. These conditional demand functions allow us to derive a unit cost function for energy that does not depend on the quantity of energy. We will use this unit cost function as the price of energy,

$$P^{\mathcal{E}}_{dj} = \left(\theta^{E}_{dj}{}^{\sigma_{\mathcal{E}}} P^{E}_{j}{}^{1-\sigma_{\mathcal{E}}} + \theta^{G}_{dj}{}^{\sigma_{\mathcal{E}}} P^{G}_{j}{}^{1-\sigma_{\mathcal{E}}}\right)^{\frac{1}{1-\sigma_{\mathcal{E}}}} \tag{46}$$

Similarly, Households will produce comfort using energy and housing in a cost-minimizing manner. The first-order conditions from minimizing the cost of producing comfort using (1) give us the following conditional demand functions for energy and housing.

$$H^{*}(C|d, j) = M^{c}_{dj}\left(\theta^{H}_{dj} P^{\mathcal{E}}_{dj}\right)^{\sigma_c} C_{dj}, \tag{47}$$

$$\mathcal{E}^{*}(C|d, j) = M^{c}_{dj}\left(\theta^{\mathcal{E}}_{dj} P^{H}_{j}\right)^{\sigma_c} C_{dj} \tag{48}$$

where $M^{c}_{dj} = \left(\theta^{\mathcal{E}}_{dj}{}^{\sigma_c} P^{H}_{dj}{}^{\sigma_c-1} + \theta^{H}_{dj}{}^{\sigma_c} P^{\mathcal{E}}_{j}{}^{\sigma_c-1}\right)^{\frac{\sigma_c}{1-\sigma_c}}$ We can use the unit cost function derived from these conditional demand functions to calculate the price of comfort

$$P^{C}_{dj} = \left(\theta^{H}_{dj}{}^{\sigma_c} P^{H}_{dj}{}^{1-\sigma_c} + \theta^{\mathcal{E}}_{dj}{}^{\sigma_c} P^{\mathcal{E}}_{dj}{}^{1-\sigma_c}\right)^{\frac{1}{1-\sigma_c}} \tag{49}$$

We also use the derived demand for comfort to yield the unconditional housing and energy demand functions:

$$H^{*}_{dj} = M^{c}_{dj}\left(P^{\mathcal{E}}_{dj}\theta^{H}_{dj}\right)^{\sigma_c} \times \frac{\alpha^{C}_{dj} W_{dj}}{\boldsymbol{\alpha_{dj}} P^{C}_{dj}} \tag{50}$$

$$E^{*}_{dj} = M^{c}_{dj}\left(P^{H}_{j}\theta^{\mathcal{E}}_{dj}\right)^{\sigma_c} M^{\mathcal{E}}_{dj}\left(P^{G}_{j}\theta^{E}_{dj}\right)^{\sigma_{\mathcal{E}}} \times \frac{\alpha^{C}_{dj} W_{dj}}{\boldsymbol{\alpha_{dj}} P^{C}_{dj}} \tag{51}$$

$$G^{*}_{dj} = M^{c}_{dj}\left(P^{H}_{j}\theta^{\mathcal{E}}_{dj}\right)^{\sigma_c} M^{\mathcal{E}}_{dj}\left(P^{E}_{j}\theta^{G}_{dj}\right)^{\sigma_{\mathcal{E}}} \times \frac{\alpha^{C}_{dj} W_{dj}}{\boldsymbol{\alpha_{dj}} P^{C}_{dj}}. \tag{52}$$

C.2 Marginal effect of climate on comfort demand

Here we see how changes in climate affect demand for electricity, gas, and housing. The derivative of electricity demand with respect to climate variable z^{l} is

$$\frac{\partial E}{\partial z^l} = \frac{\kappa_E}{\rho_\mathcal{E}(1-\rho_\mathcal{E})} E\left[\rho_\mathcal{E} + \frac{P^E E}{P^\mathcal{E}\mathcal{E}}\left(\frac{1-\rho_\mathcal{E}}{1-\rho_C}\left(1-\rho_C\frac{P^\mathcal{E}\mathcal{E}}{P^C C}\right)-1\right)\right] \tag{53}$$

This effect has three main pieces, the first term in brackets comes from the direct effect of increases in z^l increasing θ_E, this will always be positive. The second effect comes from the change in energy demand, which moves in the opposite direction as the price of energy (which moves in the same direction as the price of comfort). The final effect comes from increasing the denominator of the "share" function, $M_\mathcal{E}$, which will always be the opposite sign as the effect from changes in energy demand.

Changes in gas demand are similar, as the conditional demand function for gas has the same denominator of the share function and energy, but those are the only two effects. Thus, if energy price rises, decreasing the demand for energy, this will have a negative effect on gas demand. Additionally, the increases in the denominator of the share function for energy will further decrease demand for gas

$$\frac{\partial G}{\partial z^l} = \frac{\kappa_E}{\rho_\mathcal{E}(1-\rho_\mathcal{E})} G\frac{P^E E}{P^\mathcal{E}\mathcal{E}}\left[\frac{1-\rho_\mathcal{E}}{1-\rho_C}\left(1-\rho_C\frac{P^\mathcal{E}\mathcal{E}}{P^C C}\right)-1\right]. \tag{54}$$

Changes in housing demand depend on the change in the denominator of the share function for comfort and changes in comfort demand. If the price of comfort increases, then comfort demand will decrease, thereby decreasing housing demand. Additionally, if the price of energy increases, then this will increase (decrease) the denominator of the share function if housing and energy are complements (substitutes), causing housing demand to decrease (increase).

$$\frac{\partial H}{\partial z^l} = \frac{\kappa_E}{\rho_\mathcal{E}} H\frac{P^E E}{P^C C}\left[\frac{1}{1-\rho_C}\frac{P^H H}{P^\mathcal{E}\mathcal{E}} + 1\right] \tag{55}$$

C.3 Firm FOC derivation

In this section, we give the details on solving the firm's problem. Plugging the labor aggregator (13) into the production function (12), the firm's profit function is

$$\pi_j = B_j K_j^\alpha \left(\lambda_j S_j^{\rho_l} + (1-\lambda_j) L_j^{\rho_l}\right)^{\frac{1-\alpha}{\rho_l}} - W_j^S S_j - W_j^L L_j - rK_j.$$

Each firm chooses capital K_j, college educated labor S_j, and non-college educated labor L_j to maximize profit. Taking the derivative with respect to each choice, we have the following first order conditions,

$$
\begin{aligned}
r &= \alpha \frac{Y_j}{K_j} \\
W_j^S &= (1-\alpha)\left(\frac{Y_j}{\mathcal{L}_j}\right)\mathcal{L}_j^{1-\rho_l}\lambda_j S^{\rho_l-1} \\
W_j^L &= (1-\alpha)\left(\frac{Y_j}{\mathcal{L}_j}\right)\mathcal{L}_j^{1-\rho_l}(1-\lambda_j)L^{\rho_l-1}.
\end{aligned}
$$

We assume capital is supplied perfectly elastically on the international market at rate $\bar{r}$. Thus, capital demand is $K_j^\star = \frac{\alpha Y_j}{\bar{r}}$. Plugging this into the production function yields $Y_j = B_j^{\frac{1}{1-\alpha}}\left(\frac{\alpha}{\bar{r}}\right)^{\frac{\alpha}{1-\alpha}}\mathcal{L}_j$. Letting $\tilde{B}_j = (1-\alpha)B_j^{\frac{1}{1-\alpha}}\left(\frac{\alpha}{\bar{r}}\right)^{\frac{\alpha}{1-\alpha}}$, we have the first order conditions in equation (14).

C.4 Labor Demand Parameters

In this section, we describe our calibration and estimation of the labor demand parameters: labor elasticity of substitution σ_l and the labor input use intensities, λ_j. We suppress t-subscripts as with the above sections for exposition, but use the following procedure for each of our sample years. First, we calibrate $\sigma_l = 2$ based on Card (2009). Then we use the relative labor demand curves to identify λ_j. The relative labor demand curves are given by:[21]

$$
\underbrace{\log\left(\frac{W_j^S}{W_j^L}\right)}_{\text{Estimated}} = \underbrace{-\frac{1}{\sigma_l}}_{\text{Calibrated}} \underbrace{\log\left(\frac{S_j}{L_j}\right)}_{\text{Data}} + \underbrace{\log\left(\frac{\lambda_j}{1-\lambda_j}\right)}_{\text{Unknown}}. \tag{56}
$$

Note that the only unknowns in equation 56 are the λ_j values. We can solve for these as:

$$
\lambda_j = \frac{K_j}{1+K_j}, \tag{57}
$$

where

$$
K_j = \left(\frac{W_j^S}{W_j^L}\right)\left(\frac{S_j}{L_j}\right)^{1/\sigma_l}.
$$

[21] Note that $\rho_l - 1 = -\frac{1}{\sigma_l}$.

Next, we can solve for the firm's TFP using either first order condition for college or non-college labor as there is only one unknown.

C.5 Housing Supply Calibration

In this section, we describe the calibration of the rental supply parameters. First, we calibrate the inverse supply elasticities to those in Saiz (2010), specifically the inverse of the elasticities reported in Table VI. Some of our cities, Sacramento, Honolulu, and the census division aggregates, are not included in this table—we set the elasticity for Sacramento and the census division aggregates equal to the mean elasticity and calculate an elasticity for Honolulu using estimates from column (4) of Table III, setting land-unavailable equal to the maximum and the WRI to the mean. The remaining parameters from the housing supply curve, equation (15), are the intercepts, a_j. Since housing supply equals housing demand in equilibrium, we back these out from the data as

$$\exp a_{jt} = \frac{P^H_{jt}}{\left(\sum_d N_{djt} H_{djt}\right)^{\zeta_j}},$$

where N_{djt} is the count of housholds in demographic group d and city j in year t, and H_{djt} is housing demand.

C.6 Equilibrium Definition

An equilibrium is characterized by a set of wages and comfort prices that satisfy:

(1) **Utility Maximization.** Households make optimal location and comfort demand choices given wages, comfort prices, and amenities. Concretely, this implies $N^\star_{dj} = s^\star_{dj} \times N$ where $s^\star_{dj}$ are the choice shares constructed from (7), evaluated at equilibrium prices. Additionally, housing, electricity, and gas demand satisfy (50), (51), and (52) respectively.

(2) **Profit Maximization.** Firms maximize profits. This simply implies the firm's first order conditions are obeyed according to (14).

(3) **Market clearing.** In the model, labor supply must be equal to labor demand and housing supply must be equal to housing demand.

C.7 Equilibrium Outline

In this section, we provide an overview of how we solve for the counterfactual in which all margins can adjust. We denote the counterfactual vector of climate variables as $\tilde{\mathbf{Z}}$. Amenities are exogenous (to household location choices), so we first recalculate amenities under the new vector of climate variables $\tilde{\mathbf{Z}}$. The algorithm for obtaining the new spatial equilibrium is:

(1) Guess a vector of choice shares for each demographic group, s^0_{dj} where where 0 denotes iteration number (not time). Use this guess to calculate demographic city population levels as $N^0_{dj} = s^0_{dj} \times N$. Additionally, we guess a vector of housing prices, $P^{H,0}_j$.

(2) Use our guesses with the firms first order conditions (14) to calculate city-education wages. We then use our guesses and the counterfactual climate $\tilde{\mathbf{Z}}$ with household first order conditions (5) and (4) to calculate comfort and energy prices.

(3) We then clear the housing market since housing demand is affected by the climate. Given $P^{H,0}_j$ and our implied comfort prices, energy prices, and wages, we use the household first order condition from equation (50) to calculate housing demand, denoted as H^0_{dj}. We aggregate housing demand to the city level, $H^{0,D}_j$ and plug this into the rental supply curve in equation 15, noting that in equilibrium, the quantity of housing supplied must be equal to the quantity of housing demanded. This yields a new housing price, which we denote $\tilde{P}^{H,0}_j$. We check if $\tilde{P}^{H,0}_j = P^{H,0}_j$. If they are not equal, we update the price of housing as $P^{H,1}_j = \alpha \tilde{P}^{H,0}_j + (1-\alpha) P^{H,0}_j$ for $\alpha \in (0,1)$ and start again at the beginning of this step. Once the housing market clears, we have a new vector of housing prices, which we can use to calculate comfort prices.

(4) Re-calculate the city choice shares given the new vectors of wages and comfort prices. We denote these new choice shares as $\tilde{s}^0_{dj}$. Check if $\tilde{s}^0_{dj} = s^0_{dj}$. If not, we update our guess of the shares as $s^1_{dj} = \alpha \tilde{s}^0_{dj} + (1-\alpha) s^0_{dj}$ for $\alpha \in (0,1)$ and return to step (2).

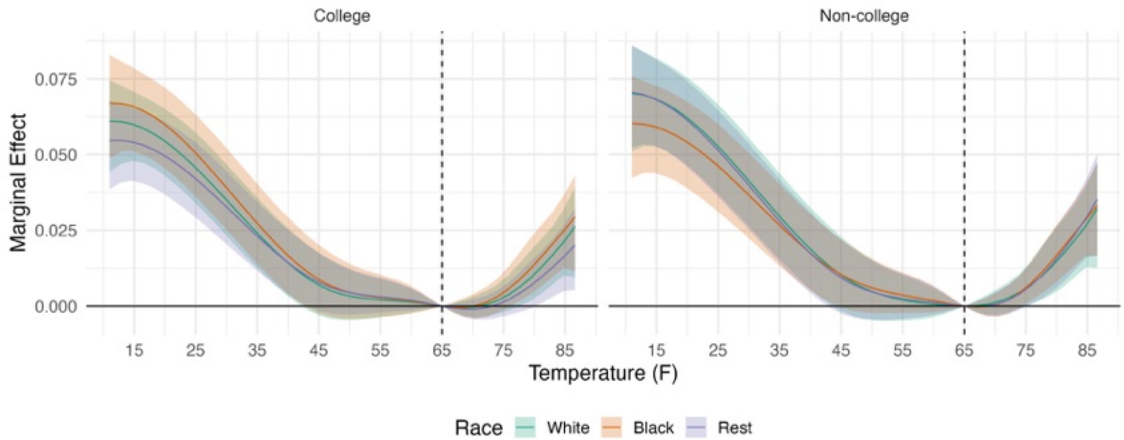
The end of Step (3) using our inital guesses is what we call the "fixed location" equilibrium, since it keeps the original allocation of population, but allows households to optimally choose electricity, gas, and housing.

Appendix D Estimation Appendix

D.1 Alternative specifications for effect of climate on comfort

We could allow for heterogeneity in the effect of climate on preferences for electricity and gas by demographic group by estimating different κ's for each demographic group. Figure A8 estimates our main specification separately for each of the six demographic groups we have in our model. While this estimation does not provide clear evidence that there are differences by race or college education, black households may have a slightly more muted gas response to cold days. This is consistent with Doremus, Jacqz, and Johnston (2022), who find similar responses in energy expenditures between high- and low-income households except among the most extreme temperature days.

(a) Estimates of the effect of climate on $\log \theta^E$.



(b) Estimates of the effect of climate on $\log \theta^G$

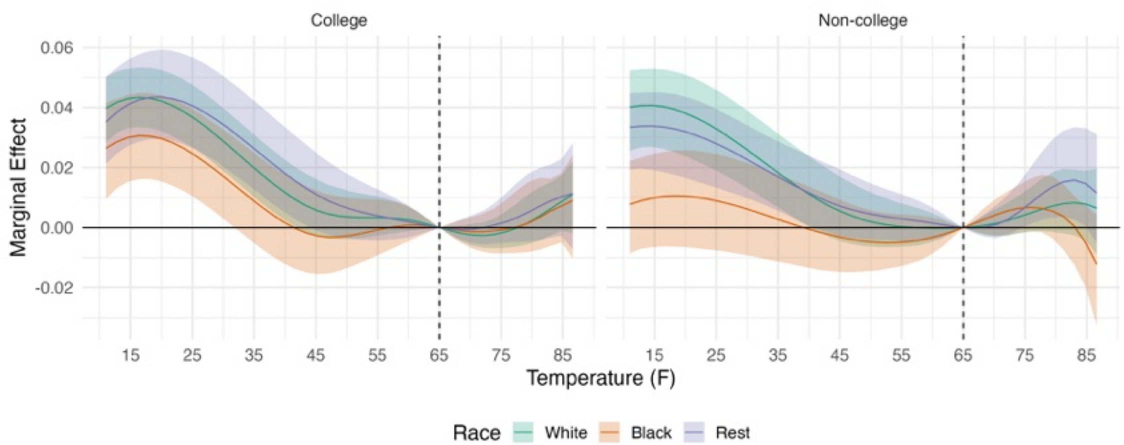


Figure A8: Estimation results for the effect of climate on comfort production using cubic B-splines of degree 7 with heterogeneity by demographic group. Standard errors are bootstrapped over 10,000 draws clustering by city and year.

However, there could still be heterogeneity in the effect of climate on comfort price since other parameters in the comfort price function are heterogeneous by demographic group. Figure A9 shows the marginal effect of a day in each temperature bin on comfort price by demographic group. There are some differences between races, though they are small in magnitude and within the bootstrapped confidence intervals.

Figure A10 shows results for an alternative specification of $\log \theta$'s using 14 temperature bins, one for every decile, plus breaking the top and bottom deciles by the top and bottom 1 and 5 percent. Coefficients are interpreted as the effect of an additional day in each temperature

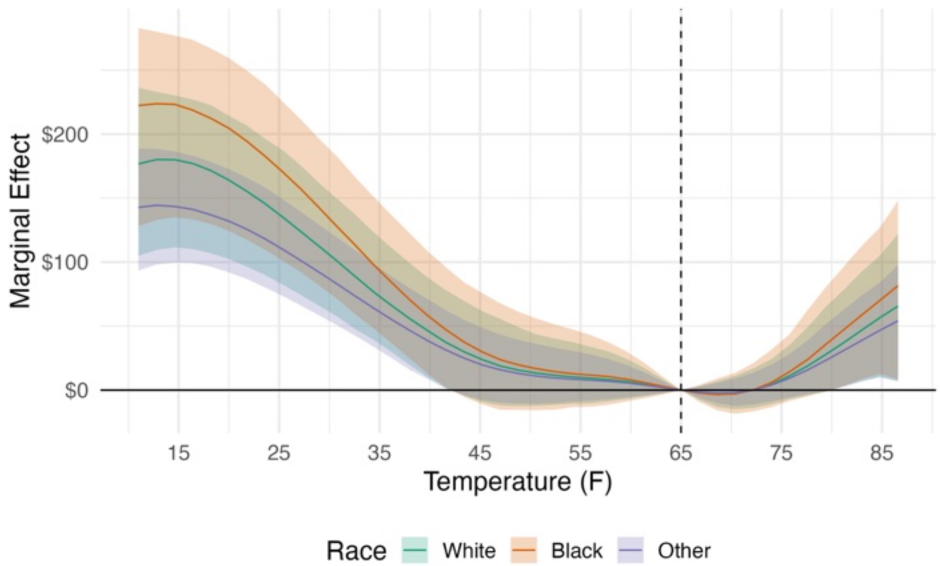
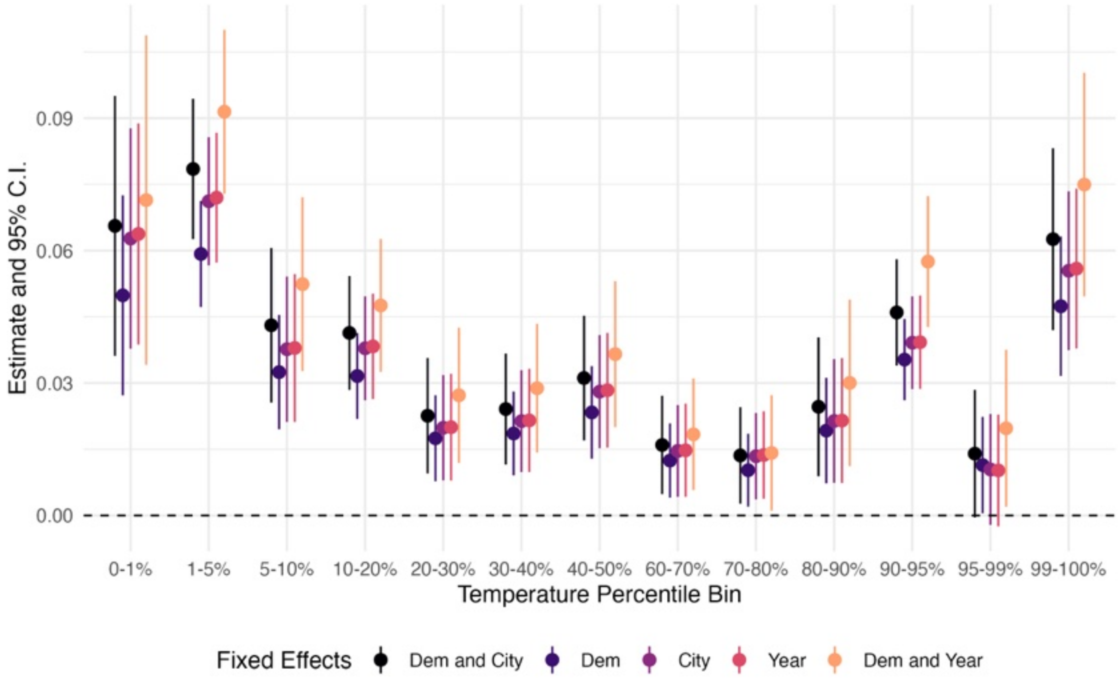


Figure A9: The effect of an additional day at temperature on comfort price by race.

bin relative to a day in the median temperature bin. Standard errors are clustered by city.

(a) Estimates of κ^E, the effect of climate on $\log \theta^E$



(b) Estimates of κ^G, the effect of climate on $\log \theta^G$

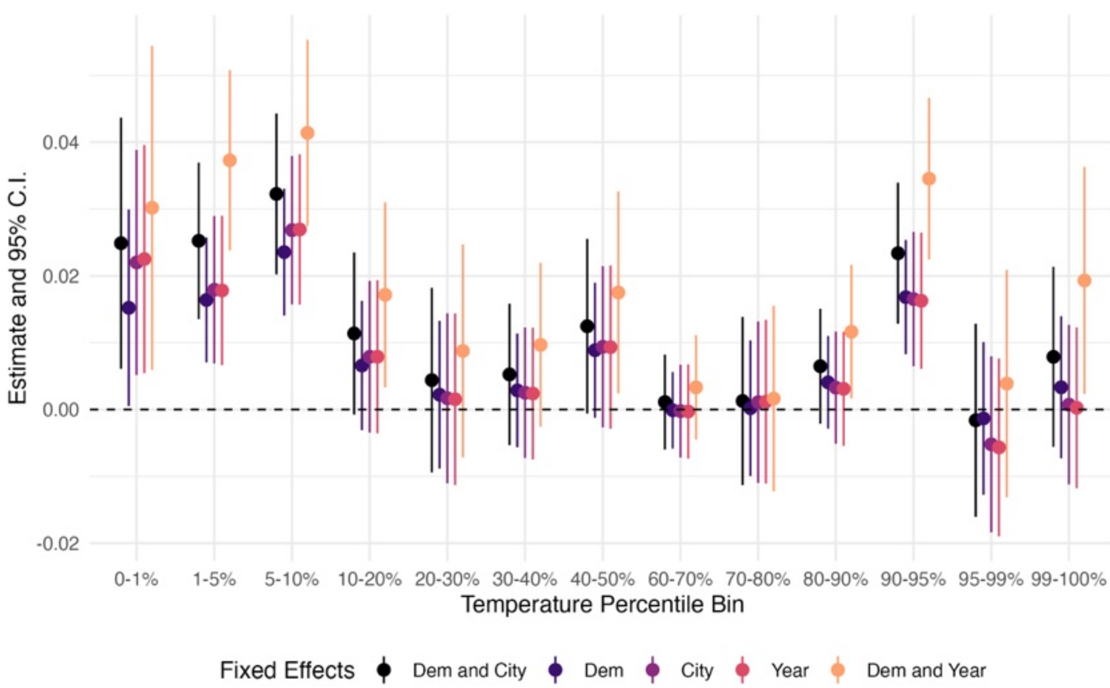


Figure A10: Estimation results for the effect of climate on comfort production, parameters κ^E and κ^G. Our preferred specification includes demographic group and city fixed effects.

D.2 Energy and comfort prices

Figure A11 shows predicted and actual comfort expenditure.

Figure A11: Predicted vs actual comfort expenditure

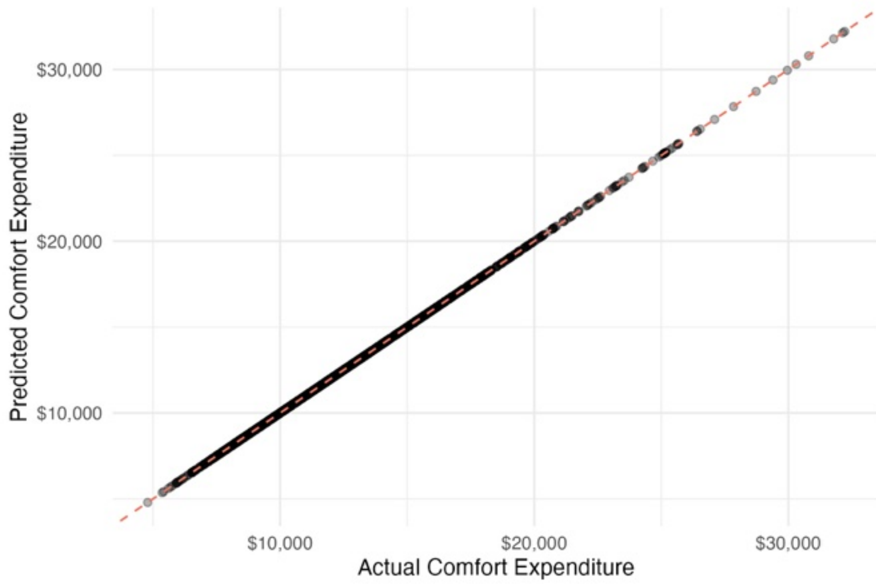
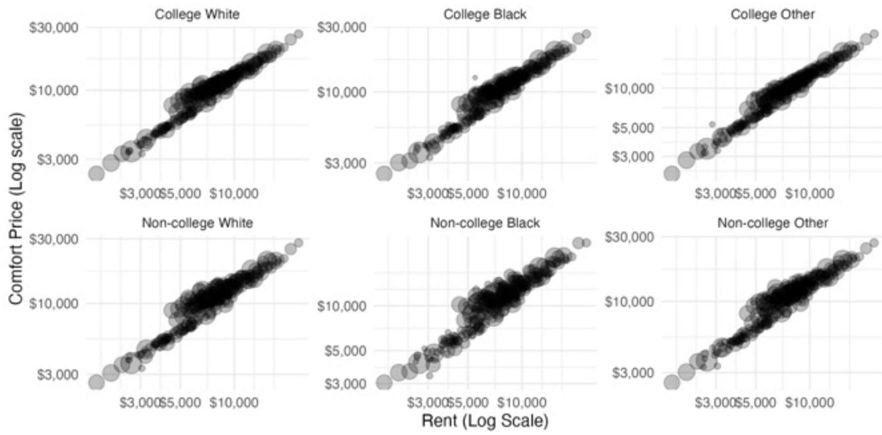


Figure A12 shows how log comfort price is correlated with log rent and log energy prices by demographic group. We expect comfort prices to be determined largely by rent, but also be affected by energy prices, since rent makes up a much larger share of expenditure than energy does. This is exactly how it turns out in our model, with comfort prices more tightly correlated with rent than energy prices, but comfort prices are increasing in both rent and energy prices for all demographic groups.

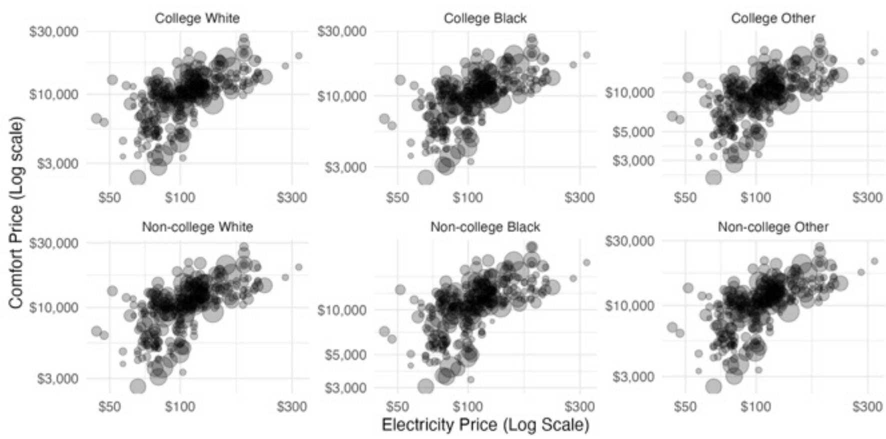
Table A3 shows average comfort and housing expenditure, as well as degree days for selected cities in 2019, ordered by the percent difference between comfort and housing expenditure. We can see that generally, the places with a larger difference between comfort and housing expenditure are cities with more extreme climates, as measured by heating and cooling degree days. Thus, climate is an important part determining the cost of comfort for households beyond just the rent that they pay. We show in the appendix, figure A12, that comfort price is positively correlated with both rent and energy prices, as we would expect.

Figure A12: Rent and Energy Prices versus Comfort Price by demographic group

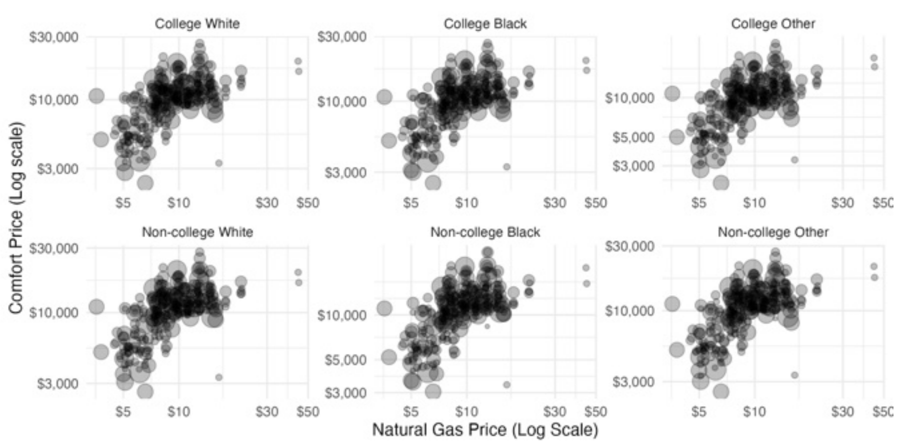
(a) Comfort Price vs Rent



(b) Comfort Price vs Electricity Price



(c) Comfort Price vs Natural Gas Price



Each observation is a city, size represents the 1990 population of each city.

City	Rank	Comfort Exp	Housing Exp	\% Diff	HDD	CDD
Highest						
Birmingham, AL	1	9,640	6,954	28	1,347	1,244
Memphis, TN	2	10,409	7,553	27	1,684	1,255
Youngstown, OH	3	7,847	5,744	27	3,364	407
Tulsa, OK	4	9,217	6,910	25	1,976	1,129
Toledo, OH	5	9,646	7,239	25	3,291	540
Middle						
Atlanta, GA	33	13,325	11,003	17	1,493	1,121
Allentown, PA	34	13,270	10,964	17	3,083	515
New Orleans, LA	35	11,968	9,912	17	596	1,873
Worcester, MA	36	14,439	11,966	17	3,561	366
Virginia Beach, VA	37	13,316	11,061	17	1,727	1,094
Lowest						
Los Angeles, CA	66	19,887	18,243	8	586	788
San Diego, CA	67	21,218	19,806	7	661	571
Oxnard, CA	68	22,177	20,802	6	824	436
San Francisco,CA	69	24,792	23,256	6	1,351	151
San Jose, CA	70	26,357	24,824	6	1,206	340

Table A3: Cities ranked by the percent difference between their average comfort expenditure and average housing expenditure in 2019.

Tables A4 shows an alternative version of A3, but using comfort prices and rent instead of expenditures. Results are largely similar, places with more extreme temperatures see a larger difference between their comfort price and rent. Note that rent here is the per-unit cost of housing, as described in section A.2.3.

City	Rank	Comfort Price	Rent	% Diff	HDD	CDD
Highest						
Youngstown, OH	1	7,589	4,399	42	3,514	475
Birmingham, AL	2	8,945	5,222	42	1,468	1,200
Buffalo, NY	3	10,246	6,044	41	3,840	365
Springfield, MA	4	10,950	6,483	41	3,581	356
Toledo, OH	5	8,205	4,876	41	3,483	529
Middle						
Albany, NY	33	12,563	7,940	37	3,988	283
Charlotte, NC	34	11,205	7,106	37	1,926	891
Knoxville, TN	35	9,013	5,721	37	2,423	634
Kansas City, MO	36	10,170	6,458	36	2,684	908
Baltimore, MD	37	14,342	9,124	36	2,854	645
Lowest						
San Francisco,CA	66	22,345	15,790	29	1,230	465
Miami, FL	67	15,053	10,701	29	113	2,268
Seattle, WA	68	16,778	11,952	29	3,899	38
Austin, TX	69	12,680	9,063	29	1,014	1,856
San Jose, CA	70	24,121	17,426	28	1,276	569

Table A4: Cities ranked by the percent difference between their average comfort price and average housing price in 2019.

Additionally, A5 shows the top and bottom cities by energy $\mathcal{E}$ and comfort C demand. This is comparable to Table 6 from Quigley and Rubinfeld (1989), who estimate "produced comfort" and "dwelling comfort", which are similar to our estimates for energy and comfort respectively. The results qualitatively match, showing that cities with mild climates spend much less on energy than those with more extreme climates.

Rank	City	Energy	Rank	City	Comfort
1	Memphis, TN	1,344.23	1	Austin, TX	1.32
2	Phoenix, AZ	1,153.55	2	Orlando, FL	1.31
3	Oklahoma City, OK	1,146.01	3	San Antonio, TX	1.31
4	Tulsa, OK	1,138.82	4	Bridgeport, CT	1.30
5	San Antonio, TX	1,114.08	5	Phoenix, AZ	1.30
6	New Orleans, LA	1,089.29	6	Tucson, AZ	1.26
7	Dallas, TX	1,073.29	7	Tampa, FL	1.25
8	Houston, TX	1,064.20	8	Miami, FL	1.24
9	Orlando, FL	1,053.08	9	Seattle, WA	1.23
10	Miami, FL	1,040.23	10	Washington, DC	1.23
61	Providence, RI	479.21	61	Oxnard, CA	1.08
62	Sacramento, CA	468.82	62	Los Angeles, CA	1.07
63	Boston, MA	461.41	63	Kansas City, MO	1.06
64	Albany, NY	461.41	64	Memphis, TN	1.06
65	Los Angeles, CA	453.56	65	Buffalo, NY	1.06
66	Honolulu, HI	438.53	66	Syracuse, NY	1.04
67	San Diego, CA	401.64	67	Albany, NY	1.03
68	Oxnard, CA	381.63	68	Youngstown, OH	1.02
69	San Jose, CA	378.38	69	Rochester, NY	1.02
70	San Francisco,CA	359.54	70	Grand Rapids, MI	0.99

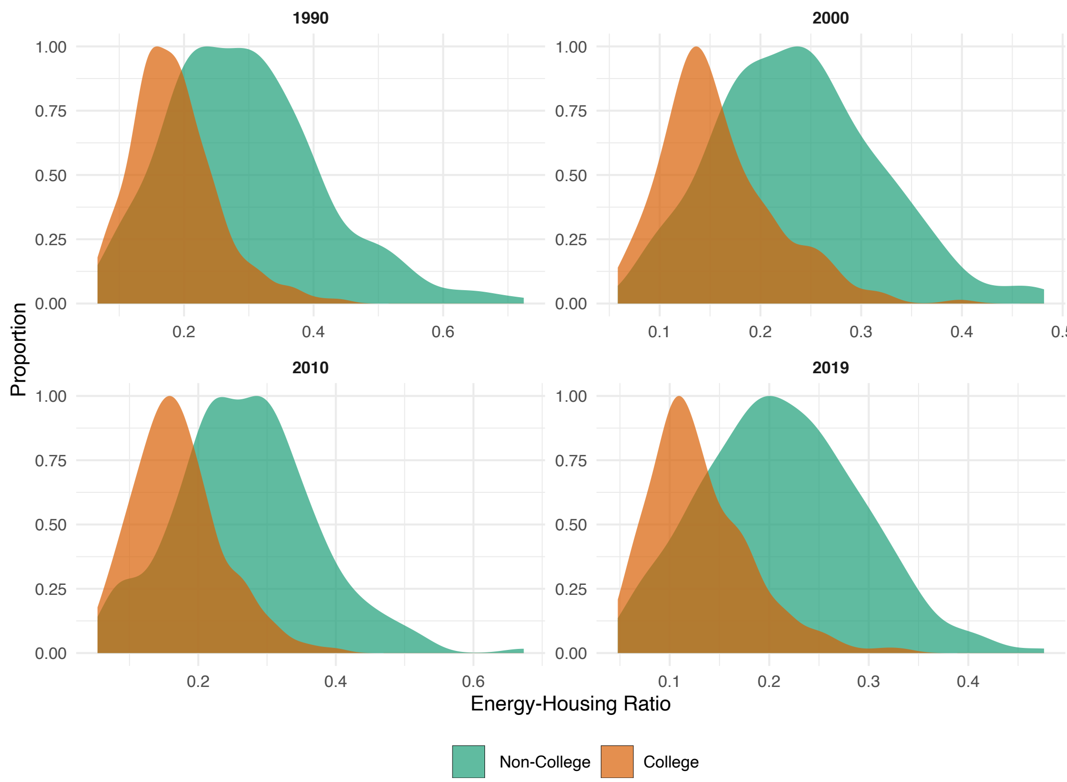
Table A5: Cities ranked by their average aggregate energy demand $\mathcal{E}$ and comfort demand C in 2019.

D.3 Energy Efficiency: Evidence

In this section, we provide evidence of heterogeneity in energy-efficiency by demographic group and across time. Specifically, we plot city-level densities of aggregate energy use $\mathcal{E}$ divided by housing, H. In each figure, $\mathcal{E}$ is calculated using equation 2 evaluated at estimates from column 1 of Table 1. Housing is calculated as in Section A.2.3. We interpret a larger value of this ratio as loosely indicative that homes in a particular city/demographic group are less energy-efficient.[22]

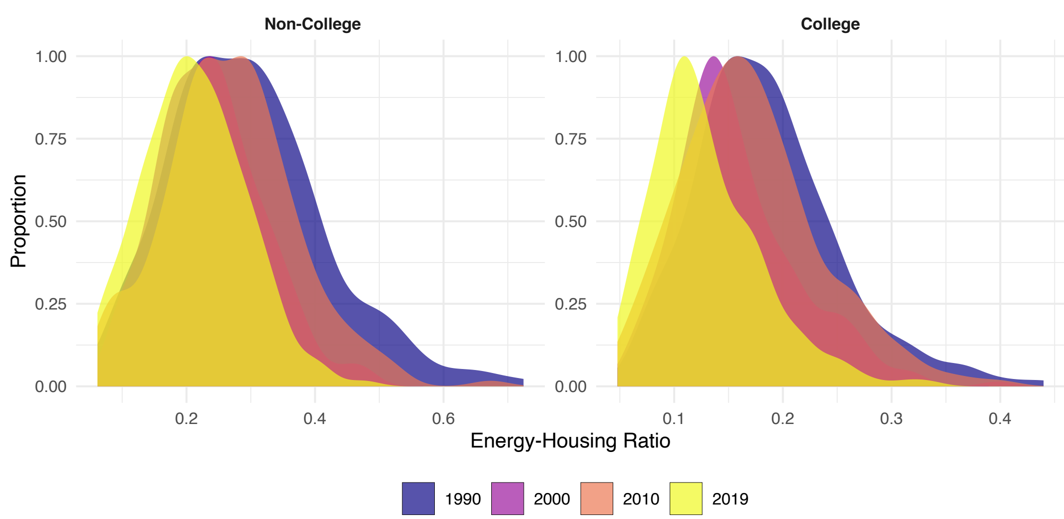
[22] However, it could also be reflect differences in the strength of preferences for housing relative to energy.

Figure A13: Energy-efficiency by education group across years and CBSAs



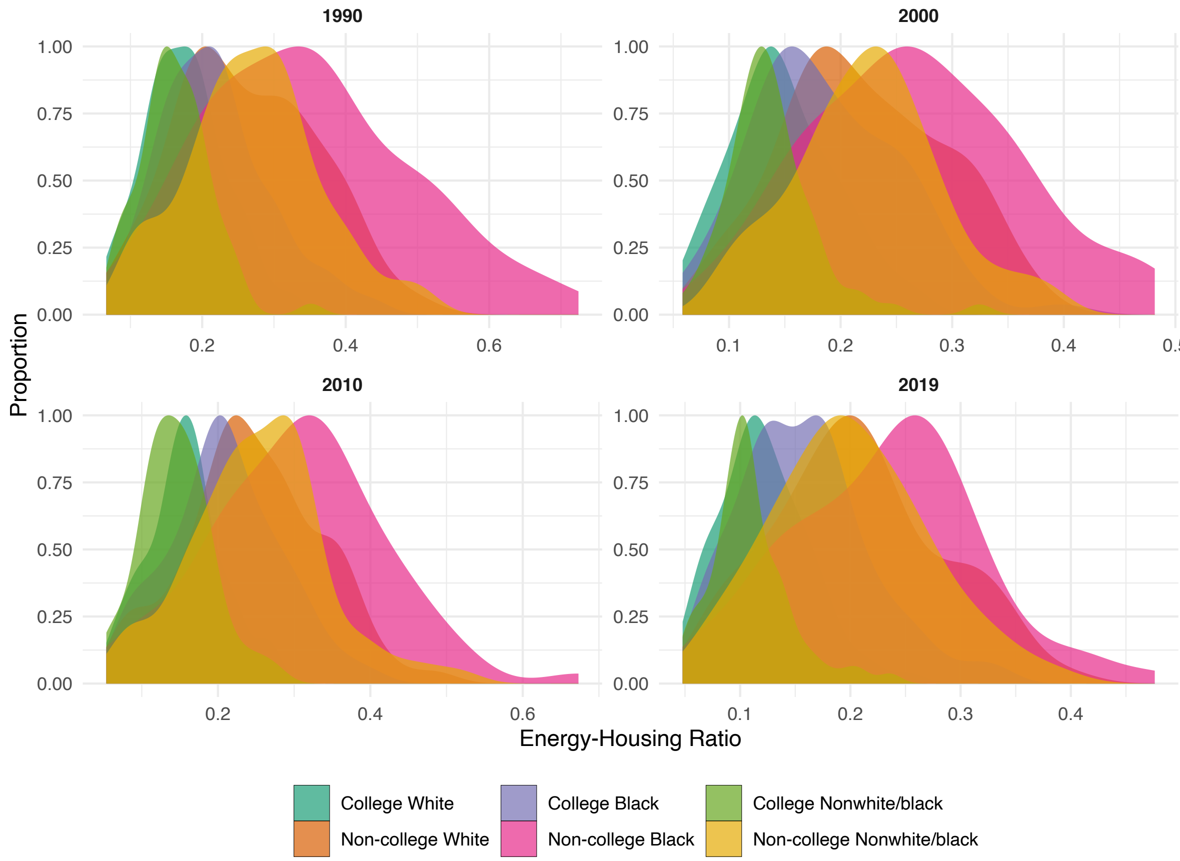
Notes: Energy-efficiency by education group across years and CBSAs.

Figure A14: Energy-efficiency by education-group across years and CBSAs



Notes: Energy-efficiency by education group across years and CBSAs.

Figure A15: Energy-efficiency by demographic-group across years and CBSAs



Notes: Energy-efficiency by demographic group across years and CBSAs.

D.4 Moving Cost Parameters for All Years

Table A6: Household moving costs estimated from equation 33 for 1990. Standard errors are in parenthesis. We estimate standard errors using numerical derivatives. Distance is measured in thousands of miles.

	Non-College			**College**		
	$\tilde{\gamma}^{st}$	$\tilde{\gamma}^{dist}$	$\tilde{\gamma}^{dist2}$	$\tilde{\gamma}^{st}$	$\tilde{\gamma}^{dist}$	$\tilde{\gamma}^{dist2}$
White	1.377	-5.052	1.439	1.264	-3.842	1.13
	(0.0003)	(0.0002)	(0.0001)	(0.0009)	(0.0006)	(0.0003)
Black	1.72	-4.878	1.672	1.645	-4.437	1.499
	(0.0026)	(0.0037)	(0.0058)	(0.0196)	(0.0359)	(0.0467)
Other	1.654	-1.277	0.197	2.137	-0.415	0.017
	(0.0455)	(0.1019)	(0.1646)	(0.0433)	(0.1649)	(0.0496)

Table A7: Household moving costs estimated from equation 33 for 2000. Standard errors are in parenthesis. We estimate standard errors using numerical derivatives. Distance is measured in thousands of miles.

	Non-College			College		
	$\tilde{\gamma}^{st}$	$\tilde{\gamma}^{dist}$	$\tilde{\gamma}^{dist2}$	$\tilde{\gamma}^{st}$	$\tilde{\gamma}^{dist}$	$\tilde{\gamma}^{dist2}$
White	1.305	-5.254	1.548	1.265	-3.961	1.191
	(0.0002)	(0.0001)	(0.0001)	(0.0006)	(0.0004)	(0.0002)
Black	1.732	-5.279	1.83	1.618	-4.589	1.578
	(0.0022)	(0.0030)	(0.0034)	(0.0130)	(0.0274)	(0.0320)
Other	1.639	-1.178	0.18	1.996	-0.452	0.036
	(0.0098)	(0.0189)	(0.0294)	(Inf)	(Inf)	(Inf)

Table A8: Household moving costs estimated from equation 33 for 2010. Standard errors are in parenthesis. We estimate standard errors using numerical derivatives. Distance is measured in thousands of miles.

	Non-College			College		
	$\tilde{\gamma}^{st}$	$\tilde{\gamma}^{dist}$	$\tilde{\gamma}^{dist2}$	$\tilde{\gamma}^{st}$	$\tilde{\gamma}^{dist}$	$\tilde{\gamma}^{dist2}$
White	1.215	-5.224	1.484	1.267	-4.039	1.196
	(0.0002)	(0.0002)	(0.0001)	(0.0005)	(0.0003)	(0.0001)
Black	1.752	-5.223	1.762	1.671	-4.527	1.54
	(0.0008)	(0.0012)	(0.0013)	(0.0264)	(0.0225)	(0.0195)
Other	1.746	-1.119	0.164	2.056	-0.49	0.045
	(0.0294)	(0.0865)	(0.1664)	(13.7887)	(0.0622)	(0.0271)

Table A9: Household moving costs estimated from equation 33 for 2019. Standard errors are in parenthesis. We estimate standard errors using numerical derivatives. Distance is measured in thousands of miles.

	Non-College			College		
	$\tilde{\gamma}^{st}$	$\tilde{\gamma}^{dist}$	$\tilde{\gamma}^{dist2}$	$\tilde{\gamma}^{st}$	$\tilde{\gamma}^{dist}$	$\tilde{\gamma}^{dist2}$
White	1.146	-5.335	1.547	1.252	-4.201	1.263
	(0.0002)	(0.0002)	(0.0001)	(0.0004)	(0.0003)	(0.0002)
Black	1.7	-5.565	1.895	1.59	-4.654	1.588
	(0.0011)	(0.0014)	(0.0015)	(0.0074)	(0.0056)	(0.0056)
Other	1.784	-1.116	0.172	1.978	-0.557	0.057
	(0.0097)	(0.0191)	(0.0170)	(0.0100)	(0.0258)	(0.0240)

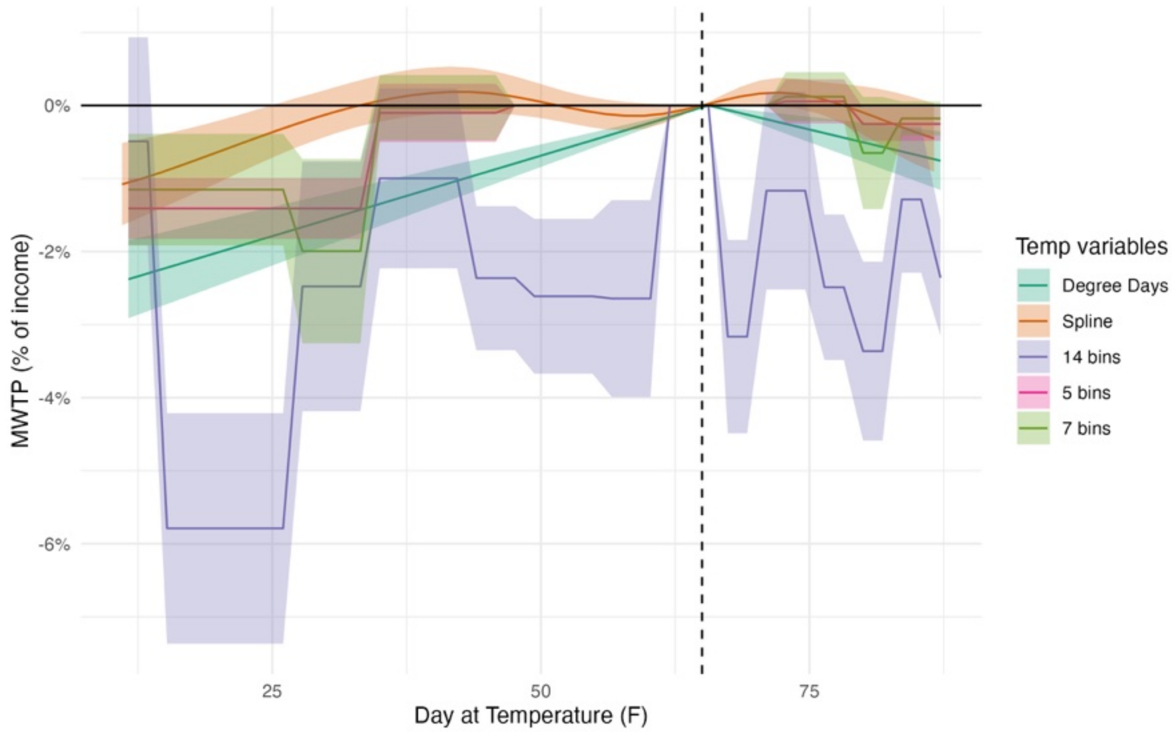


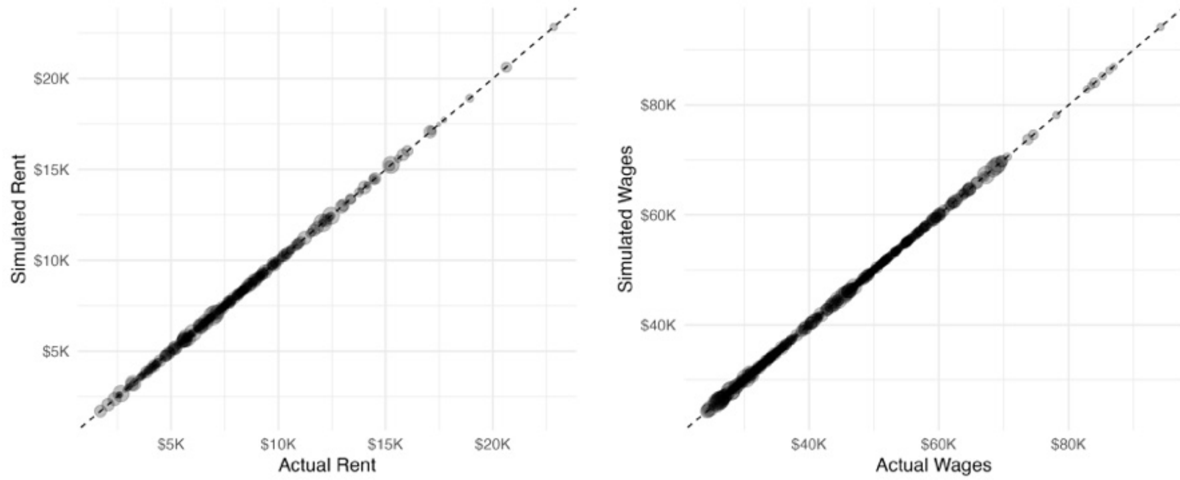
Figure A16: Estimate of MWTP as a percent of income for an additional day at the given temperature, normalized to a day at 65 degrees F. This is calculated by rescaling $\hat{\beta}_e^Z(\tau)$ by β_e^w. Standard errors are calculated with clustered bootstrapping using 10,000 draws, clustered by city-year. We have limited the range of temperature to between the 1st and 99th percentile of average daily temperature, weighted by 1990 population.

D.5 Climate amenities

Figure A16 shows the effect of temperature on climate amenities using different measures of temperature—splines, temperature bins, and degree days.

D.6 Model fit

Figure A17 shows model fit for rents and wages when comparing baseline simulations to actual data.



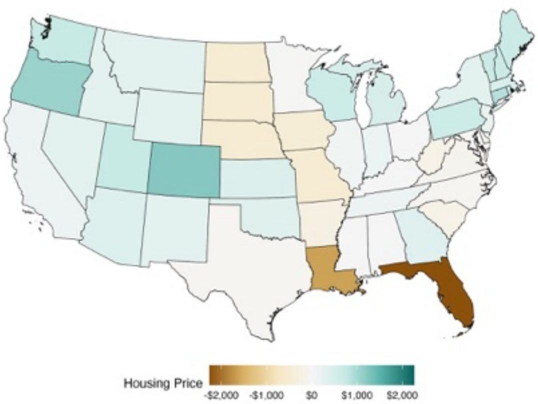
(a) Simulated vs actual rents.

(b) Simulated vs actual wages.

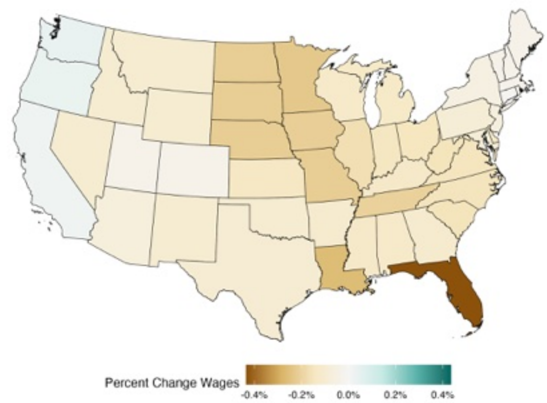
Figure A17: Model fit when using observed climate to simulate the model. Each observation is a demographic group for a particular city and a particular baseline year (1990, 2000, 2010, or 2019). The size of dots represents the number of households in that demographic group-cbsa in the actual data.

Appendix E Additional Results

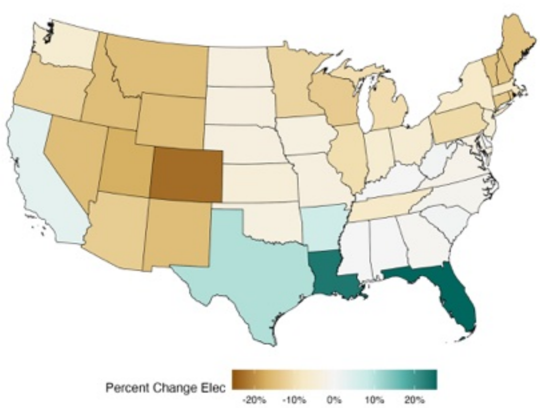
Table A10 has the welfare effects across different decompositions in levels for both white and black households.



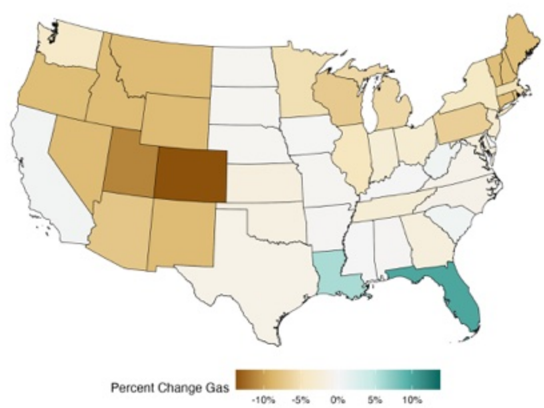
(a) Average change in rent.



(b) Average percent change in wages.



(c) Average percent change in electricity demand.



(d) Average percent change in gas demand.

Figure A18: Change in prices and demand across states. Averages are weighted by population. For states without any CBSAs in them, we use the value for the census division in which the state is located.

Table A10: Decomposition of welfare effects. Values are CV as a percent of income.

	Climate Effect From		
	Both	Amenities	Comfort
Fixed Location			
White	5.09	4.70	7.63
Black	-0.52	-0.64	2.57
Difference	**-5.61**	**-5.34**	**-5.05**
Fixed Location, adjust comfort			
White	-2.16	4.70	0.38
Black	-2.97	-0.64	0.13
Difference	**-0.81**	**-5.34**	**-0.25**
Sorting, fixed prices			
White	-2.59	4.36	0.38
Black	-3.45	-1.00	0.12
Difference	**-0.87**	**-5.35**	**-0.26**
Full Effects			
White	-2.48	-2.82	0.37
Black	-2.95	-3.17	0.25
Difference	**-0.47**	**-0.35**	**-0.12**

Table A11 shows the top and bottom 10 cities by change in population under this historical climate today counterfactual. We see that people generally leave the places that are getting hotter—such as Florida and California, and move to the places that become more pleasant, in the upper Midwest.

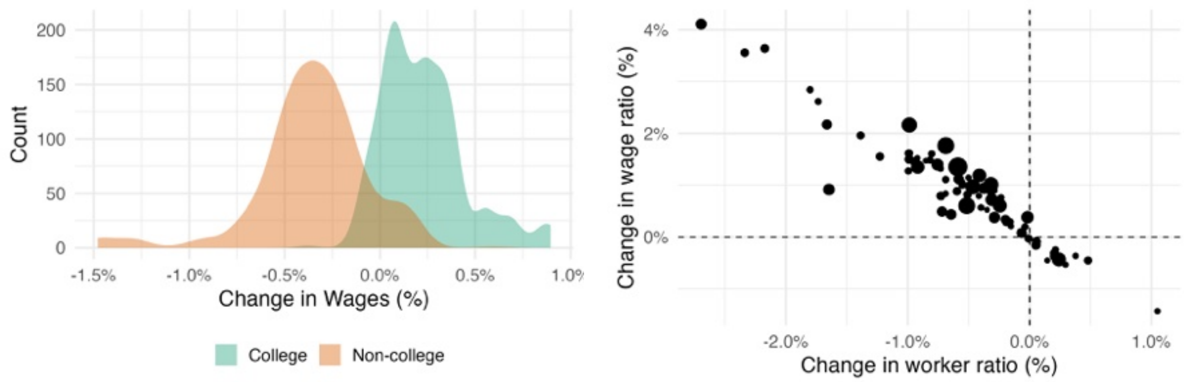
Table A11: Changes in population using 1990 climate as a counterfactual in 2019

City	Change in Pop (%)
Growing Cities	
Grand Rapids-Wyoming, MI	23.4
Hartford-West Hartford-East Hartford, CT	17.0
San Antonio, TX	16.2
Cincinnati-Middletown, OH-KY-IN	15.2
Denver-Aurora, CO	14.8
Tulsa, OK	14.5
Oklahoma City, OK	14.5
Kansas City, MO-KS	14.4
Albany-Schenectady-Troy, NY	14.2
New Haven-Milford, CT	14.1
Declining Cities	
Richmond, VA	-2.9
Youngstown-Warren-Boardman, OH-PA	-4.5
Columbus, OH	-4.7
South Atlantic Division	-4.7
Omaha-Council Bluffs, NE-IA	-5.0
West South Central Division	-7.0
St. Louis, MO-IL	-7.1
Dayton, OH	-8.4
Houston-Baytown-Sugar Land, TX	-9.5
Louisville, KY-IN	-9.6

Climate change has contributed to the increase in the college wage gap. Figure A19a shows the distribution of wage changes across cities. We find that wages increase for college households and decrease for non-college households. To see why, recall that the firm's FOC (14) implies that the ratio of college to non-college workers pins down the wage ratio, and these ratios are inversely related since college and non-college workers are imperfectly substitutable ($\rho_l < 1$). Since college households are more mobile than non-college households, the college-noncollege worker ratio tends to decrease, as shown in Figure A19b—more so in cities where the climate is deteriorating. Thus, college wages increase in those deteriorating cities, and non-college wages decrease.

E.1 IRA Subsidies

Figure A20 shows the share of each state's population that lives in a disadvantaged community according to census block group level population from the 2020 Census.



(a) Change in wages by education level.

(b) Effect of worker ratio on wage ratio.

Figure A19: College and non-college wages comparing present day climate to that of 1990. The worker ratio is college workers divided by non-college workers. The size of the points reflect a city's baseline population.

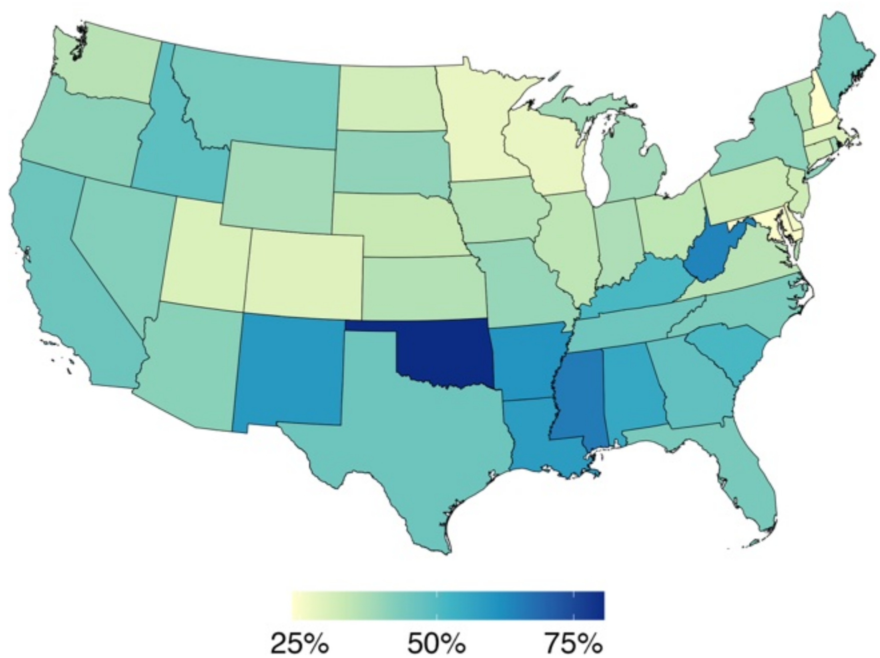


Figure A20: Share of the population living in a disadvantaged community. We use the EPA's Disadvantaged Communities Map to define census tracts as disadvantaged. The total population in each census tract comes from the 2020 Decennial Census (Walker and Herman, 2024).

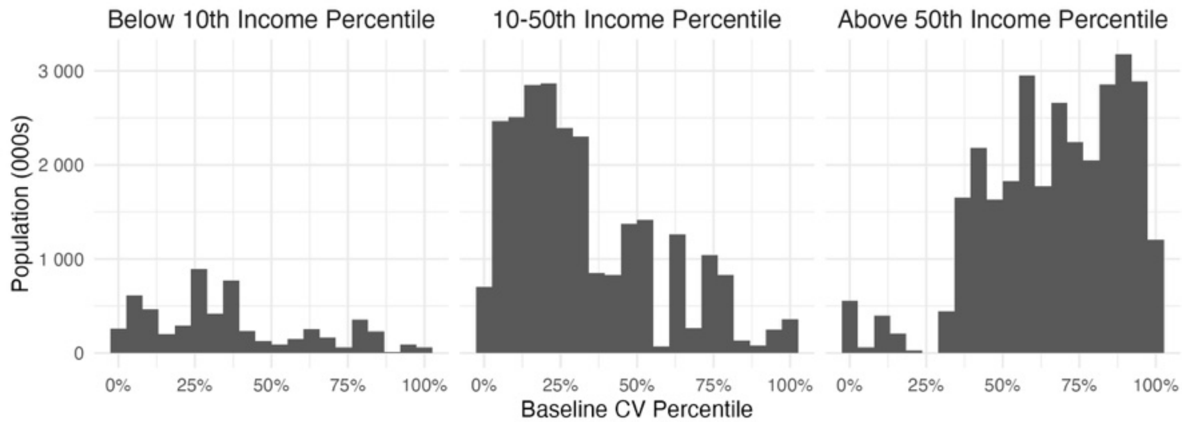


Figure A21: Distribution of baseline CV by income group. The X-axis is a household's percentile in CV from the baseline simulation comparing 2019 and 1990 climates. We split the figure into three income bins, below 10th percentile, 10th-50th percentile, and above 50th percentile based on household expected income in the baseline simulation.

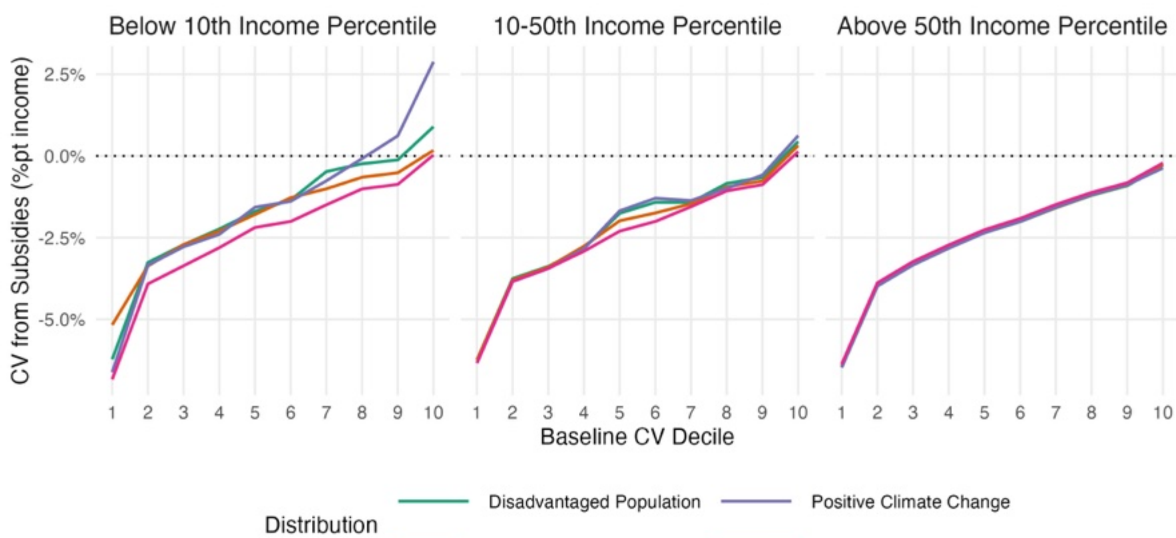


Figure A22: CV for 2019 climate with and without subsidies relative to the 1990 climate without subsidies. The X-axis is a household's decile in CV from the baseline simulation comparing 2019 and 1990 climates. The Y-axis is average CV under 2019 cliamte relative to without subsidies under the 1990 climate. We split the figure into three income bins, below 10th percentile, 10th-50th percentile, and above 50th percentile based on household expected income in the baseline simulation. See description in the text on the subsidy distributions

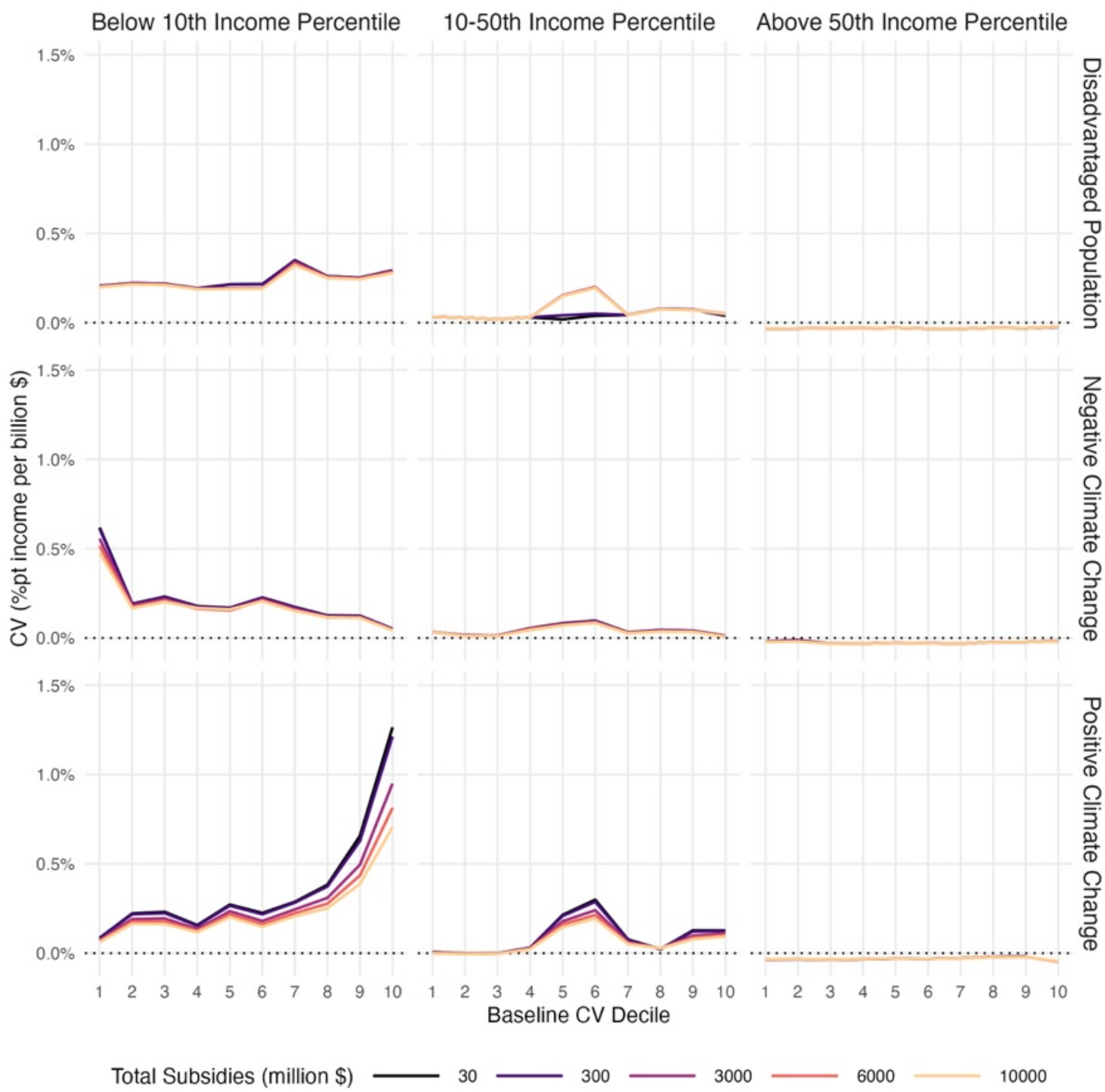


Figure A23: CV for 2019 climate with and without subsidies relative to the 1990 climate without subsidies for different magnitudes, G. The X-axis is a household's decile in CV from the baseline simulation comparing 2019 and 1990 climates. The Y-axis is average CV under 2019 cliamte relative to without subsidies under the 1990 climate. We split the figure into three income bins, below 10th percentile, 10th-50th percentile, and above 50th percentile based on household expected income in the baseline simulation. See description in the text on the subsidy distributions

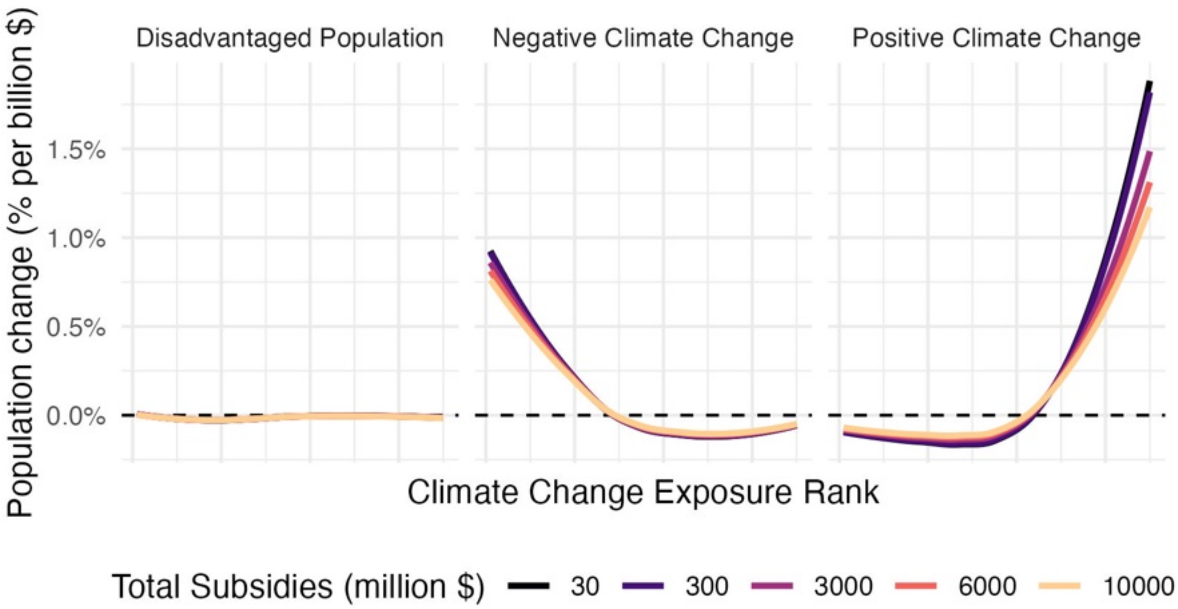


Figure A24: Percent change in population under different subsidy program magnitudes and distributions. The underlying data are city-level, and the plotted lines are smoothed fit from a generalized additive model weighted by city population. The X-axis represents a city's rank in change in climate amenties from 1990 to 2019. The Y-axis is the percent change in population divided by the total size of the program, and the different sizes are differentiated by color.

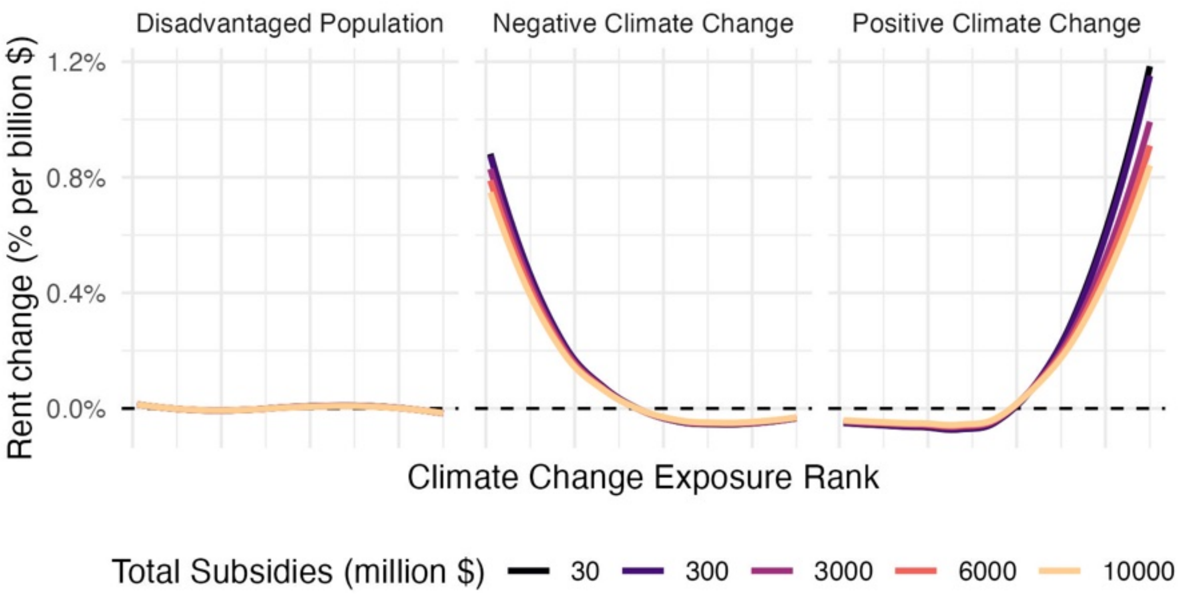


Figure A25: Percent change in rents under different subsidy program magnitudes and distributions. The underlying data are city-level, and the plotted lines are smoothed fit from a generalized additive model weighted by city population. The X-axis represents a city's rank in change in climate amenties from 1990 to 2019. The Y-axis is the percent change in rents divided by the total size of the program, and the different sizes are differentiated by color.

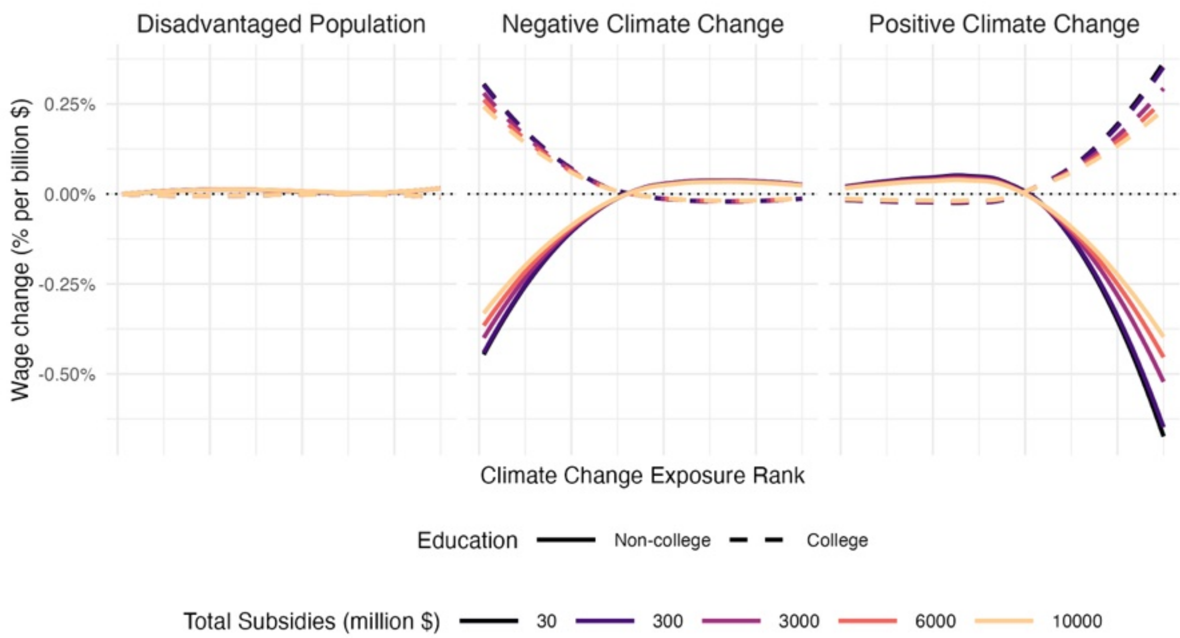


Figure A26: Percent change in wages under different subsidy program magnitudes and distributions. The underlying data are city-education-level, and the plotted lines are smoothed fit from a generalized additive model weighted by city population. The X-axis represents a city's rank in change in climate amenties from 1990 to 2019. The Y-axis is the percent change in wages divided by the total size of the program, and the different sizes are differentiated by color. We differentiate between college and non-college educated wages.