The Distributional Impacts of Climate Change across US Local Labor Markets

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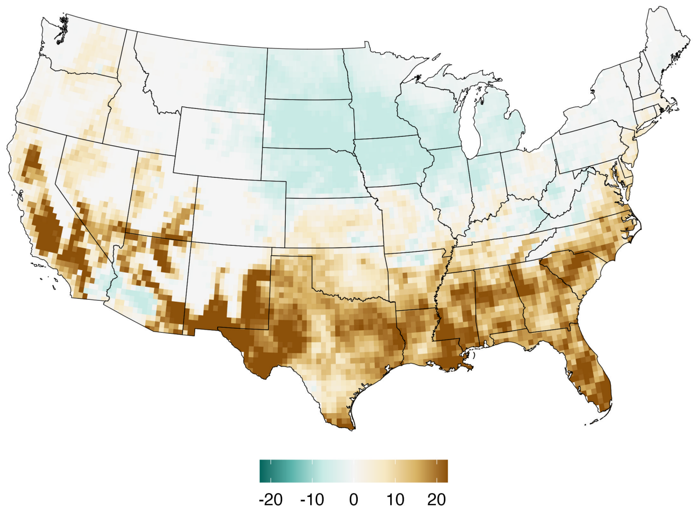
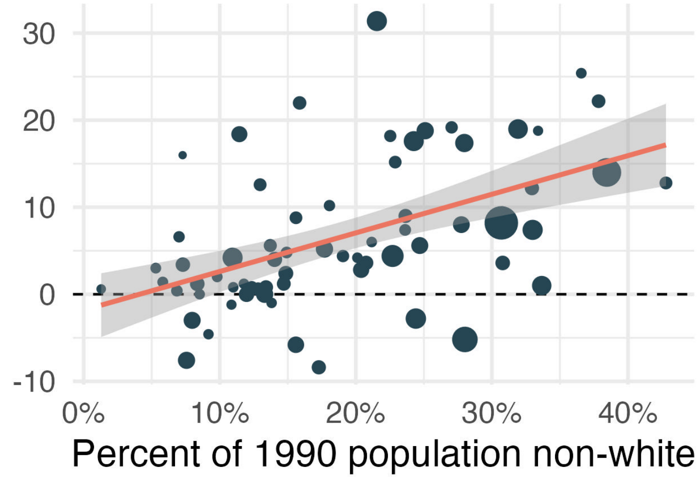
Differential exposure to climate change

Change in hot days, 1990 to 2019





Disadvantaged HH's are more exposed.

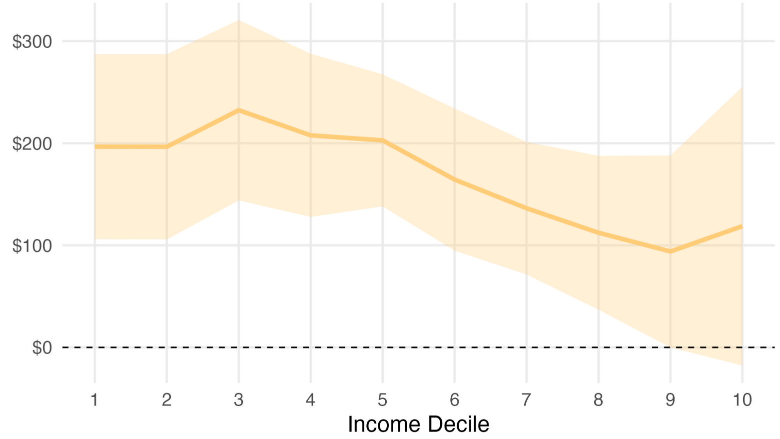
- The avg non-white household experienced **5% more CDDs** in 1990
- CDDs **increased by 13% more** between 1990 and 2019 for non-white households relative to white households

Differential ability to adapt

Disadvantaged households may be less able to adapt to **climate change**

- Low-income HH's have **larger barriers to migration**
- **Energy Justice** literature shows black HH's spend more on energy relative to observably similar white HH's

Conditional Black-White Energy Expenditure Gap



Q: What are distributional consequences of climate change given differential ability to adapt and differential exposure?

What we are going to do...

1. Create a **spatial equilibrium model** of US labor markets
   - Heterogeneous households choose **where to live** and **electricity, natural gas, and housing consumption**
   - Climate impacts energy demand and city's amenity value
2. Structurally **estimate the model**
   - Household data from the census and ACS
   - Historical climate data from PRISM
3. Simulate **counterfactual climate** scenarios
   - To-date, climate damages are over **2x larger** for black vs white HH's
   - Black-white gap will **continue to grow** under emissions projections
   - Mainly driven by differences in exposure and ability to migrate

Contribution to the literature

Contribute to understanding of **heterogeneous effects** of climate change

- Dynamic spatial equilibrium model with adaptation through trade, sectoral switching, and migration (Rudik et. al. 2022)
- Hedonic estimates of the amenity value of climate (Albouy 2016)
- Effect of climate on residential energy use (Auffhammer 2022)

Our paper extends this work by focusing on **distributional impacts** and decomposing relative value of different **adaptation mechanisms**.

We build on the **quantitative spatial equilibrium** literature

- Worker skill sorting and endogenous amenities (Diamond 2016)
- Moving costs in China (Liang, Song, and Timmins 2020)
- Emissions and land use restrictions (Colas and Morehouse 2022)

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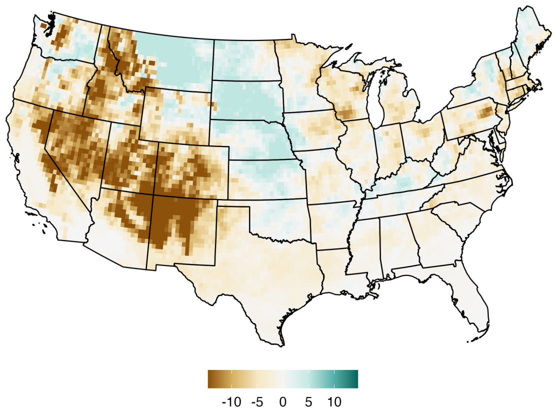
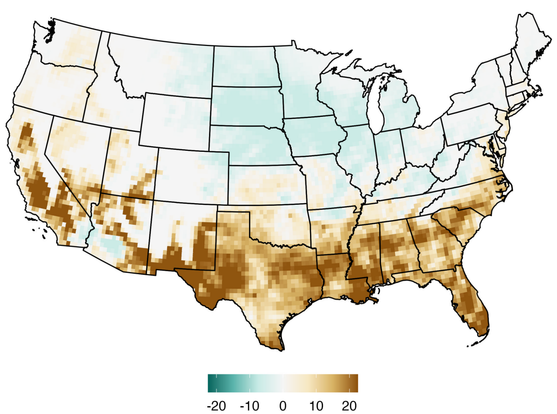
Change in **cold** days



Change in **hot** days



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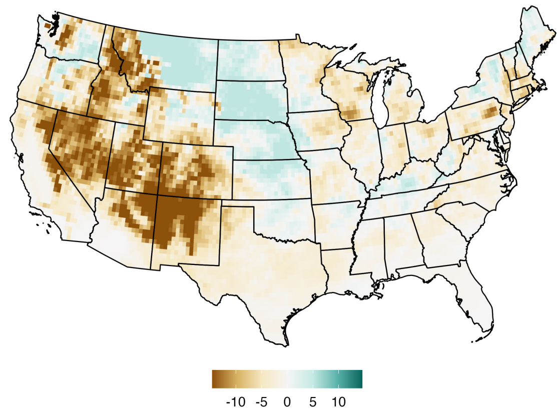

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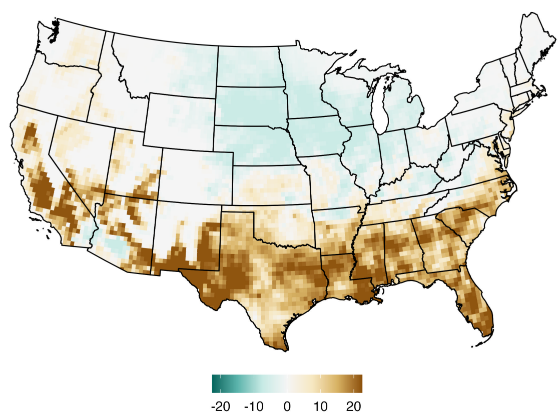


Model

Overview

Main ingredients

Households choose **where to live** based on...

- Wages they could earn
- Rent they would have to pay
- Local amenities---includes both climate and non-climate factors
- Moving costs

Conditional on location, they choose **electricity, gas, and housing demand**

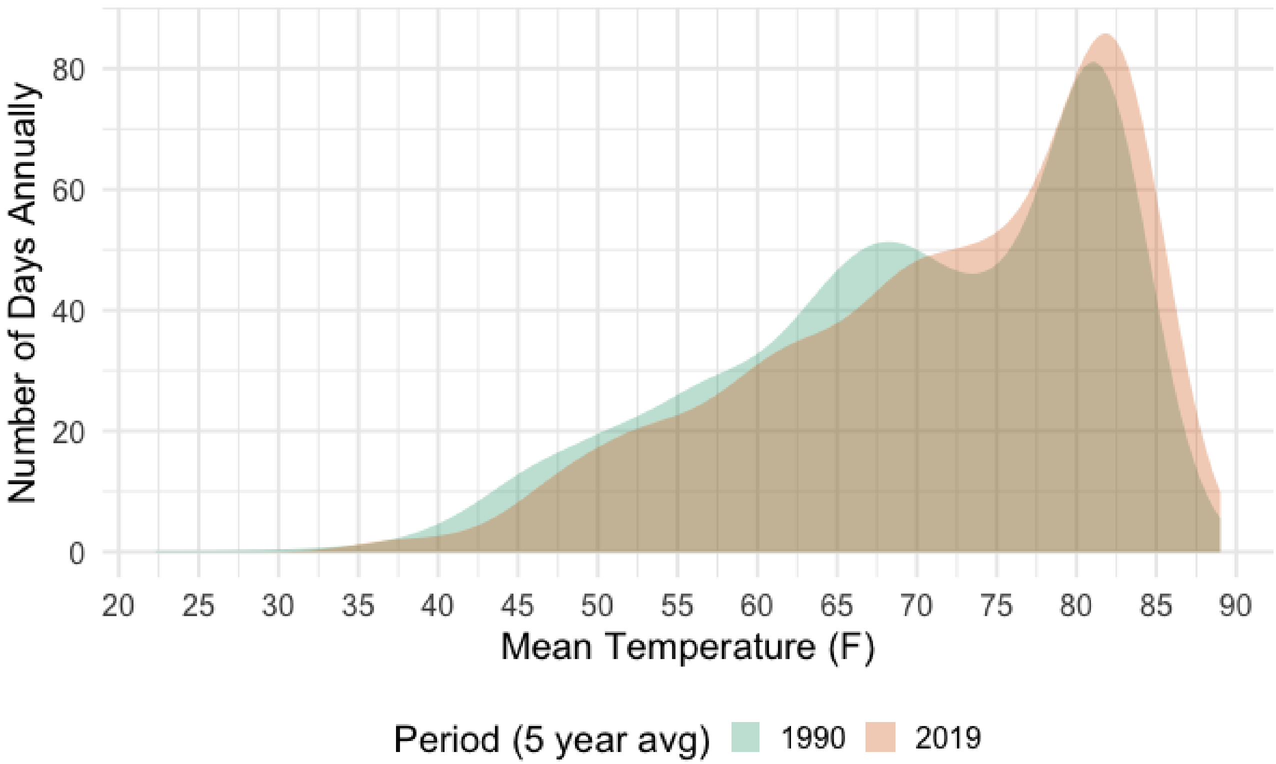
- They use housing, electricity, and natural gas to produce **comfort**
- The comfort production function is **affected by climate**
- Allow for heterogeneity in comfort production technology across demographic groups

Wages and rents **endogenously adjust** based on a city's population.

Key intuition

Consider Jacksonville, FL as an example

There are now more hot days than there were in the 80's



Key intuition

Consider Jacksonville, FL as an example

There are now more hot days than there were in the 80's

- **Amenities decrease** relative to other cities
- **More costly to produce comfort** as HH's use A/C more intensely

$\implies$ conditional on living in Jacksonville, utility has decreased.

- Some households **migrate**, equilibrium wages and rents adjust

Mechanisms that could cause unequal distribution

1. **Greater exposure to climate change** based on *ex-ante* location
2. **Moving costs are higher**, more difficult migrate to mitigate welfare loss
3. **Comfort costs are higher**, may be more sensitive to climate

Model

Household Choices

Household preferences

Household i of demographic group d living in city j gets utility from a composite X, "comfort at dwelling" $\mathcal{C}$, and location-specific amenities $\mathbb{A}$.

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

Amenities are affected by **climate variables**, moving costs, a shared, unobservable component, and an idiosyncratic taste shock

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

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Household comfort

Households produce **comfort** using **energy** $\mathcal{E}$ and housing H

$$\mathcal{C}(H, \mathcal{E}|d, j) = \left(\theta_{dj}^{H} H^{\rho_c} + \theta_{dj}^{\mathcal{E}} \mathcal{E}^{\rho_c}\right)^{1/\rho_c}$$

Energy $\mathcal{E}$ aggregates **electricity** E and **natural gas** G.

$$\mathcal{E}(E, G|d, j) = \left(\theta_{dj}^{E} E^{\rho_{\mathcal{E}}} + \theta_{dj}^{G} G^{\rho_{\mathcal{E}}}\right)^{1/\rho_{\mathcal{E}}}$$

Climate impacts the production of comfort through θ_{dj}^{m}, where $\theta_{dj}^{m} = f_m(Z_j)$ for $m \in \{E, G\}$, where Z_j is a vector of climate variables in city j.

The Price of Comfort

We can solve two, nested **cost-minimzation** problems...

1. Households pick the cost-minimizing combination of **electricity** and **gas** to produce a given level of **energy**
2. Then pick the cost-minimizing combination of housing and **energy** to produce a given level of **comfort**

The result is the unit cost function for **comfort**, or the **price of comfort**

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

where P_j^H is the price of housing (rent) and $P_{dj}^{\mathcal{E}}$ is a similarly-defined unit cost function for energy, $\mathcal{E}$.

[details]

Labor supply

Indirect utility function

Conditional on choosing city j, household i gets indirect utility V_{ij}, as

$$\log V_{ij} = \tilde{\alpha}_d \log(W_{dj}) - \alpha_d^{\mathcal{C}} \log(P_{dj}^{\mathcal{C}}) + \alpha_d^{Z} \cdot Z_j + g(j, \boldsymbol{b}_i) + \xi_{dj} + \sigma_d \varepsilon_{ij}$$

[details]

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- W_{dj} are wages for demographic group d in city j

[details]

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- W_{dj} are wages for demographic group d in city j
- $P_{dj}^{\mathcal{C}}$ is the price of comfort, a function of climate

[details]

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- W_{dj} are wages for demographic group d in city j
- $P_{dj}^{\mathcal{C}}$ is the price of comfort, a function of climate
- Z_j is a vector of climate variables in city j
- $g(j, \boldsymbol{b}_i)$ are moving costs that depend on birth-state b_i^{st}

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

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[details]

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Households pick the city which gives them the **highest indirect utility**

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Climate affects utility through **comfort prices** and **climate amenities**

Model

Housing supply and Firms

Housing supply

Each city is characterized by a long-run, upward sloping rental supply curve,

$$\log(P_j^H) = a_j + \zeta_j \log(H_j)$$

- a_j captures variation in construction costs
- ζ_j is the inverse housing supply elasticity, reflecting variation in the amount of land available for development and land-use restrictions
- H_j is aggregate housing demand in city j

[details]

Firms

Firms producing the output good Y using labor $\mathcal{L}$ with capital K in perfectly competitive markets

$$Y_j = B_j K_j^{\alpha} \mathcal{L}_j^{1-\alpha}.$$

- B_j is city-specific total factor productivity
- $\mathcal{L}_j$ is a CES aggregator of college S and non-college L educated labor

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

We can solve the firm's profit maximization problem to derive labor demand curves

[details]

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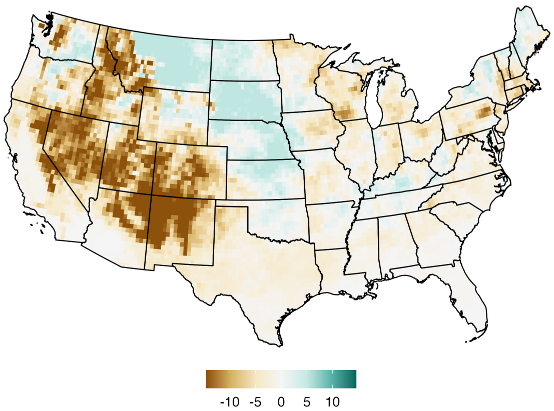

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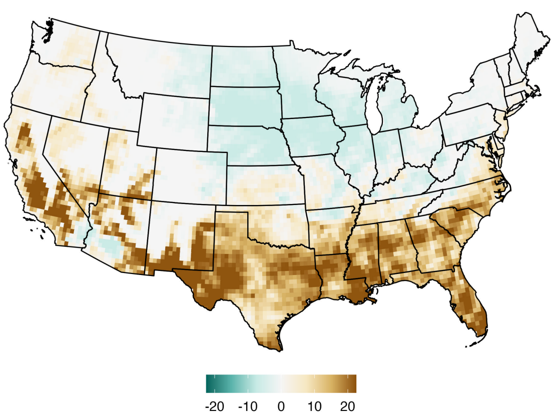

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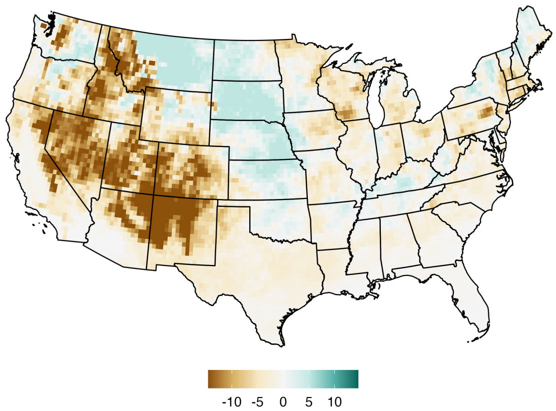

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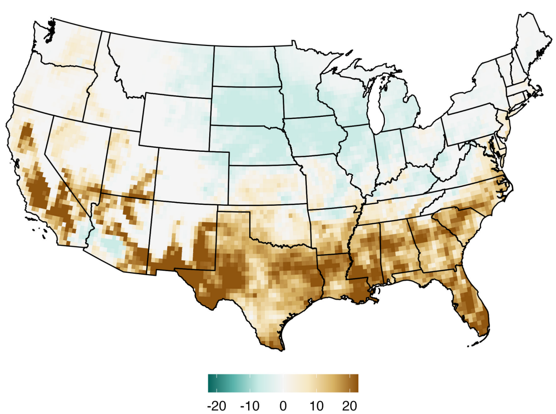


Data

Data and Estimation

We structurally estimate the model using...

1. **Household Data**: Repeated cross sections of the 1990 and 2000 census and 2010 and 2019 5-year ACS
2. **Climate Data**: Daily temperature and precipitation from PRISM and natural disaster risk from the First Street Foundation
3. **Energy Prices**: Annual, state average residential electricity and gas prices from the EIA

Household data

We use the 1990, 2000 census and 2010, 2019 5-year ACS, for HH location, demographics, income, energy, and housing expenditure.

Market level indices

We construct indices for rent, wages, and energy.

- **Rent**: We decompose housing expenditure into rent and housing quantity by regressing housing expenditure on a city-year fixed effect and house characteristics [details]
- **Wages**: We perform a similar process for wages, additionally adjusting for unemployment [details]
- **Energy**: We divide energy expenditure by state level prices from the EIA, then control for observable characteristics [details]

Climate data

PRISM historical climate data

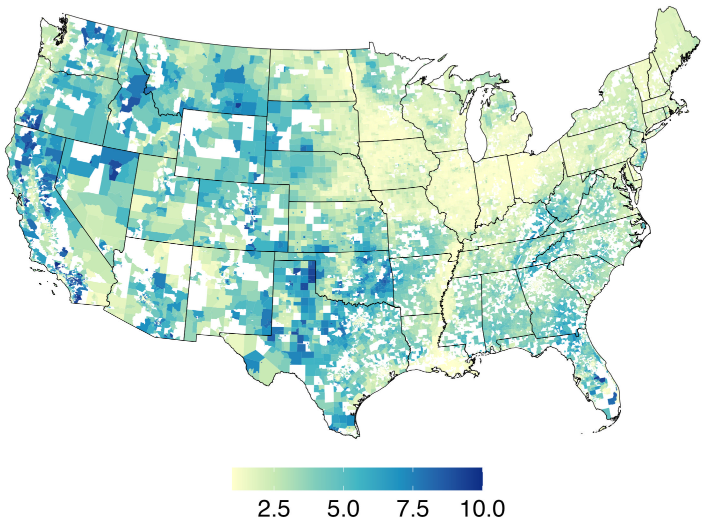
- Average daily temperature and total precipitation for the continental US on a 4km grid from 1981 to 2019
- Take population weighted averages of grid cells within each CBSA
- Calculate annual and 5-year moving average measures of climate

First Street Foundation

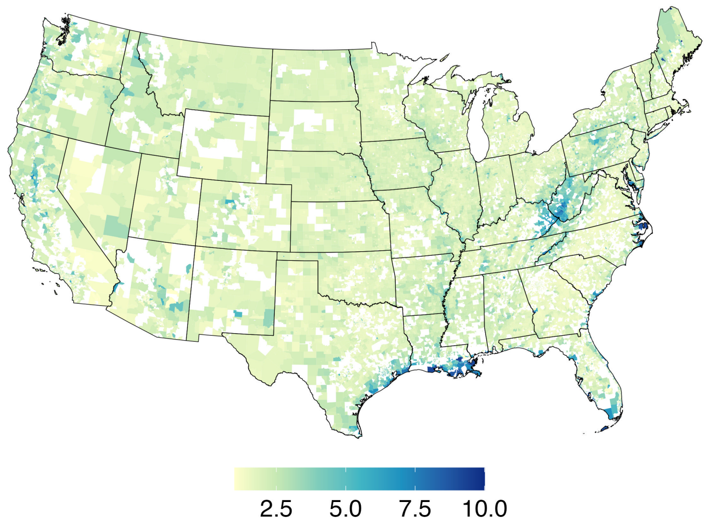
- State of the art disaster risk modeling for fire and flood
- Assign individual properties a risk score between 1 and 10, with 1 being least at-risk and 10 being the most at-risk
- Currently, we have zip-code-level counts of properties at each score, integrated over potential (discounted) future climate scenarios

Spatial variation in FSF data

Mean Fire Risk



Mean Flood Risk



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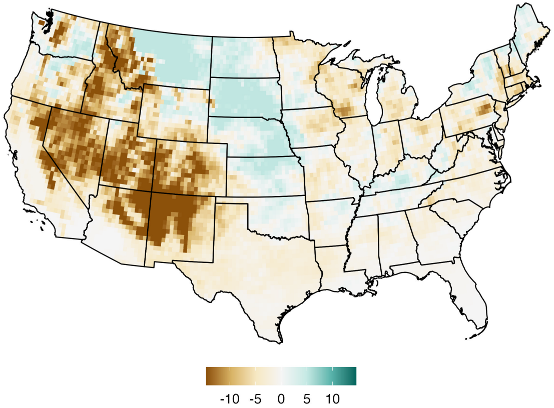

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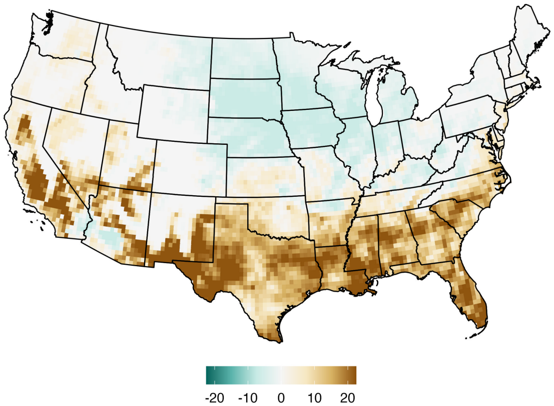

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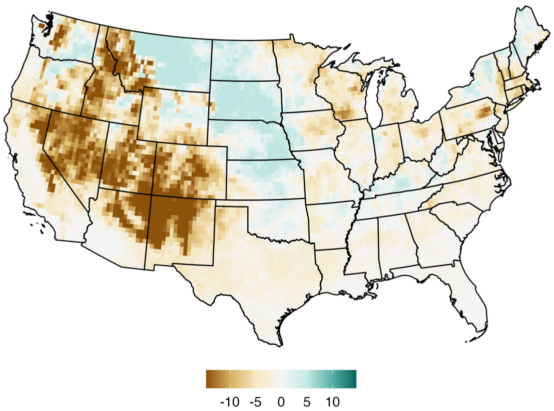

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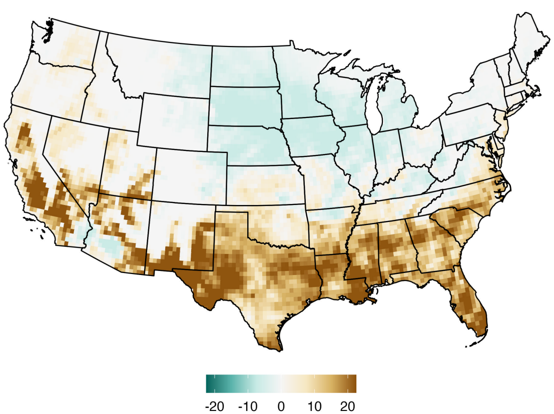

Estimation

Estimation overview

We have to estimate the following...

1. **Comfort parameters** *(Price of comfort)*: Relative demand functions
2. **Labor supply** *(Moving costs, climate amenities)*: Two-step BLP
3. **Labor demand** *(College and non-college wages)*: Calibrated (Card 2010)
4. **Housing supply** *(Elasticity of housing supply, city intercepts)*: Elasticities calibrated, then back out the intercepts (Saiz 2010)

We'll focus on the parameters of the utility function.

[labor demand details] [housing supply details]

Comfort elasticities

Recall the **price of energy** and **price of comfort**

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

$$P^{\mathcal{C}}_{dj} = \left({\theta^{H}_{dj}}^{\sigma_{c}} {P^{H}_{j}}^{1-\sigma_{c}} + {\theta^{\mathcal{E}}_{dj}}^{\sigma_{c}} {P^{\mathcal{E}}_{dj}}^{1-\sigma_{c}} \right)^{\frac{1}{1-\sigma_{c}}}$$

We proceed in two steps...

1. Estimate $\sigma_{\mathcal{E}}$ and $\sigma_{\mathcal{C}}$ using relative demand functions, taking care of price-quantity endogeneity using first differences and supply-side shocks to electricity, gas, and housing prices [details]
2. Use data, estimated parameters, and a normalization to back out $\log \theta^{E}_{djt}$ and $\log \theta^{G}_{djt}$, regress these on climate variables

Effect of climate on comfort production

We parameterize θ's using $D_{\tau jt}$, the number of days at temperature τ:

$$\log \theta^E_{djt} = \sum_\tau \kappa_E(\tau) D_{\tau jt} + \psi^E_j + \psi^E_d + \nu^E_{djt}$$

$$\log \theta^G_{djt} = \sum_\tau \kappa_G(\tau) D_{\tau jt} + \psi^G_j + \psi^G_d + \nu^G_{djt}$$

Effect of climate on comfort production

We parameterize θ's using $D_{\tau jt}$, the number of days at temperature τ:

$$\log \theta_{djt}^{E} = \sum_{\tau} \kappa_E(\tau) D_{\tau jt} + \psi_j^E + \psi_d^E + \nu_{djt}^E$$
$$\log \theta_{djt}^{G} = \sum_{\tau} \kappa_G(\tau) D_{\tau jt} + \psi_j^G + \psi_d^G + \nu_{djt}^G$$

- $\kappa_m(\tau)$ are cubic B-spline's, allowing for flexible, non-linear effect of an additional day at temperature τ on electricity and gas demand

Effect of climate on comfort production

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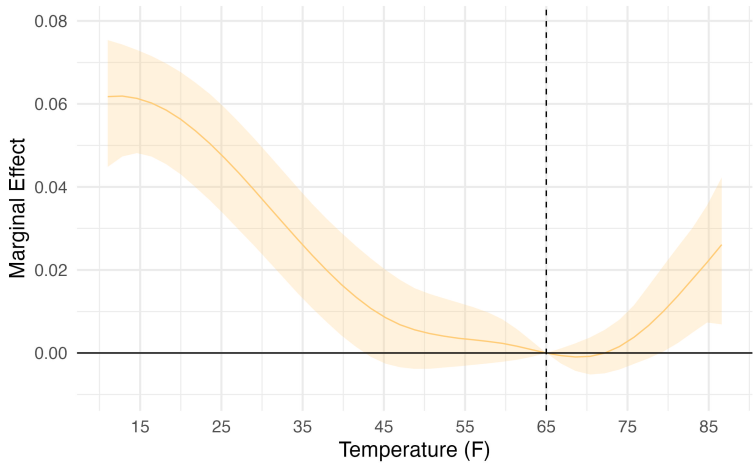
- $\kappa_m(\tau)$ are cubic B-spline's, allowing for flexible, non-linear effect of an additional day at temperature τ on electricity and gas demand
- ψ^m_j and ψ^m_d are city and demographic group fixed effects

Climate's effect on comfort production

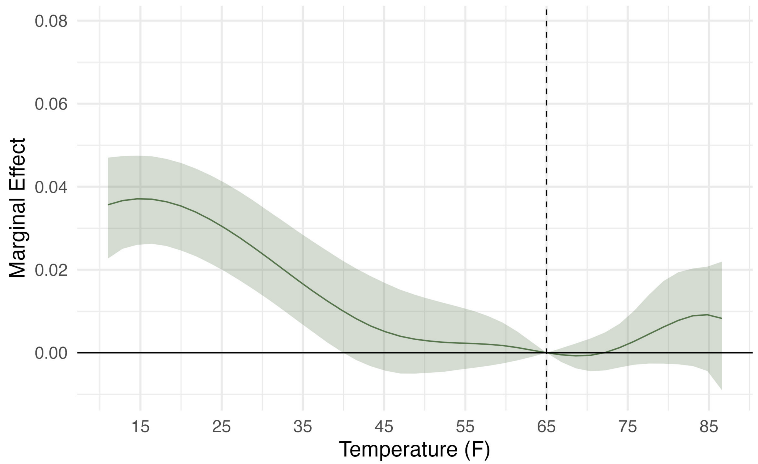
Effect of an additional day at temperature

Relative to a day at 65 degrees

for electricity benefit



for gas benefit



- Corresponds to marginal benefit of electricity or gas use
- Don't find evidence of heterogeneity, but with limited power [details]

Estimating Labor Supply

We now estimate the remaining utility parameters. First, we define the **mean utility** associated with each city,

$$\delta_{djt} = \beta_e^w \log(W_{djt}) + \beta_e^{\mathcal{C}} \log(P_{djt}^c) + \beta_e^Z \cdot Z_{jt} + \xi_{djt}$$

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$$\delta_{djt} = \beta_e^w \log(W_{djt}) + \beta_e^{\mathcal{C}} \log(P_{djt}^c) + \beta_e^Z \cdot Z_{jt} + \xi_{djt}$$

We can then write probability of household i choosing city j as

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

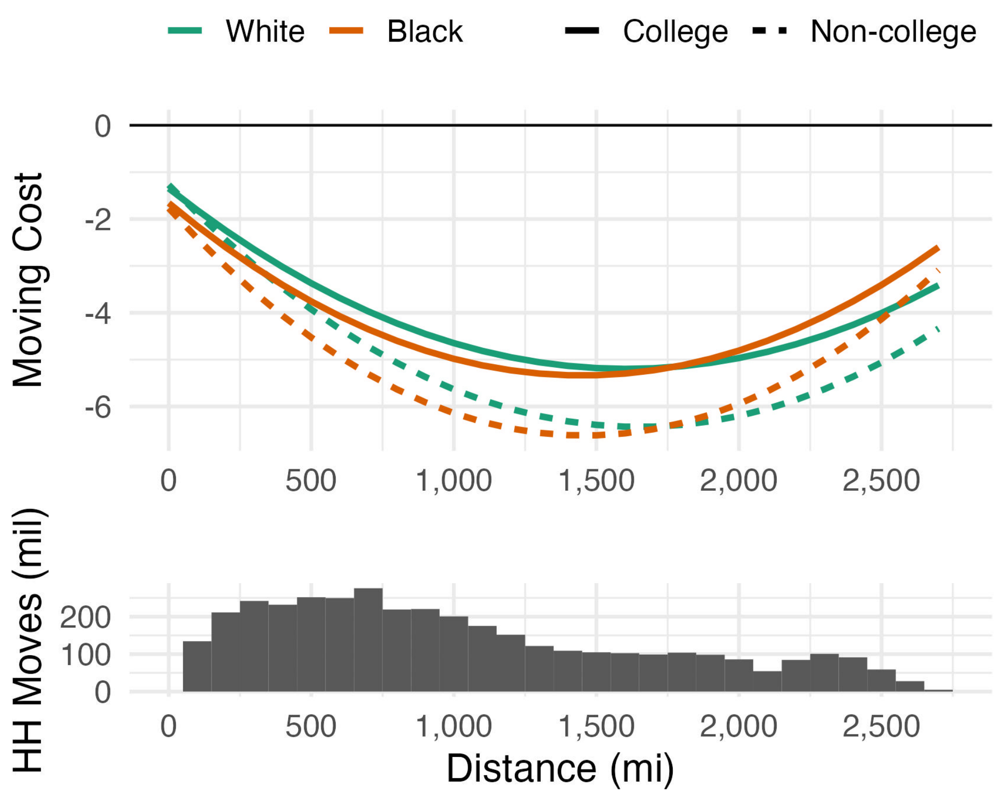
Given these choice probabilities, the log-likelihood function is

$$LL(\delta_{djt}; \boldsymbol{\gamma}_{dt}) = \sum_i \sum_j \mathbb{I}_{idjt} \log(P_{ijt}(\delta_{djt}; \boldsymbol{\gamma}_{dt})),$$

which we maximize by making guesses of $\boldsymbol{\gamma}_{dt}$ using the Nelder-Mead algorithm, recovering the δ_{djt}'s using BLP contraction mapping.

Moving cost parameter estimates

We can calculate **total moving costs** for each dem group and year as a function of distance with the estimated parameters, $\hat{\gamma}_{dt}$. Here for 2019,



Mean utility decomposition

We then decompose the mean utilities, δ_{djt}, to estimate climate amenities

1. Calibrate coefficients on $\log W_{djt}$ using **Diamond (2016)**
2. Calibrate coefficients on $\log(P^c_{djt})$ using **comfort expenditure shares**
3. Calculate residual, $\hat{\delta}_{djt} = \delta_{djt} - \beta^w_e \log(W_{djt}) + \beta^{\mathcal{C}}_{djt} \log(P^c_{djt})$
4. Regress residual on 5-year average of climate variables,

$$\hat{\delta}_{djt} = \beta^Z_1 \text{Fire}_j + \beta^Z_2 \text{Flood}_j + \beta^Z_3 \text{Precip}_{jt} + \beta^Z_4 \text{No Rain}_{jt} + \sum_{\tau} \beta^Z_5(\tau) D_{\tau jt} + \omega_d + \omega_t + \xi_{djt}$$

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- Fire_j and Flood_j are median fire and flood risk scores in city j

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- $\mathbf{Fire}_j$ and $\mathbf{Flood}_j$ are median fire and flood risk scores in city j
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- Fire_j and Flood_j are median fire and flood risk scores in city j
- Precip_{jt} and $\mathrm{No\ Rain}_{jt}$ are total precip and Pr(<1mm of precip) in year t
- $\beta^Z_5(\tau)$ is a cubic B-spline over days at temperature τ, $D_{\tau jt}$

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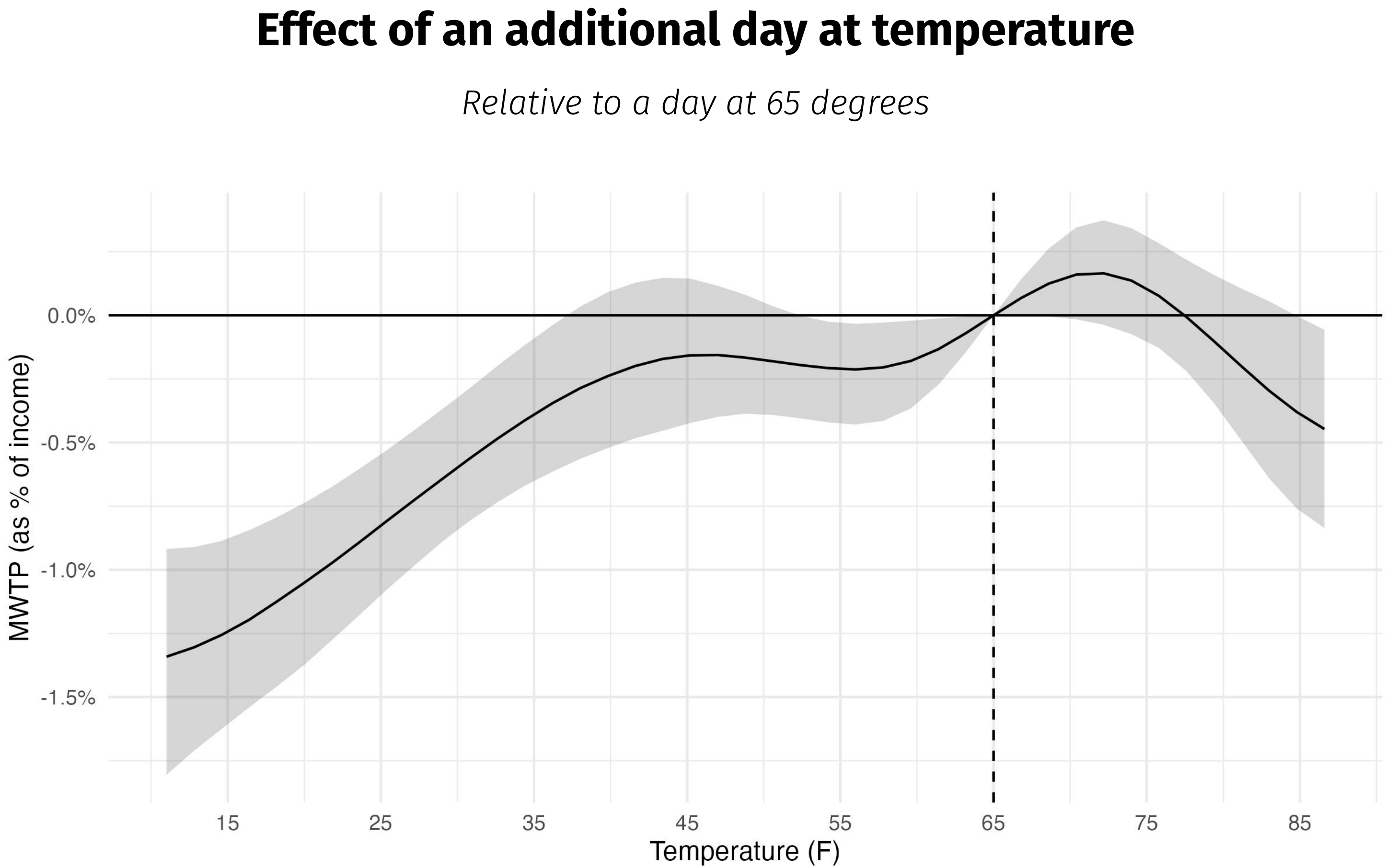
- ω_d and ω_t are demographic group and year fixed effects

Climate's effect on amenities



- Robust to alternative model specifications [details]
- Limited evidence of heterogeneity [details]

Climate's effect on amenities

Dep. Var.	Mean Utility Residual		
College	Full sample	College	Non-college
Model:	(1)	(2)	(3)
Variables			
Annual Precipitation	0.000	0.001	-0.001
	(0.001)	(0.001)	(0.001)
Pr(No Rain)	7.804**	9.297**	7.064*
	(3.197)	(4.034)	(4.054)
Median Fire Risk	-0.685***	-0.351**	-0.834***
	(0.126)	(0.175)	(0.151)
Median Flood Risk	-0.597***	-0.557***	-0.610***
	(0.143)	(0.186)	(0.174)
Fixed-effects			
Dem Group	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	1,680	840	840
R^2	0.91	0.50	0.69
Within R^2	0.30	0.23	0.37

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

Climate amenity rankings in 2019

We can use the estimated coefficients to calculate the amenity value of climate in each city using actual climate data in 2019,

$$\hat{\boldsymbol{\beta}}^{\boldsymbol{Z}} \cdot \boldsymbol{Z}_{\boldsymbol{j},\mathbf{2019}}$$

Here are the best/worst cities, ranked according to their climate amenities

Climate amenity rankings in 2019

Rank	City	Hot	Cold	Rain	Risks
Best Cities					
1	San Jose-Sunnyvale-Santa Clara, CA	21	36	7	32
2	Los Angeles-Long Beach-Santa Ana, CA	50	16	2	55
3	San Diego-Carlsbad-San Marcos, CA	41	25	5	65
4	Sacramento--Arden-Arcade--Roseville, CA	38	28	9	58
5	Fresno, CA	52	20	6	54
6	Baton Rouge, LA	60	9	63	4
Worst Cities					
65	Worcester, MA	6	65	32	48
66	New Orleans-Metairie-Kenner, LA	64	6	62	68
67	Albany-Schenectady-Troy, NY	13	62	40	37
68	Rochester, NY	8	64	53	42
69	Minneapolis-St. Paul-Bloomington, MN-WI	9	70	20	22
70	Syracuse, NY	4	69	67	45

[changes]

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[changes]

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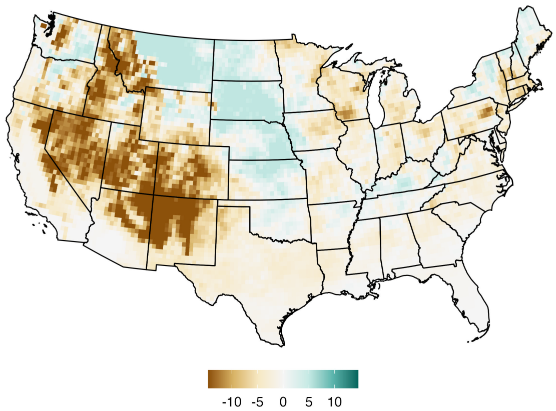
Change in **cold** days



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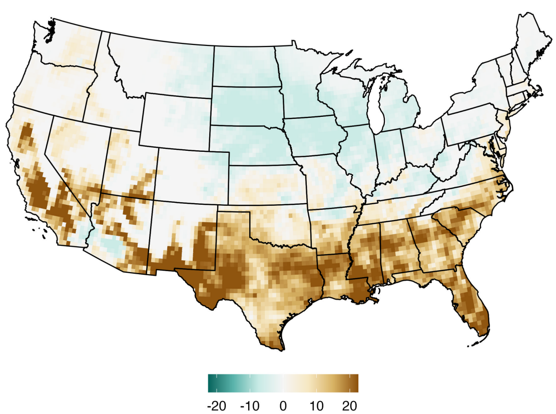

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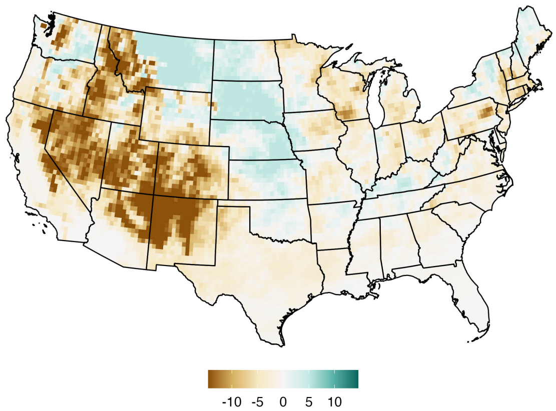

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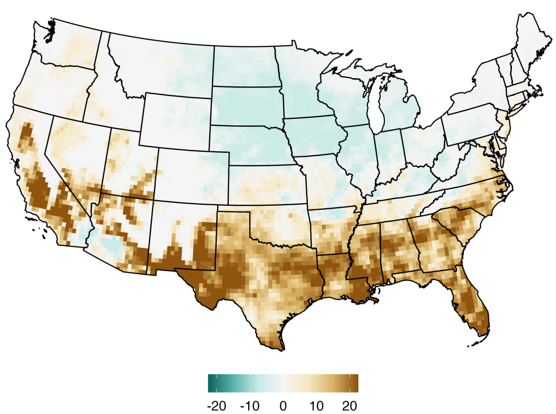

Calculating welfare effects

Household i's compensating variation for the counterfactual climate, $\tilde{\mathbf{Z}}$ relative to the baseline climate, $\mathbf{Z}$

$$CV_i = \Big(\mathbb{E}[V_i(\tilde{\mathbf{Z}})] - \mathbb{E}[V_i(\mathbf{Z})]\Big) \times \frac{1}{\beta_e^w}$$

[details]

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[details]

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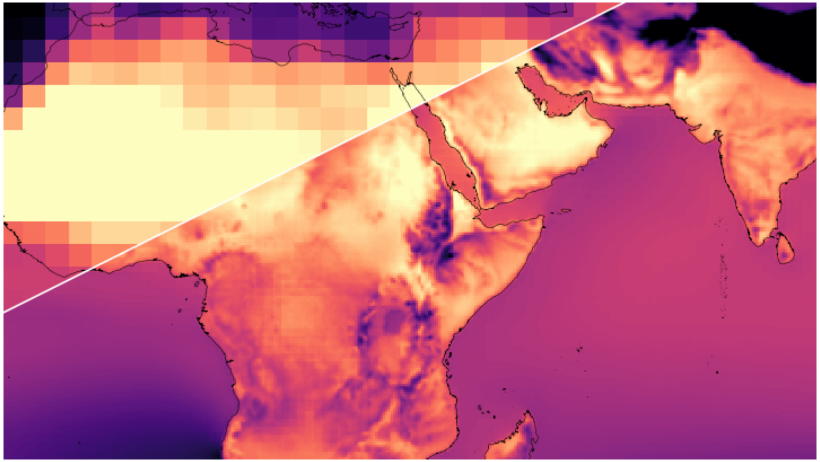
- $V_i(\mathbf{Z}) = v_{ij}(\mathbf{Z}, j^*)$ is household i's indirect utility with climate $\mathbf{Z}$ evaluated at equilibrium choices j^* and prices
- Multiplying by $\frac{1}{\beta_e^w}$ converts utility units into percent of income
- Can also multiply by wages to turn it into a dollar value

[details]

Simulations

With the model estimated, we run two types of counterfactuals,

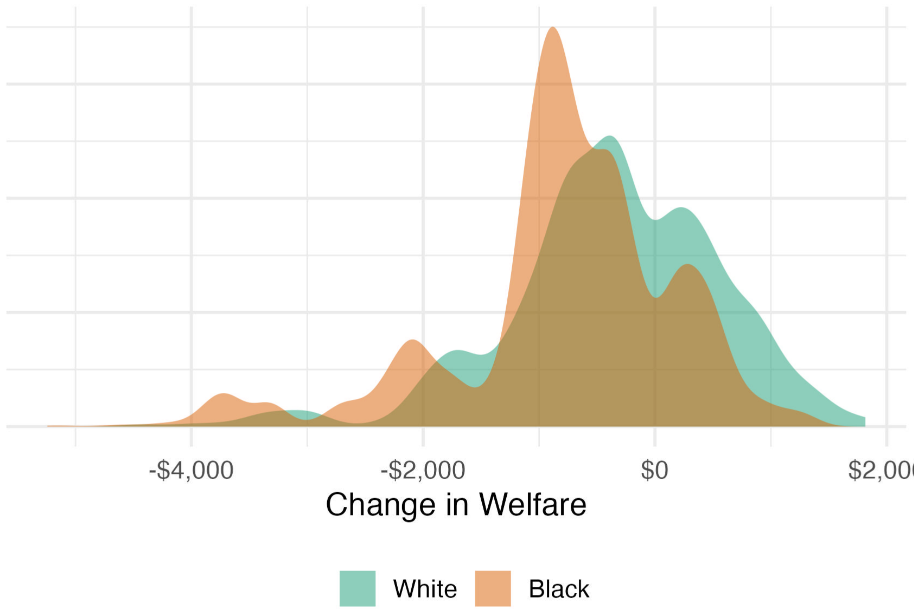
1. **Effect of Climate Change To-Date**: Plug in 1980's average climate to today's economy for effect of climate change thus far
2. **Future Effects of Climate Change**: We use an ensemble of 26 climate models, downscaled and de-biased by the Climate Impact Lab to estimate the potential effects of future climate change [details]



[model fit]

Effect of climate change to-date

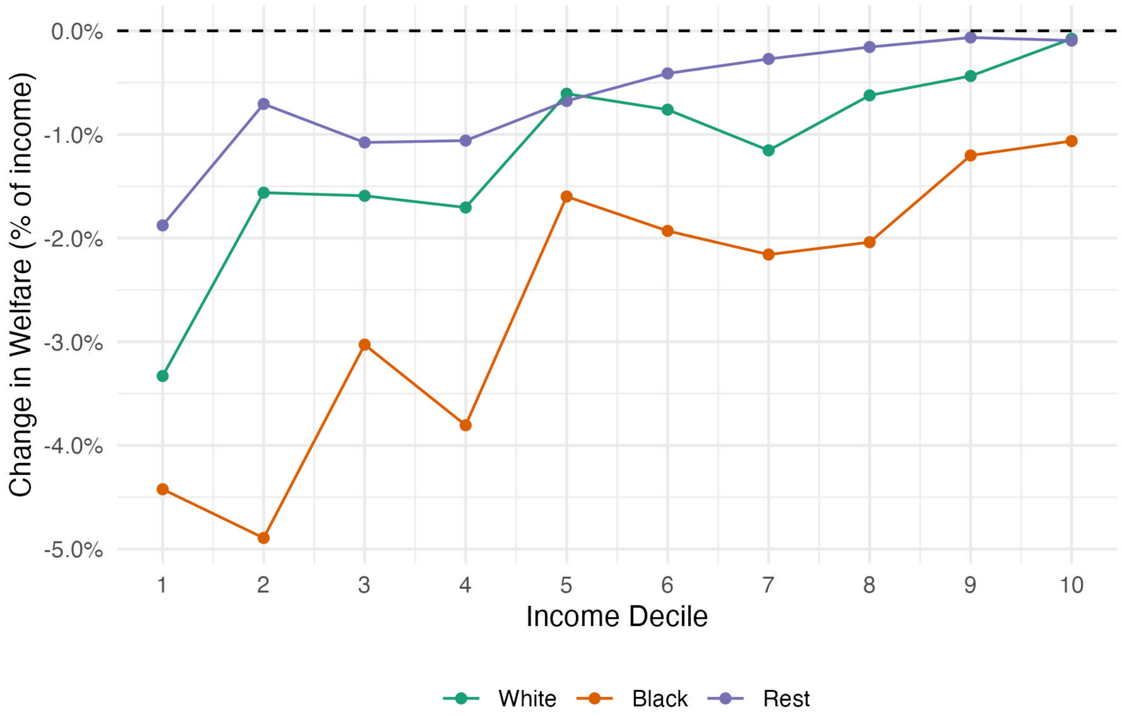
Compare present day climate with that of 1990



- Welfare loss for median black HH over **2x larger** than median white HH
- This amounts to damages of $750 vs $350 (or 1.7% vs 0.6% of income)

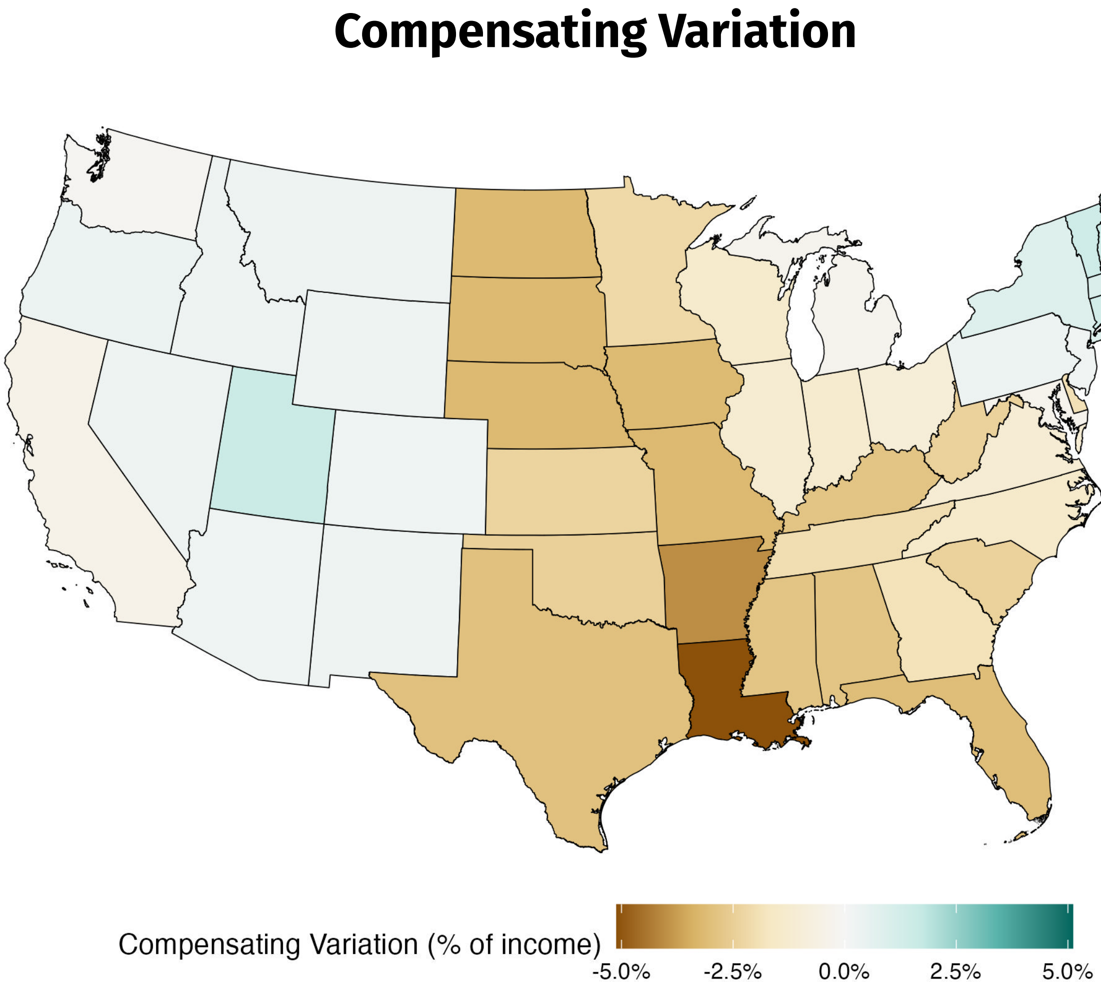
Effect of climate change to-date

Low-income households worse off



But black households are worse off relative to white households throughout the income distribution

Spatial variation



What is driving the gap?

Recall we had three proposed mechanisms

1. **Greater exposure to climate change** based on *ex-ante* location
2. **Moving costs are higher**, more difficult migrate to mitigate welfare loss
3. **Comfort costs are higher**, may be more sensitive to climate

We decompose these mechanisms with different simulations:

1. **Fixed Location**: Fix locations, rent, and wages
2. **Sorting**: Allow migration, but wages are fixed and rent is same as (2)
3. **Full effects**: Allow migration, wages and rent endogenously adjust

For each of these we look at welfare gap between black and white households both *on average* and *conditional on baseline city*.

Decomposing black-white welfare gap

Simulation	Unconditional	Within City
Fixed Location	-1.64	-0.01
Sorting, fixed prices	-1.57	-1.09
Fully Flexible	-1.27	-0.98

Decomposing black-white welfare gap

Simulation	Unconditional	Within City
Fixed Location	-1.64	-0.01
Sorting, fixed prices	-1.57	-1.09
Fully Flexible	-1.27	-0.98

Black HHs worse off by **1.64%** of income on average with fixed locations and prices, but **this is entirely explained by differences in exposure**.

- Suggests differences in price of comfort are not playing a role

Decomposing black-white welfare gap

Simulation	Unconditional	Within City
Fixed Location	-1.64	-0.01
Sorting, fixed prices	-1.57	-1.09
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Allowing households to sort **marginally reduces** the average black-white welfare gap, but the conditional welfare gap **grows to nearly 1%**.

- Suggests white households are better able to migrate to mitigate welfare losses from climate change

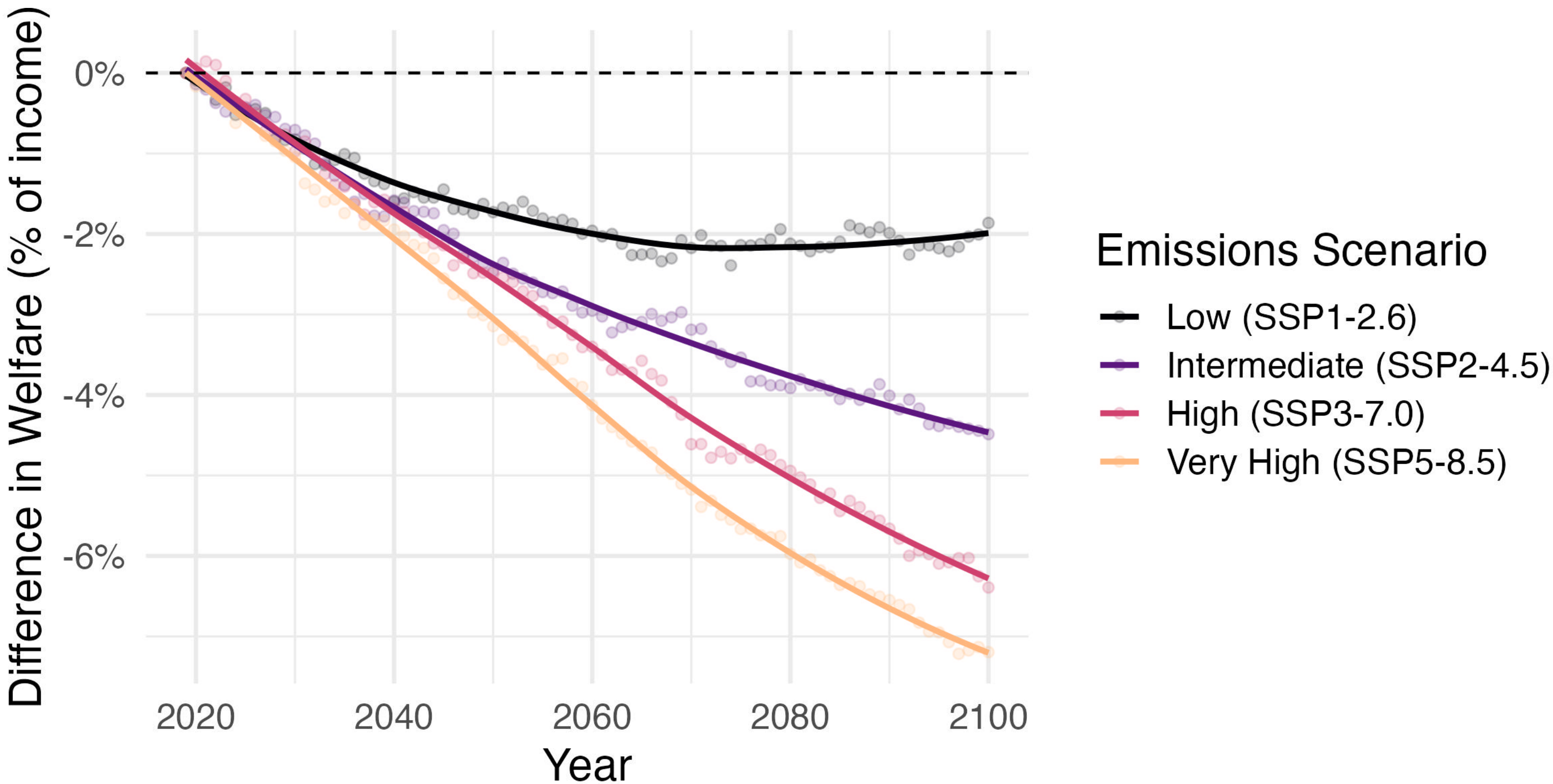
Decomposing black-white welfare gap

Simulation	**Unconditional**	**Within City**
Fixed Location	-1.64	-0.01
Sorting, fixed prices	-1.57	-1.09
Fully Flexible	-1.27	-0.98

Wage and rent adjustments in equilibrium dampen the welfare gaps.

Black-white gap grows with emissions

The **difference in welfare effects** of climate change between black and white HH's grows under future emissions scenarios.



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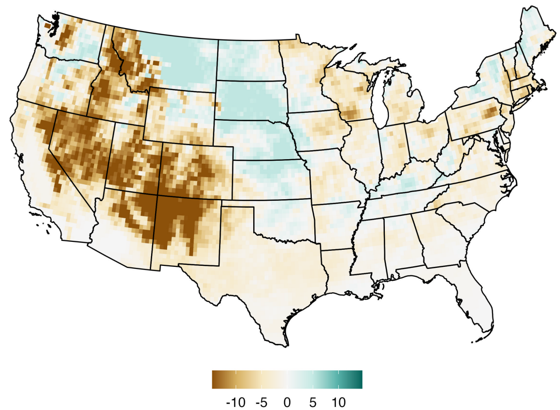
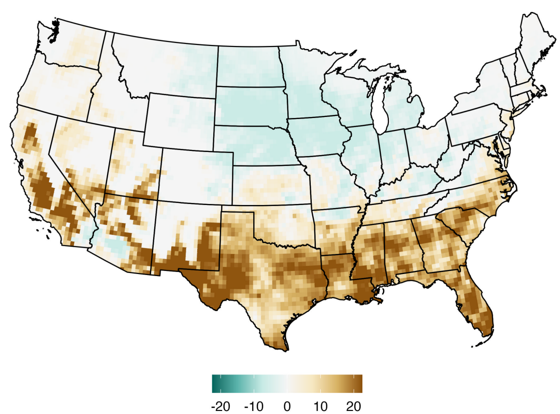


Change in **hot** days



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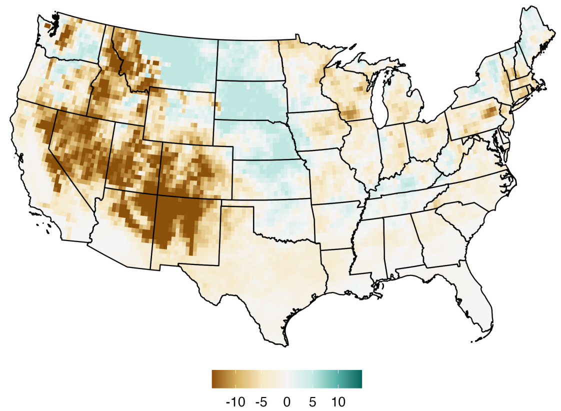

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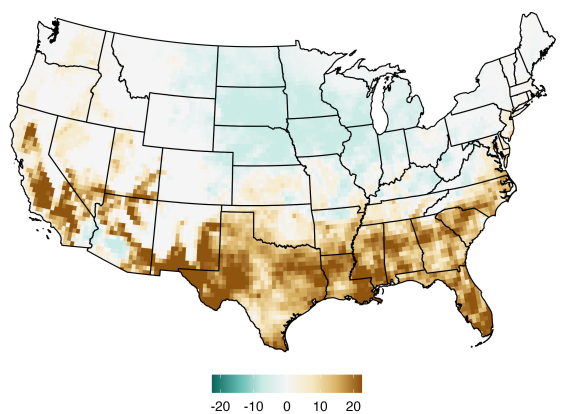

Conclusions and next steps

Significant distributional effects of climate change

- Black HHs have faced **2x larger** climate damages to-date
- Low income HHs are worse off relative to high-income HHs
- Largely driven by differences in **ex-ante** location and **ability to migrate**

Policy Implications

Our model is well suited to analyze the effectiveness of various policies at reducing the observed welfare gap. Policies that may be effective include,

- Reduce moving costs through housing or job search assistance
- Subsidies to relocate from high-climate-risk areas

but, further work is required to determine the full implications.

Thank you

Emmett Saulnier

PhD Candidate, University of Oregon
ORISE Research Fellow, US EPA Office of Water
https://www.emmettsaulnier.com

Other Research

Vertical Migration Externalities **RSUE, 2023**.
Optimal Subsidies for Residential Solar *under review*.
Perinatal Health Effects of Herbicides *working paper*.
Means Tested Solar Subsidies *in progress*.
Valuing Water Quality: Benefits transfer with distance decay *in progress*.

Appendix

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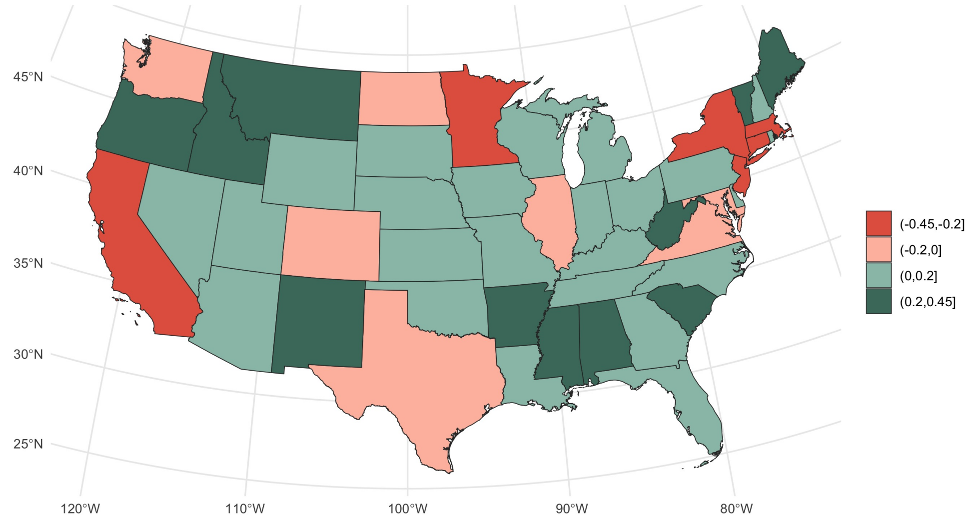
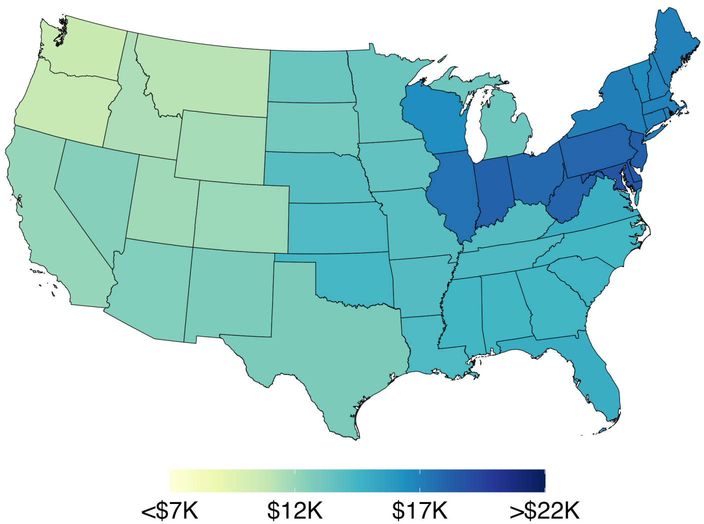
Vertical Migration Externalities



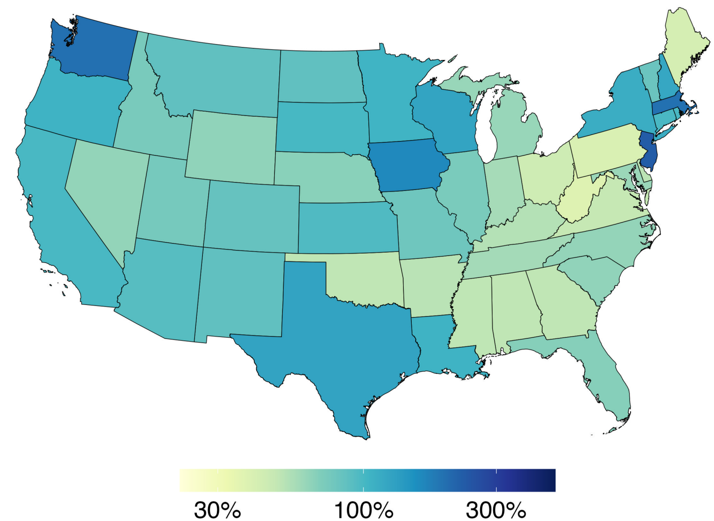
State income taxes affect federal income tax revenue by shifting the spatial distribution of households between high- and low-productivity states, thereby changing household incomes and tax payments.

- We express these fiscal externalities in terms of estimable statistics
- The externalities vary widely by state from positive to negative
- Every dollar of California tax revenue raised decreases federal income tax revenue by 39 cents

Optimal Subsidies for Residential Solar



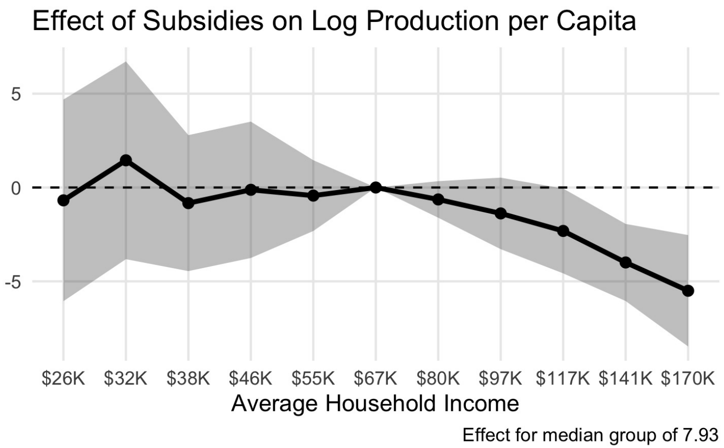
Optimal solar subsidies

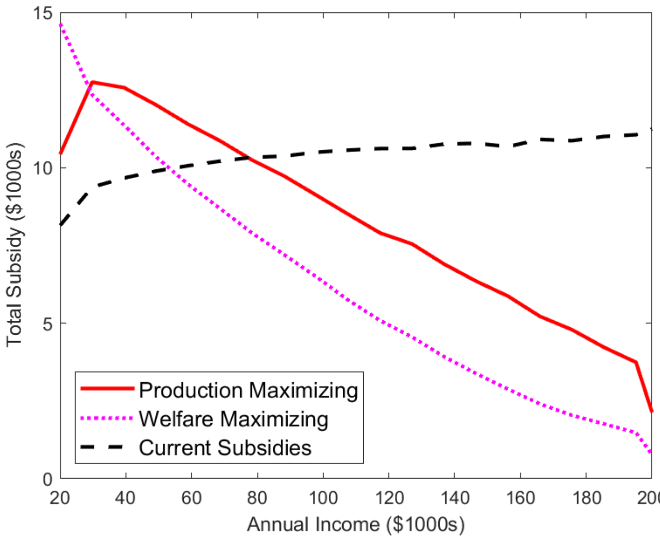


Installations as a % of optimal

We study the optimal design of spatially differentiated subsidies for residential solar panels. We build a structural model of solar panel demand and electricity production across the US and estimate the model by combining 1) remotely sensed data on residential solar panels, 2) power-plant-level data on hourly production and emissions, and 3) a state-of-the-art air pollution model. The current subsidies lead to severe spatial misallocation. National funding for subsidies under the current system exceeds the unconstrained optimum by seven-fold.

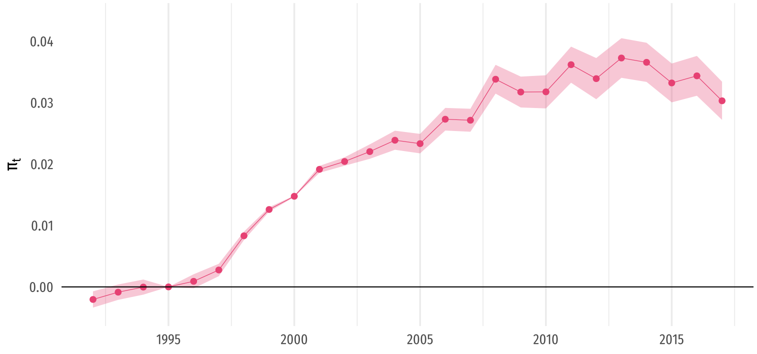
Means Tested Solar Subsidies

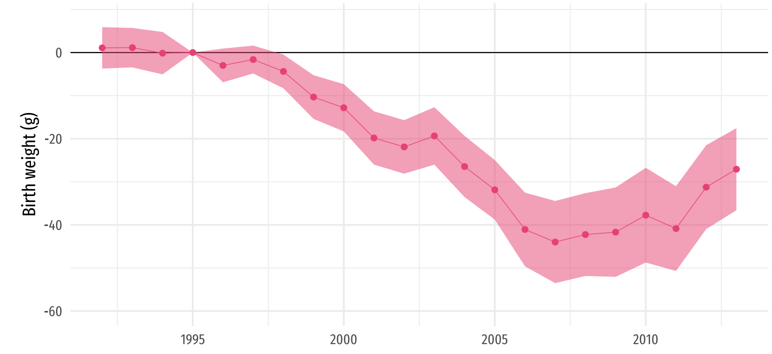




We study optimal design of income-contingent subsidies for residential solar panels. We document that the responsiveness of installation rates to subsidies is twice as high among low-income locations compared to high-income locations. Using these empirical elasticities, we estimate a model which embeds a solar panel installation decision into a dynamic consumption/savings framework with borrowing constraints. Counterfactual simulations reveal that switching to the production-maximizing income-contingent subsidies leads to a three-fold increase in public funds received by low-income households and a 4% increase in national solar production. Means-tested subsidies are justified on both equity and efficiency grounds.

Perinatal Health Effects of Glyphosate





Research Question What are the health effects of the most widely used herbicide in the world?

Methods Leverage the timing of the release of GM technology paired with spatial variation in the suitability for crops with GM varieties to estimate a causal effect of glyphosate on infant health.

Main Finding Glyphosate causes a decrease in birthweight and gestation length. These effects come from local spraying rather than that from upstream. Effects are concentrated among most at risk births.

Model Appendix

[return]

Household comfort

We can simplify the household's problem by **solving nested cost-minimization problems**. First, for energy production with elec and gas:

$$\min_{E,G} P_j^E E + P_j^G G \quad \text{s.t.} \quad \bar{\mathcal{E}} = \left(\theta_{dj}^E E^{\rho_\mathcal{E}} + \theta_{dj}^G G^{\rho_\mathcal{E}}\right)^{1/\rho_\mathcal{E}}$$

The unit cost function gives the **price of energy**

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

Where $\sigma_\mathcal{E} = \frac{1}{1-\rho_\mathcal{E}}$ is the elasticity of substitution for electricity and gas.

[details]

Household comfort

We then solve the outer cost minimization problem for the price of comfort

$$\min_{\mathcal{E},H} P^{\mathcal{E}}_{dj}\mathcal{E} + P^{H}_{j} H \quad \text{s.t.} \quad \bar{\mathcal{C}} = \left(\theta^{H}_{dj} H^{\rho_c}_{dj} + \theta^{\mathcal{E}}_{dj}\mathcal{E}^{\rho_c}_{dj}\right)^{1/\rho_c}$$

The unit cost function gives the **price of comfort**

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

Where $\sigma_c = \frac{1}{1-\rho_c}$ is the elasticity of substitution for housing and energy.

Once we have $P^{\mathcal{C}}_{dj}$, we can solve the model like a typical Cobb-Douglas.

$$\max_{X,\mathcal{C}} X^{\alpha^X_d} \mathcal{C}^{\alpha^C_d} \exp(\mathbb{A}_{ij}) \quad \text{s.t.} \quad X + P^{\mathcal{C}}_{dj}\mathcal{C}_{dj} = W_{dj}$$

[details]

Cost minimization of energy

$$\min_{E,G} P_j^E E + P_j^G G \quad \text{s.t.} \quad \bar{\mathcal{E}} = \left(\theta_{dj}^E E^{\rho_\mathcal{E}} + \theta_{dj}^G G^{\rho_\mathcal{E}}\right)^{1/\rho_\mathcal{E}}$$

The first-order conditions give us the following conditional demand functions for electricity E^* and natural gas G^*,

$$E^*(\mathcal{E}|d,j) = M_{dj}^{\mathcal{E}}\left(P_{dj}^G \theta_{dj}^E\right)^{\sigma_\mathcal{E}}\mathcal{E} \qquad G^*(\mathcal{E}|d,j) = M_{dj}^{\mathcal{E}}\left(P_j^E \theta_{dj}^G\right)^{\sigma_\mathcal{E}}\mathcal{E}$$

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

The unit cost function gives the "price of energy"

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

which we can then use to solve the outer nest, $\mathcal{C}$. [return]

Cost minimization of comfort

$$\min_{\mathcal{E},H} P_j^{\mathcal{E}}\mathcal{E} + P_j^H H \quad \text{s.t.} \quad \bar{\mathcal{C}} = \left(H_{dj}^{\rho_c} + \theta_{dj}^{\mathcal{E}}\mathcal{E}_{dj}^{\rho_c}\right)^{1/\rho_c}$$

The first-order conditions give us the following conditional demand functions for energy $\mathcal{E}^*$ and housing H^*,

$$H^*(C|d,j) = M_{dj}^c\left(P_{dj}^{\mathcal{E}}\right)^{\sigma_c}\mathcal{C}_{dj} \qquad \mathcal{E}^*(\mathcal{C}|d,j) = M_{dj}^c\left(P_j^H\theta_{dj}^{\mathcal{E}}\right)^{\sigma_c}\mathcal{C}_{dj}$$

where $M_{dj}^c = \left({\theta_{dj}^{\mathcal{E}}}^{\sigma_c} {P_{dj}^H}^{\sigma_c-1} + {P_j^{\mathcal{E}}}^{\sigma_c-1}\right)^{\frac{\sigma_c}{1-\sigma_c}}$

Again, the unit cost function gives the "price of comfort"

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

Once we have P_j^c, we can solve the model like a typical Cobb-Douglas.

[return]

Labor Supply

City choice probabilities

Assuming ε are type 1 extreme value, we get city choice probabilities as

$$P_{ij} = \frac{\exp\left(\tilde{V}_{ij}\right)}{\sum_j \exp(\tilde{V}_{ij})} \quad \text{where} \quad \tilde{V}_{ij} = (V_{ij} - \varepsilon_{ij})/\sigma_d$$

Since we have cobb-douglas utility, $\mathcal{C}^*_{dj} = \frac{\alpha^{\mathcal{C}}_{dj} W_{dj}}{\boldsymbol{\alpha_{dj}} P^c_{dj}}$

$$H^*_{dj} = M^c_{dj}\left(P^E_{dj}\right)^{\frac{1}{1-\rho_c}} \times \frac{\alpha^{\mathcal{C}}_d W_{dj}}{\tilde{\alpha}_d}$$

$$E^*_{dj} = M^c_{dj}\left(P^h_j \theta^{\mathcal{E}}_{dj}\right)^{\frac{1}{1-\rho_c}} M^E_{dj}\left(P^g_j \theta^g_{dj}\right)^{\frac{1}{1-\rho_E}} \times \frac{\alpha^{\mathcal{C}}_d W_{dj}}{\tilde{\alpha}_d}$$

$$G^*_{dj} = M^c_{dj}\left(P^h_j \theta^{\mathcal{E}}_{dj}\right)^{\frac{1}{1-\rho_c}} M^E_{dj}\left(P^e_j \theta^e_{dj}\right)^{\frac{1}{1-\rho_E}} \times \frac{\alpha^{\mathcal{C}}_d W_{dj}}{\tilde{\alpha}_d}.$$

[return] [delta decomp]

Effect of climate on utility

We can build intuition on how the climate affects household choices by taking derivatives in partial equilibrium, holding prices (rent, wages, electricity, and gas) fixed.

1. Effect of climate on indirect utility, v_{ij}

$$\frac{\partial v_{ij}}{\partial z_j^l} = \alpha_d^l - \frac{\alpha_d^{\mathcal{C}}}{P_{dj}^{\mathcal{C}}} \times \frac{\partial P_{dj}^{\mathcal{C}}}{\partial z_j^l}$$
$$= \alpha_d^l + \frac{\kappa_E}{\rho_{\mathcal{E}}} \frac{P_j^E E_{dj}}{W_{dj}}$$

2. Effect of climate on probability of choosing a city, P_{ij}

$$\frac{dP_{ij}}{dz_j^l} = \frac{1}{\sigma_d} \frac{\partial v_{ij}}{\partial z_j^l} \frac{P_{ij}(1 - P_{ij})}{\exp(\tilde{v}_{ij})}$$

[return]

Housing supply

Each city is characterized by a long-run, upward sloping rental supply curve,

$$\log(P_j^H) = a_j + \zeta_j \log(H_j)$$

- a_j captures variation in construction costs
- ζ_j is the inverse housing supply elasticity, reflecting variation in the amount of land available for development and land-use restrictions
- H_j is aggregate housing demand in city j

[return]

Firm FOC Derivation

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. FOC's from this profit function are

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

[return]

Firm FOC Derivation pt. 2

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.

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

[return]

Equilibrium

Equilibrium is characterized by a set of wages and comfort prices satisfying:

1. **Utility Maximization**. Households make optimal location and comfort demand choices given wages, comfort prices, and amenities. Concretely, this implies $N^{\star}_{dj} = \boldsymbol{s}^{\star}_{dj} \times N$ where $\boldsymbol{s}^{\star}_{dj}$ are the choice shares constructed from P_{ij}, evaluated at equilibrium prices. Additionally, housing, electricity, and gas demand satisfy derived demand curves.
2. **Profit Maximization**. Firms maximize profits. This simply implies the firm's first order conditions are obeyed.
3. **Market clearing**. In the model, labor supply must be equal to labor demand and housing supply must be equal to housing demand.

[return]

Data and Estimation Appendix

[return]

Housing and Rent indices

We decompose gross housing expenditure $\mathbb{E}^H_{ijt}$ into quantity $\boldsymbol{H}$ and price $\boldsymbol{P}^H_{jt}$ by regressing log expenditure on a city-year fixed effect and a vector of observable characteristics about the house, $\boldsymbol{X}_{ijt}$

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

Rent is $\boldsymbol{P}^H_{jt} = e^{\mu_{jt}}$ and housing quantity is $\boldsymbol{H}_{ijt} = \mathbb{E}^H_{ijt}/\boldsymbol{P}^H_{jt}$.

- $\boldsymbol{X}_{ijt}$ includes 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
- We limit the sample to renters here

[return]

Rent regression results

Dependent Variable:	log(Annual Rent)
Model:	(1)
Variables	
log(Rooms) $\times$ Year = 1990	0.1311*** (0.0328)
log(Rooms) $\times$ Year = 2000	0.1365*** (0.0153)
log(Rooms) $\times$ Year = 2010	0.2032*** (0.0167)
log(Rooms) $\times$ Year = 2019	0.1703*** (0.0183)
log(Bedrooms) $\times$ Year = 1990	-0.1014*** (0.0268)
log(Bedrooms) $\times$ Year = 2000	0.1075*** (0.0231)
log(Bedrooms) $\times$ Year = 2010	0.1714*** (0.0278)
log(Bedrooms) $\times$ Year = 2019	0.1832*** (0.0230)
log(People per Room) $\times$ Year = 1990	0.0162 (0.0115)
log(People per Room) $\times$ Year = 2000	-0.0302*** (0.0084)
log(People per Room) $\times$ Year = 2010	0.0054 (0.0089)
log(People per Room) $\times$ Year = 2019	0.0304*** (0.0087)
log(Units in Structure) $\times$ Year = 1990	0.1003*** (0.0227)
log(Units in Structure) $\times$ Year = 2000	0.0163* (0.0089)
log(Units in Structure) $\times$ Year = 2010	0.0156* (0.0094)
log(Units in Structure) $\times$ Year = 2019	0.0278*** (0.0075)
Fixed-effects	
City x Year	Yes
Decade Built x Year	Yes
Fit statistics	
Observations	4,900,375
R^2	0.23096
Within R^2	0.02207

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

[return]

Wage indices

Total income for a household of a dem 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. Let $l_{dt} = E_{dt} \times \tilde{l}_{dt}$, where

- E_{dt} is the probability that a household in the demographic group d is employed in year t
- $\tilde{l}_{dt}$ is productivity conditional on working

We calculate E_{dt} by defining employment as whether the household head or their spouse reports they are employed, work at least 48 weeks per year, and at least 35 hours per week

Wage indices

We estimate the following regression for workers,

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

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.

Income is then calculated as

$$I_{djt} = E_{dt} \times \exp(\hat{\nu}_{ejt} \times \bar{X}'_{dt}\hat{\beta}_{et})$$

[return]

Wage regression results

Dependent Variable:	log(Income)
Model:	(1)
Variables	
College × Year = 1990 × Married	0.1332*** (0.0044)
Non-college × Year = 1990 × Married	0.2317*** (0.0048)
College × Year = 2000 × Married	0.1536*** (0.0050)
Non-college × Year = 2000 × Married	0.2674*** (0.0050)
College × Year = 2010 × Married	0.1422*** (0.0046)
Non-college × Year = 2010 × Married	0.2497*** (0.0056)
College × Year = 2019 × Married	0.1473*** (0.0057)
Non-college × Year = 2019 × Married	0.2528*** (0.0049)
College × Year = 1990 × High Experience	0.0463*** (0.0057)
Non-college × Year = 1990 × High Experience	0.1726*** (0.0078)
College × Year = 2000 × High Experience	0.1300*** (0.0047)
Non-college × Year = 2000 × High Experience	0.1765*** (0.0096)
College × Year = 2010 × High Experience	0.1488*** (0.0040)
Non-college × Year = 2010 × High Experience	0.2052*** (0.0115)
College × Year = 2019 × High Experience	0.1755*** (0.0041)
Non-college × Year = 2019 × High Experience	0.2522*** (0.0085)
College × Year = 1990 × White	0.2505*** (0.0161)
Non-college × Year = 1990 × White	0.1988*** (0.0165)
College × Year = 2000 × White	0.2811*** (0.0186)
Non-college × Year = 2000 × White	0.2283*** (0.0199)
College × Year = 2010 × White	0.3150*** (0.0167)
Non-college × Year = 2010 × White	0.2193*** (0.0188)
College × Year = 2019 × White	0.3106*** (0.0158)
Non-college × Year = 2019 × White	0.1870*** (0.0143)
Fixed-effects	
City x College x Year	Yes
Fit statistics	
Observations	11,237,656
R^2	0.27599
Within R^2	0.08324

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

[return]

Energy indices

A concern with energy data 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 use the EIA's Residential Energy Consumption Survey (RECS) to correct this feature of the census data, as it directly reports energy consumption.

1. Estimate city-demographic group-year level energy consumption for single-family homeowners in the census data
2. Adjusting those estimates by the difference between single-family homeowners and renters in the RECS data.

Energy indices

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

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

- e^m_{idjt} is use of energy type $m \in \{elec, gas\}$
- X'_{idjt} are controls including the number of people in the household, the number of children, and the age of the household head.

We then take the national average of the controls for each year-demographic group, $\bar{X}'_{dt}$ to predict energy use for single-family homeowners for each city, demographic group, and year

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

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

Energy indices

Then, we turn to the RECS to estimate the following regression,

$$e_{it}^{m} = \alpha_{mt}^{1} MultiFam_{it} + \alpha_{mt}^{2} Rent_{it} + \alpha_{mt}^{3} MultiFam_{it} \times Rent_{it} + X_{it}' \beta_{mt} + \varepsilon_{it}$$

- $MultiFam_{it}$ 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 for the census division, number of children, household size, age of the household head, and an indicator for whether the household head is white.

Energy indices

To estimate energy usage for each demographic group, we use the estimated coefficients to adjust the single-family owners estimates,

$$E_{djt} = \pi_{djt}^{SFO} E_{djt}^{SFO} + \pi_{djt}^{MFO} E_{djt}^{SFO} e^{\hat{\alpha}^1_{elec,t}} + \pi_{djt}^{SFR} E_{djt}^{SFO} e^{\hat{\alpha}^2_{elec,t}} + \pi_{djt}^{MFR} E_{djt}^{SFO} e^{\sum_k \hat{\alpha}^k_{elec,t}}$$
$$G_{djt} = \pi_{djt}^{SFO} G_{djt}^{SFO} + \pi_{djt}^{MFO} G_{djt}^{SFO} e^{\hat{\alpha}^1_{gas,t}} + \pi_{djt}^{SFR} G_{djt}^{SFO} e^{\hat{\alpha}^2_{gas,t}} + \pi_{djt}^{MFR} G_{djt}^{SFO} e^{\sum_k \hat{\alpha}^k_{gas,t}}$$

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

Electricity regression results

Gas regression results

Estimation strategy for $\mathcal{E}$

The relative demand function from the cost-minimization problem give us

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

Taking first differences yields our estimating equation:

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

- Concerned with endogeneity between prices and quantity demanded
- Instrument for price ratio with lagged commercial elec and gas prices to isolate shocks to supply

Use $\hat{\sigma_{\mathcal{E}}}$ and residuals to calculate $\mathcal{E}$ and $P_{\mathcal{E}}$

[return]

Estimation strategy for $\mathcal{C}$

The relative demand function from the cost-minimization problem give us

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

Taking first differences yields our estimating equation,

$$\Delta \log\left(\frac{\mathcal{E}_{djt}}{H_{djt}}\right) = \sigma_{\mathcal{C}} \Delta \log\left(\frac{P^{H}_{jt}}{P^{\mathcal{E}}_{jt}}\right) + \Delta \epsilon_{djt}$$

We use a **Bartik instrument interacted with land availability** for $\Delta \log(P^{H}_{jt}/P^{\mathcal{E}}_{jt})$, taking care of endogeneity caused by unobserved amenities being correlated with both rent and housing demand.

[return]

Comfort Elasticity of Substitution

Dep. Var.	$\log(E/G)$				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
$\log(P_g/P_e)$	0.511***	0.525***	0.439***	0.432***	0.432***
	(0.062)	(0.066)	(0.070)	(0.086)	(0.087)
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

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

Dep. Var.	$\log(\mathcal{E}/H)$				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
$\log(P_h/P_{\mathcal{E}})$	0.569***	0.463***	0.316***	0.293	0.570
	(0.082)	(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), $\log(P_h/P_{\mathcal{E}})$	134.61	65.63	143.79	1.78	0.90

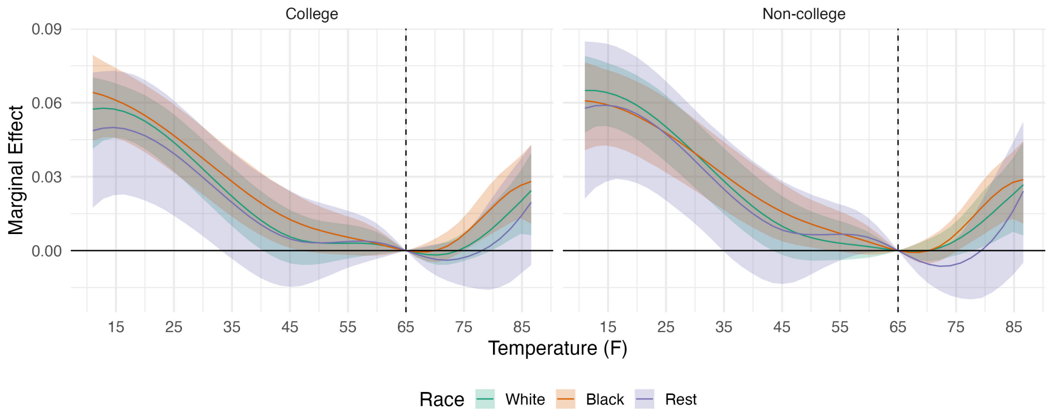
Clustered (City) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

[return]

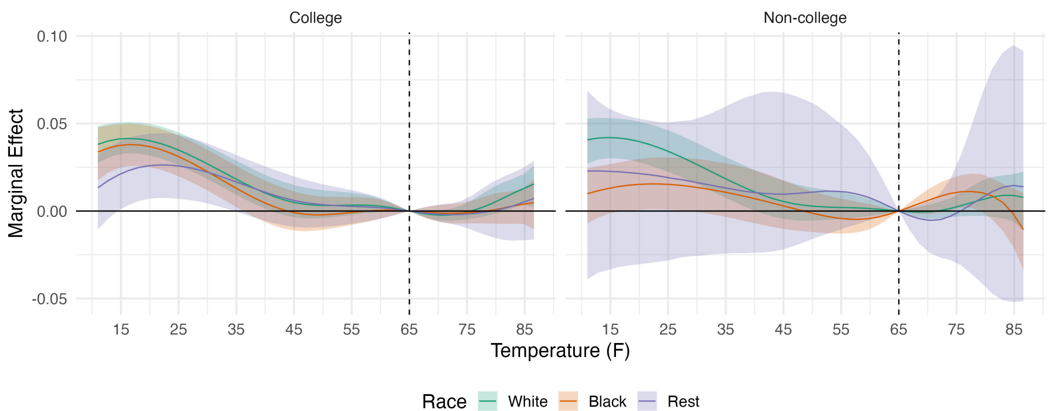
Heterogeneity in comfort production

Effect of an additional day at temperature

for electricity benefit

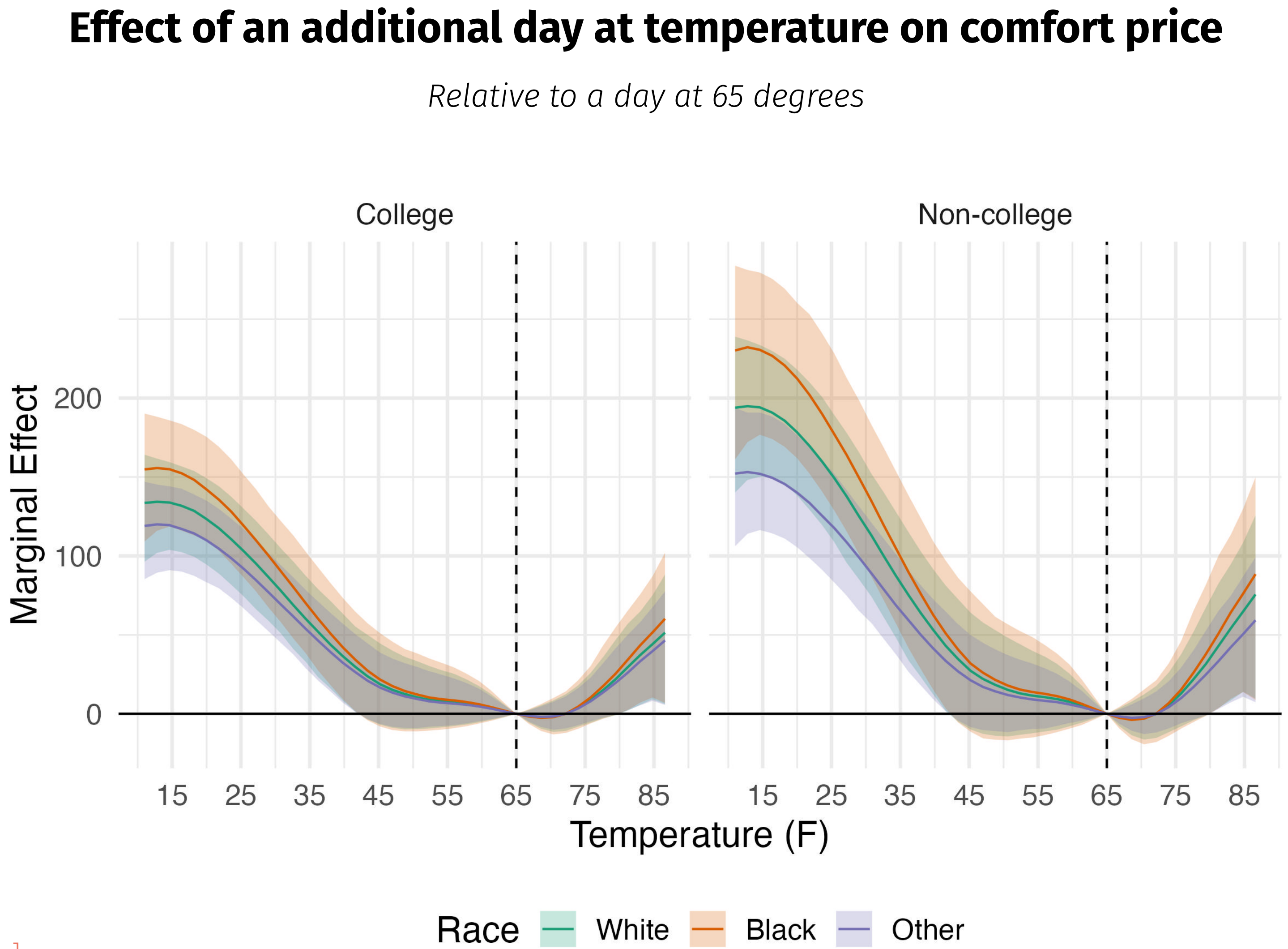


for gas benefit



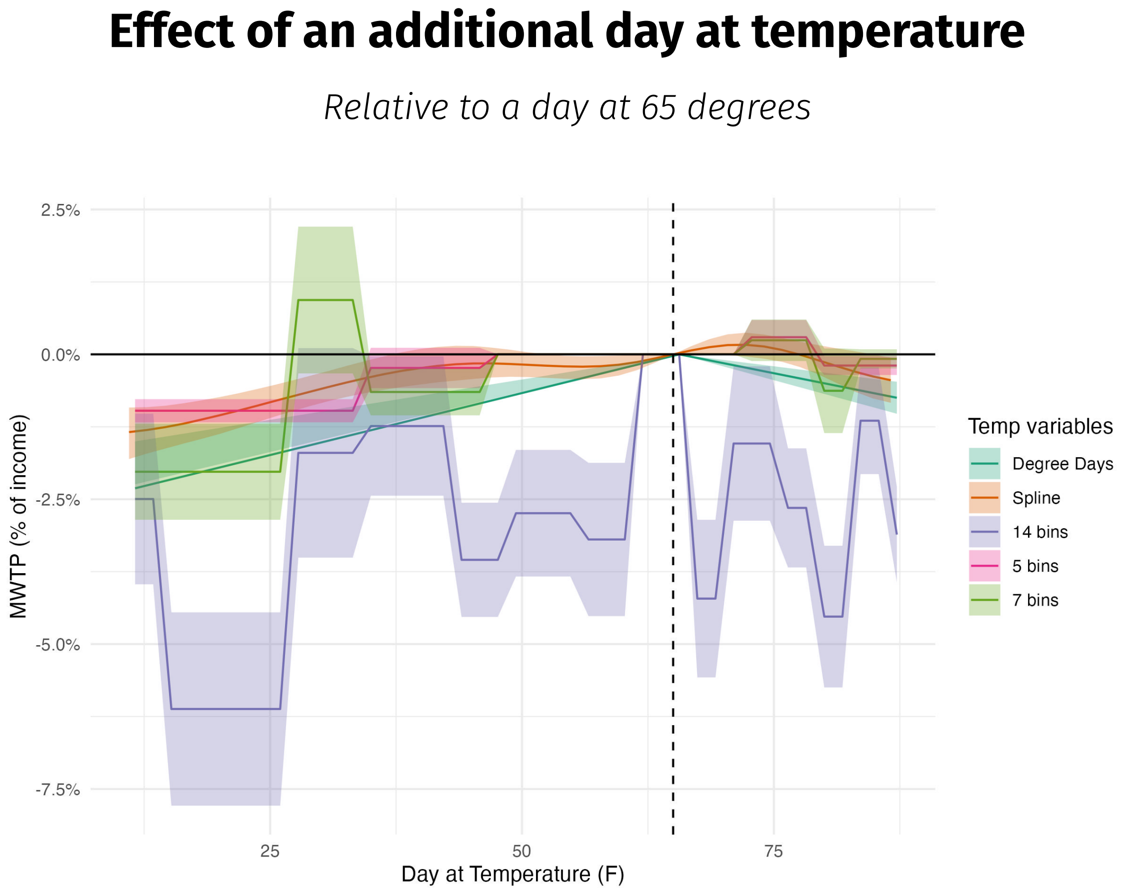
[return]

Effect of climate on comfort price



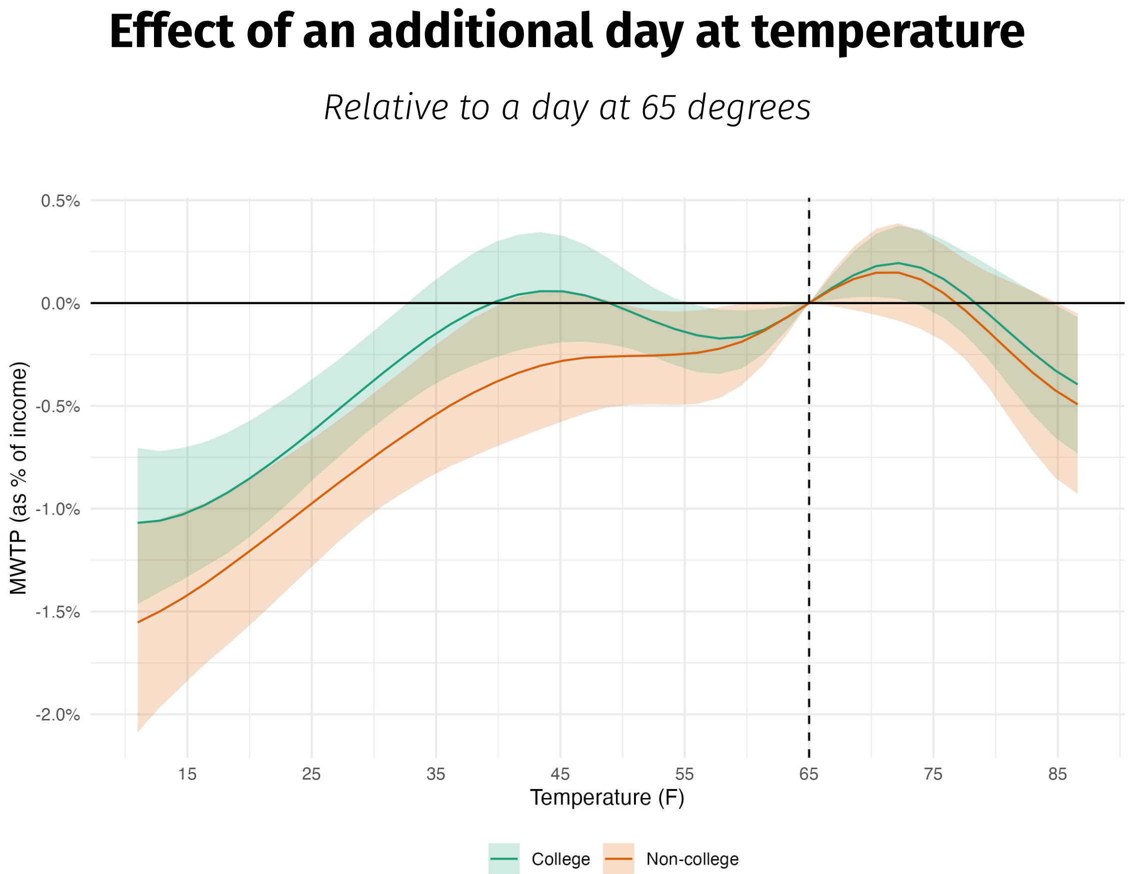
[return]

Climate's effect on amenities



[return]

Climate's effect on amenities



[return]

Change in climate amenities

City	Log Diff	Hot	Cold	Rain
Improving Cities				
Denver-Aurora, CO	56.8	-95.1	165.0	-13.2
Hartford-West Hartford-East Hartford, CT	56.3	-166.1	214.5	8.0
New Haven-Milford, CT	49.4	-136.5	180.3	5.6
Albany-Schenectady-Troy, NY	46.5	-152.2	217.2	-18.5
Worcester, MA	45.1	-117.8	175.9	-12.9
Grand Rapids-Wyoming, MI	43.2	-57.4	102.4	-1.8
Worsening Cities				
Fresno, CA	-49.4	-82.5	47.2	-14.1
Tampa-St. Petersburg-Clearwater, FL	-67.0	-77.3	61.4	-51.1
Orlando, FL	-71.6	-136.2	113.0	-48.4
Jacksonville, FL	-73.0	-173.3	163.1	-62.9
New Orleans-Metairie-Kenner, LA	-84.3	-231.3	208.6	-61.6
Miami-Fort Lauderdale-Miami Beach, FL	-95.2	-117.2	69.4	-47.4

[return]

Labor Demand Calibration

We calibrate the labor elasticity of substitution σ_l and the labor input use intensities, λ_j. First, we calibrate $\sigma_l = 2$ based on Card (2010). Then we use the relative labor demand curves to identify λ_j,

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

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

$$\lambda_j = \frac{K_j}{1+K_j} \qquad \text{where} \qquad K_j = \left(\frac{W_j^S}{W_j^L}\right)\left(\frac{S_j}{L_j}\right)^{1/\sigma_l}$$

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.

[return]

Housing Supply Calibration

We calibrate the inverse supply elasticities, ζ_j, to those in Saiz (2010). The remaining parameters from the housing supply curve are the intercepts, a_j. Since housing supply equals housing demand in equilibrium, we back these out from the data as

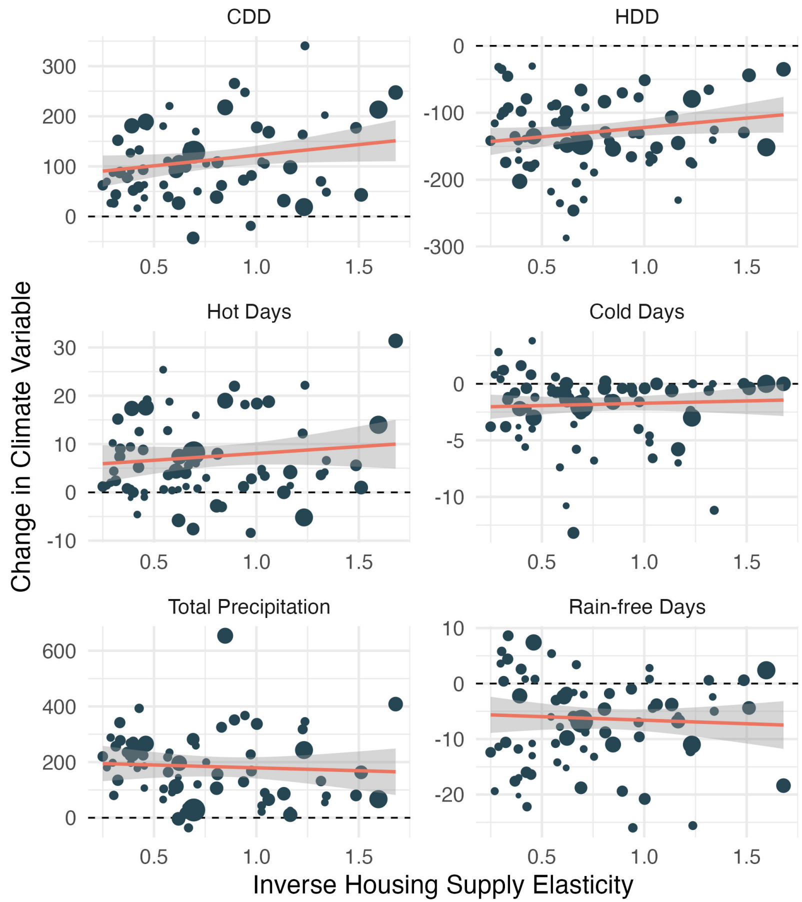
$$\exp a_{jt} = \frac{P^H_{jt}}{\left(\sum_d N_{djt} H_{djt}\right)^{\zeta_j}}$$

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

[return]

Housing Supply Elasticity Variation

There is a slight positive correlation between the inverse housing supply elasticities and changes in climate between 1990 and 2019.



Simulation Appendix

[return]

Calculating welfare effects

Household i's compensating variation for the counterfactual climate, $\tilde{\mathbf{Z}}$ relative to the baseline climate, $\mathbf{Z}$

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

- $V_i(\mathbf{Z}) = v_{ij}(\mathbf{Z}, j^*)$ is household i's indirect utility with climate $\mathbf{Z}$ evaluated at equilibrium choices j^* and prices
- Multiplying by $\frac{1}{\beta_e^w}$ converts utility units into percent of income

Taking the expectation over the idiosyncratic shocks gives us

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

where $\bar{\gamma}$ is Euler's constant.

[return]

CMIP6 climate models

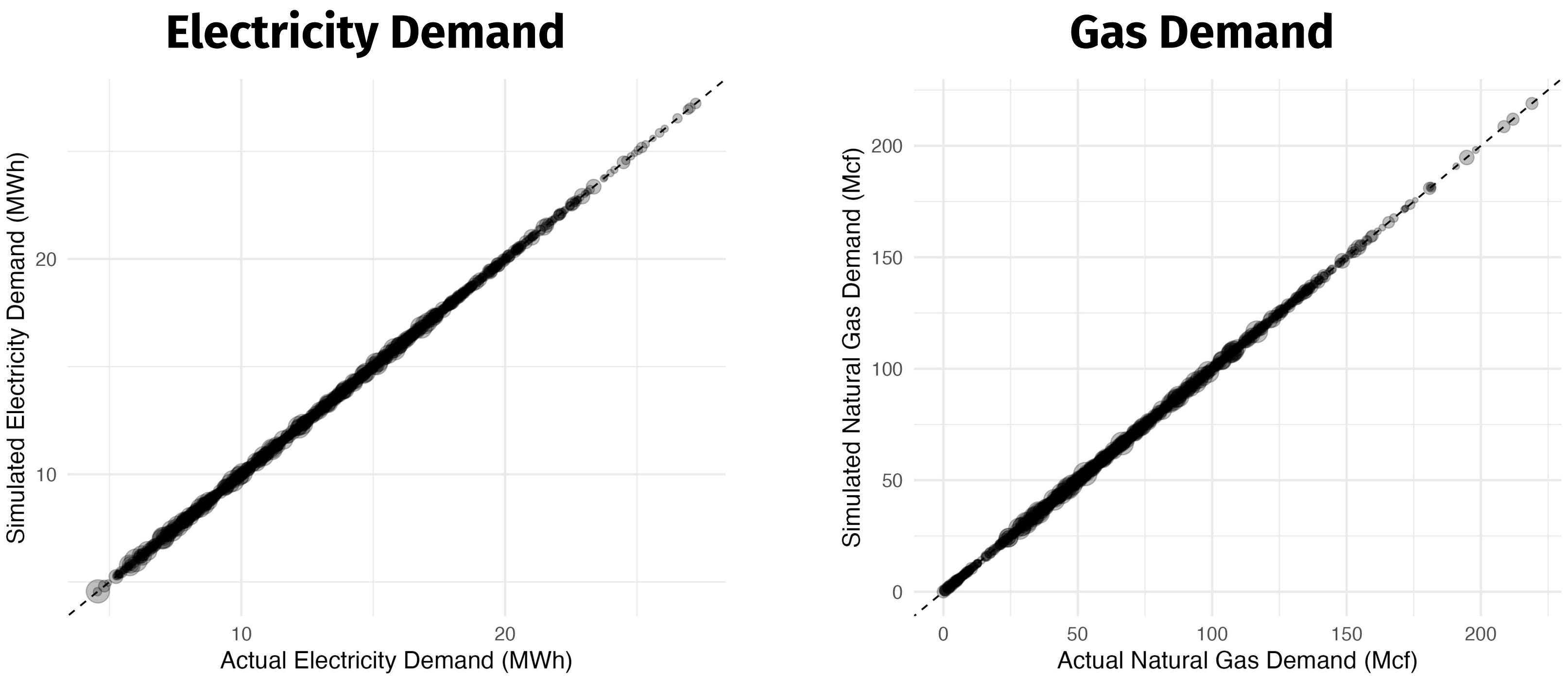
These are made publicly available on the Microsoft Planetary Computer.

- Most recent generation of climate models used for the IPCC's AR6
- Global daily temperature and precipitation (among others) for 1950-2100 under various emissions scenarios
- We take the population weighted mean from each climate model for each city
- Then take ensemble mean, min, and maximum across climate models
- Main results use the ensemble mean

[return]

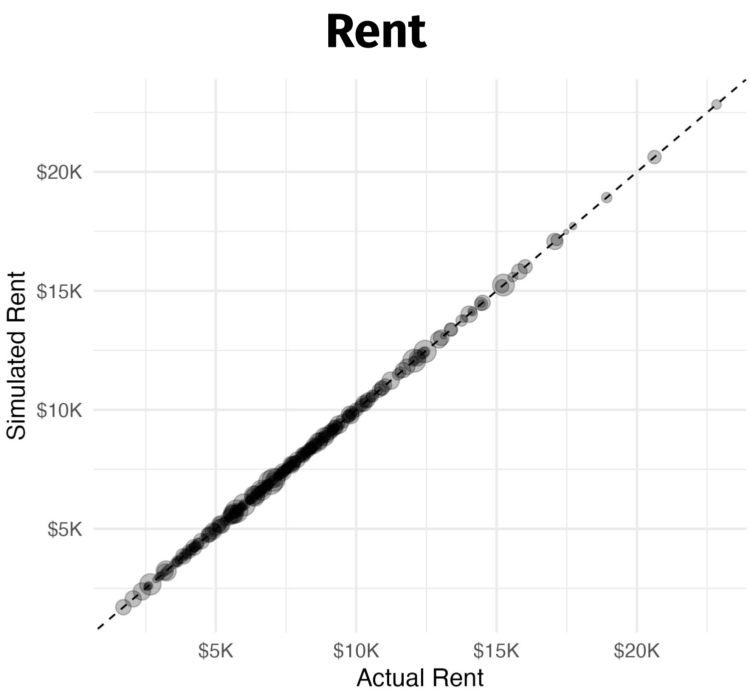
GE simulation model fit

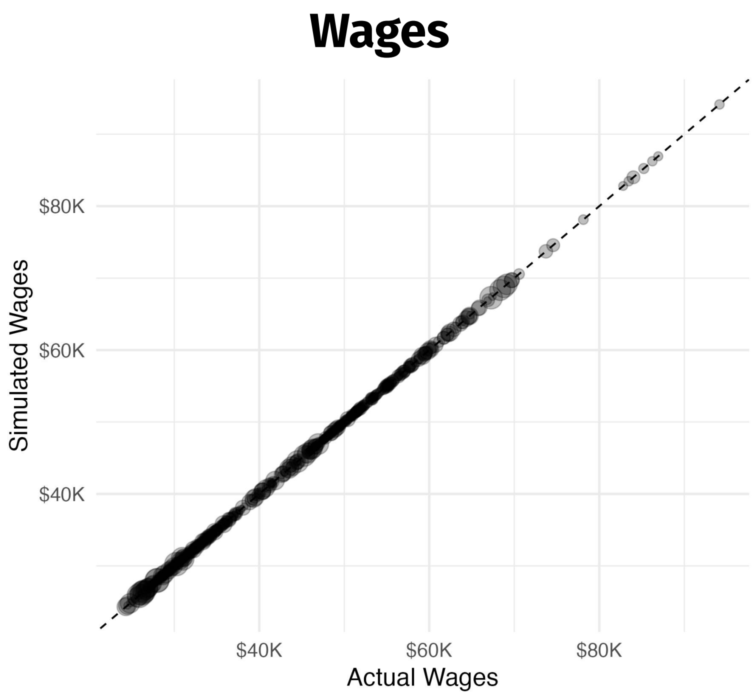
The simulation matches actual data under the baseline (factual) climate



[return]

Model fit





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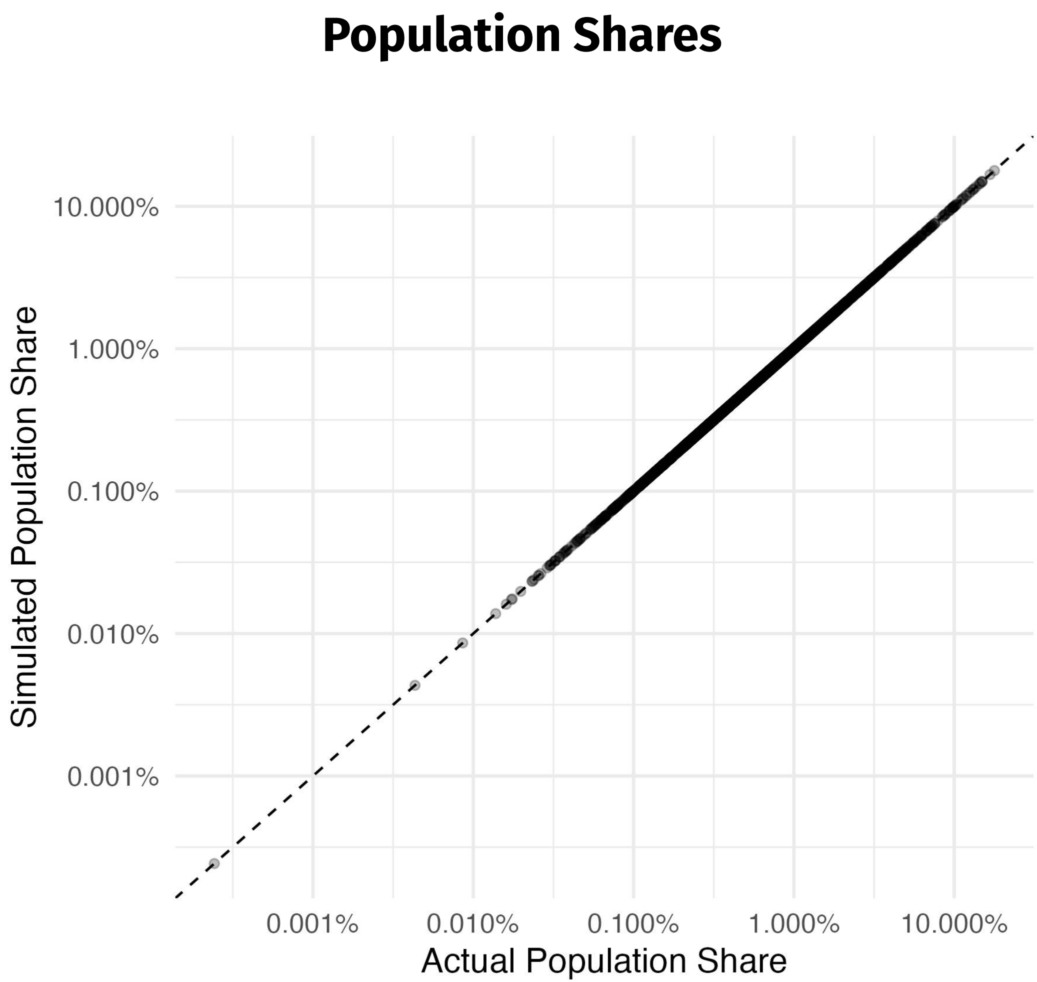
Model fit



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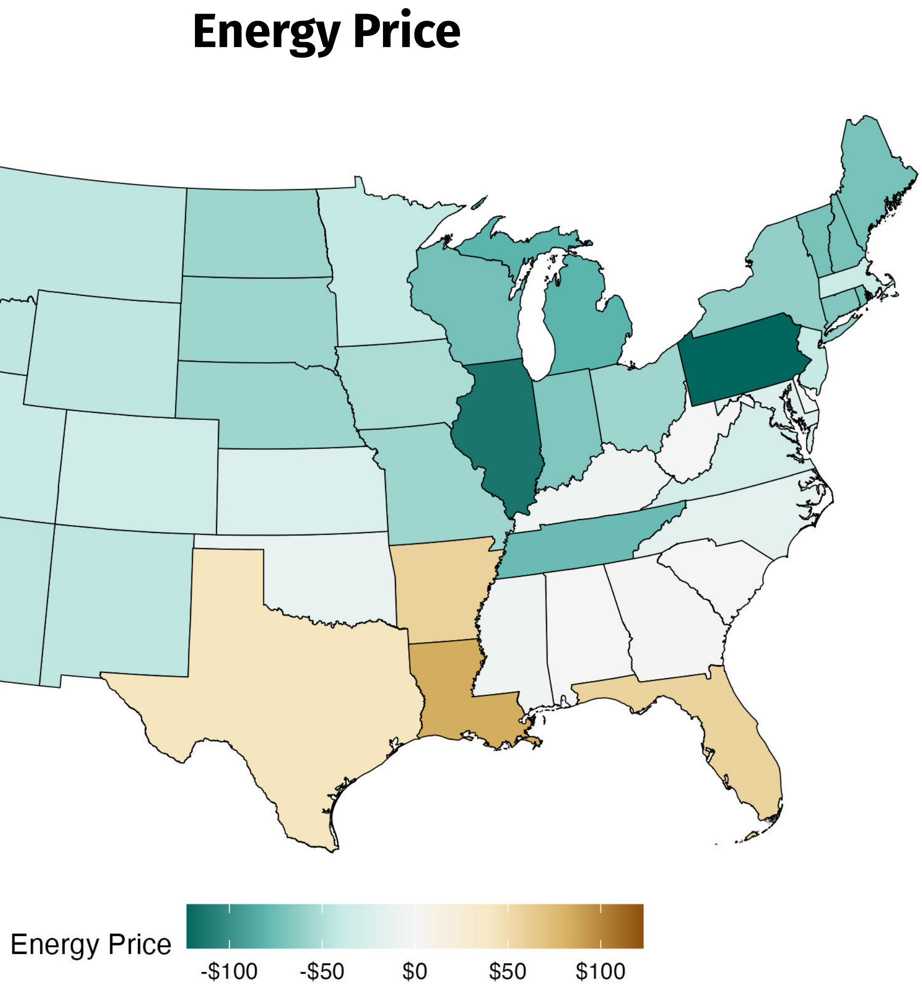
Results Appendix

[return]

Spatial variation



Different effects of warming in hot vs cold states

CV Gaps by race and education

Table : Differences in Compensating Variation by Demographic Group

Dependent Variable	CV (% of income)					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Constant	-1.22***			-0.34**		
	(0.28)			(0.15)		
Black	-1.24***	-0.96***	-0.76***	-0.82***	-0.50***	-0.63***
	(0.21)	(0.11)	(0.11)	(0.12)	(0.07)	(0.06)
Rest	0.69***	0.34*	0.36**	0.35**	0.13	0.18
	(0.22)	(0.18)	(0.17)	(0.13)	(0.13)	(0.12)
Non-college				-1.53***	-1.32***	
				(0.22)	(0.16)	
Black $\times$ Non-college				-0.35**	-0.38***	-0.18**
				(0.17)	(0.14)	(0.09)
Rest $\times$ Non-college				0.59***	0.45***	0.32***
				(0.16)	(0.15)	(0.11)
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	0.32	0.40	0.11	0.37	0.40
Within R^2		0.02	0.02		0.10	0.02

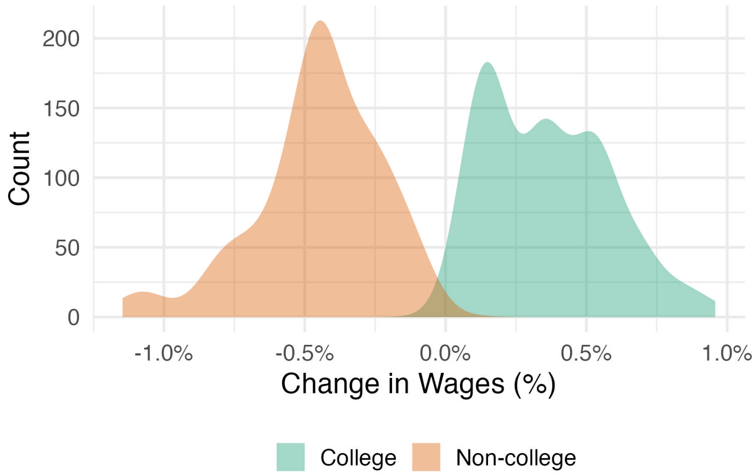
Clustered (City) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

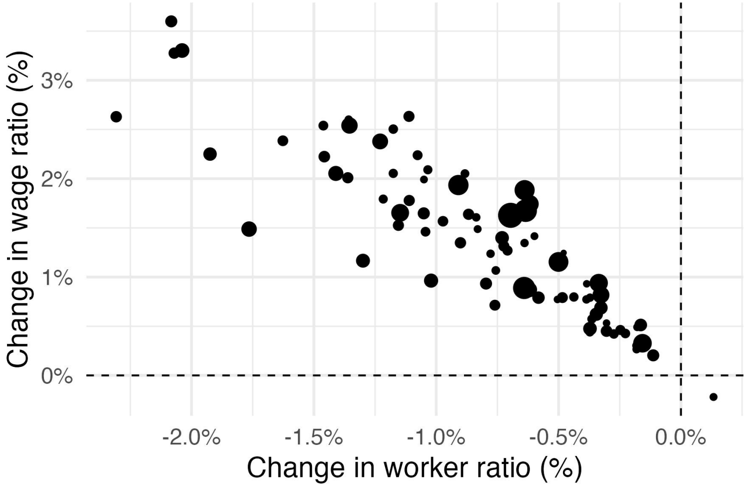
Levels for decomposition

	Climate Effect From		
	Both	Amenities	Comfort
Fixed Location			
White	-0.61	-1.10	0.49
Black	-2.25	-2.33	0.08
Difference	**-1.64**	**-1.24**	**-0.40**
Sorting, fixed prices			
White	-1.47	-1.78	0.44
Black	-3.04	-2.98	0.07
Difference	**-1.57**	**-1.21**	**-0.37**
Full Effects			
White	-1.19	-1.58	0.46
Black	-2.45	-2.58	0.19
Difference	**-1.27**	**-1.00**	**-0.27**

Wage differentials

Climate change has contributed to the increase in the college wage gap. Since college households are more mobile than non-college households, the college-noncollege worker ratio tends to decrease---more so in cities where the climate is deteriorating. Thus, college wages increase in those deteriorating cities, and non-college wages decrease.





Population Changes

City	Change in Pop (%)
Growing Cities	
Grand Rapids-Wyoming, MI	28.6
Hartford-West Hartford-East Hartford, CT	26.2
Albany-Schenectady-Troy, NY	25.6
Denver-Aurora, CO	25.1
Scranton--Wilkes-Barre, PA	24.4
New Haven-Milford, CT	20.6
Declining Cities	
Tampa-St. Petersburg-Clearwater, FL	-16.6
Orlando, FL	-19.7
Jacksonville, FL	-21.5
Fresno, CA	-22.3
Miami-Fort Lauderdale-Miami Beach, FL	-22.6
New Orleans-Metairie-Kenner, LA	-25.4