Climate Adaptive Response Estimation:
Quantifying the Long Run Impacts of Climate Change on Electricity and Natural Gas Consumption Using Big Data

Maximilian Auffhammer
University of California at Berkeley
National Bureau of Economic Research & CESifo

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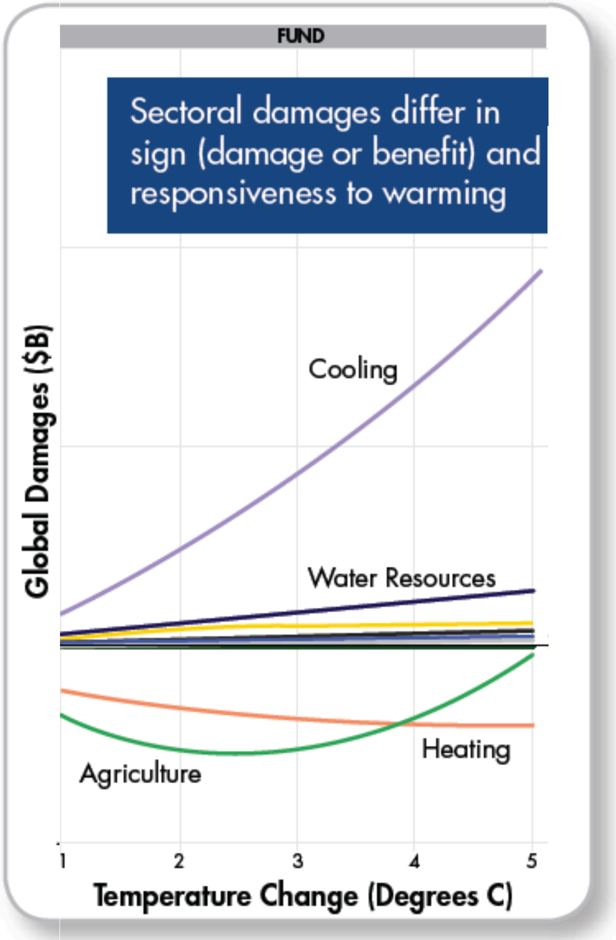
Berkeley
UNIVERSITY OF CALIFORNIA

Motivation

- Large benefits from indoor cooling (e.g. productivity, health)
- Large costs from high demand (e.g. outages, investment in “peakers”)
- Growing incomes, dropping prices of durables and artificially low electricity/energy prices will drive increasing demand for cooling in the presence and absence of climate change (e.g. Davis and Gertler, PNAS)
- (Some) integrated assessment models of climate change predict that increased energy consumption is the main driver of costs/damages.
- The short and long run temperature response of energy demand is not well understood.
- There will be savings from gas/heating oil - don’t just count bad stuff!

Integrated Assessment Models: Global Damages



In the FUND model the **space cooling** impacts are calculated from this equation:

$$SC_{t,r} = \alpha_r Y_{1990,r} \left(\frac{T_t}{1.0}\right)^{\beta} \left(\frac{y_{t,r}}{y_{1990,r}}\right)^{\epsilon} \left(\frac{P_{t,r}}{P_{1990,r}}\right) / \prod_{s=1990}^{t} AEEI_{s,r}$$

In the FUND model the **space cooling** impacts are calculated from this equation:

$$SH_{t,r} = \alpha_r Y_{1990,r} \frac{\operatorname{atan} T_t}{\operatorname{atan} 1.0} \left(\frac{y_{t,r}}{y_{1990,r}}\right)^{\epsilon} \left(\frac{P_{t,r}}{P_{1990,r}}\right) \Big/ \prod_{s=1990}^{t} AEEI_{s,r}$$

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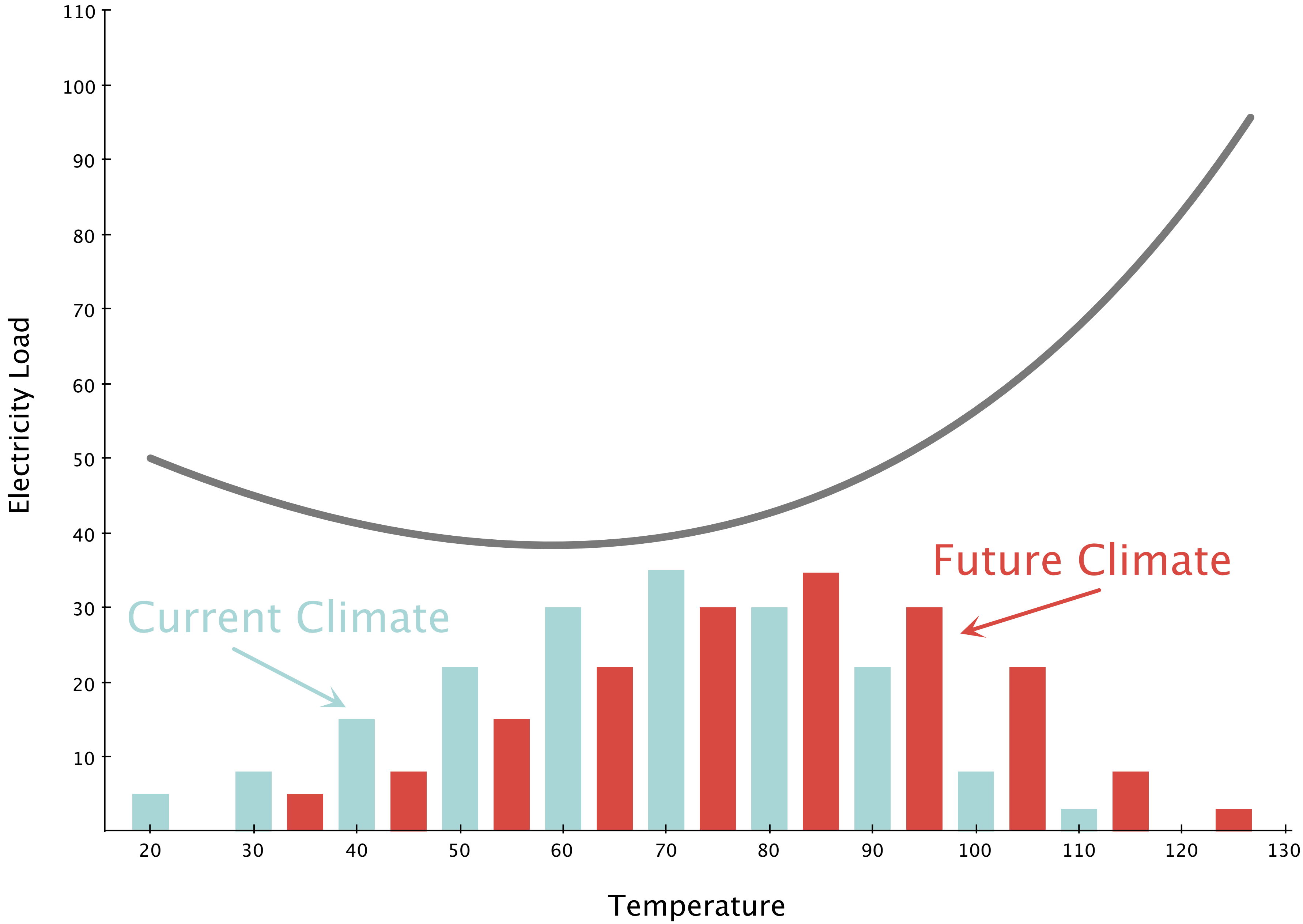
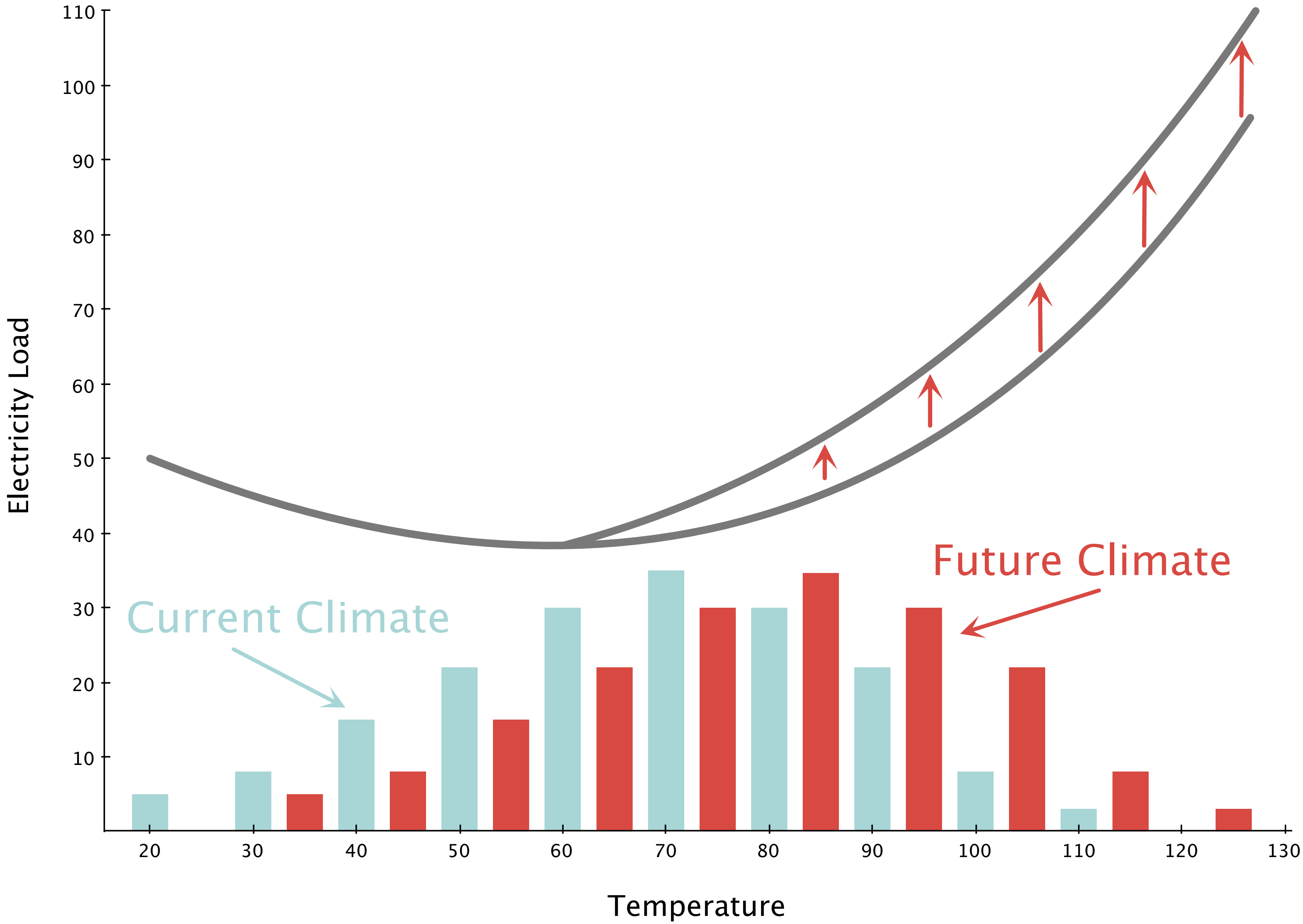
What consumers do when it gets hot…

Operating existing air conditioners more increases load



What consumers do when it gets hot where it wasn't before.

Changing climate moves the temperature load curve



Research Question

1. How much would **residential electricity consumption change** if we imposed projected end of century climate on today's economy
    - holding **air conditioner penetration constant** (intensive margin)
    - letting **air conditioner penetration change** (extensive margin)

2. How much will residential **natural gas consumption change** if we imposed projected end of century climate on today's economy **holding technology constant.**

The obligatory literature overview

Model 1.0: Time Series Regressions - Weather elasticity

- Franco and Sanstad, 2008; Auffhammer, Baylis and Hausman, 2017
- Sensitive to any time series regression issues

Model 2.0: Ricardian Models - Climate Elasticity

- Mendelsohn (19xx/20xx); Mansur and Mendelsohn (20xx)
- Sensitive to omitted variables bias

Model 3.0: Panel Models - Weather elasticity

- Auffhammer, Ramanathan and Vincent (2006), Deschenes and Greenstone (2007)
- Exploit random nature of weather shocks to get causal effects of weather

Model 4.0: Long Difference Models - Climate elasticity

- e.g. Burke and Emerick, 2015
- Require long panels outcomes and temperatures

Preview of approach and findings

Model 5.0: **C**limate **A**daptive **R**esponse **E**stimation (**CARE**)

- Builds on insights by Hsiang and Narita, 2012; Auffhammer and Aroonruengsawat (2012), Butler et al. 2013; Barreca et al. 2016; Dell, Jones, and Olken 2012, 2014
- Use a jealousy inducing dataset on household electricity and natural gas consumption to estimate causal short run response to temperature at ZIP code level.
- Explain cross sectional variation in electricity temperature response across ZIP codes as a function of climate.
- Link to 18 state of the art downscaled climate models and calculate projections of impacts of short and long run response

Main findings:

- Accounting for extensive margin adjustments increases moderate impacts for electricity consumption by 50-70%
- Natural Gas impacts as large and negative, offsetting the electricity increases

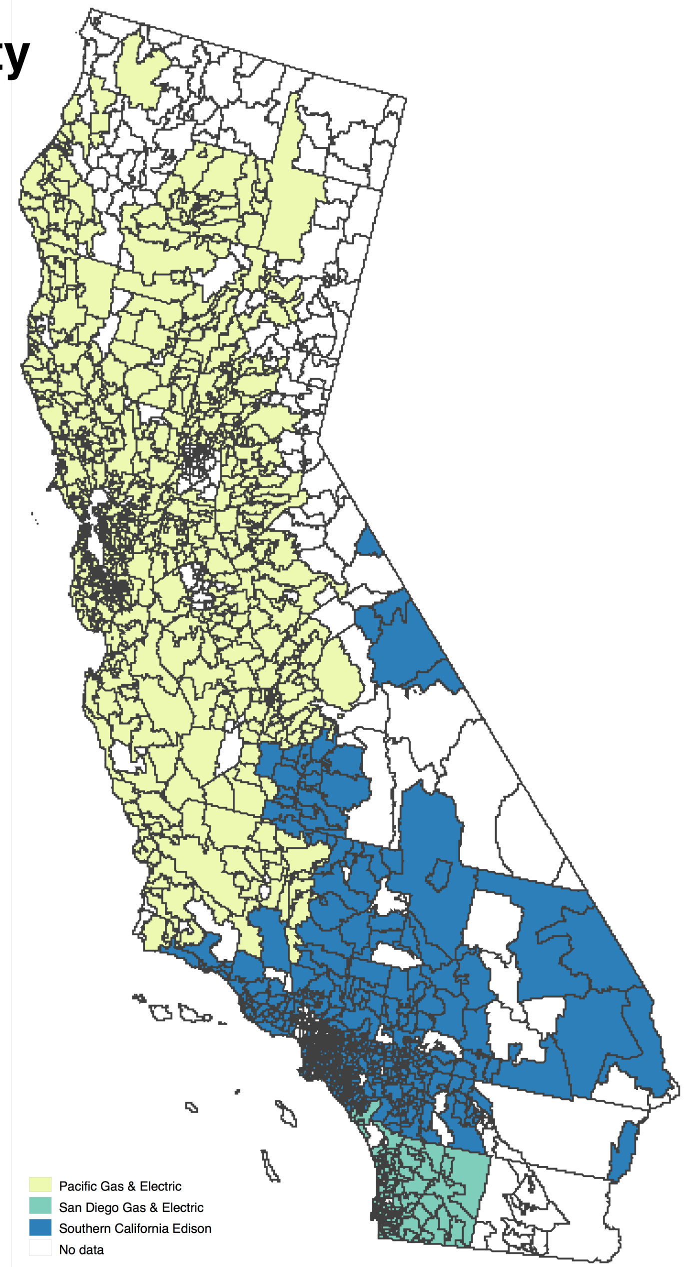
The billing data

- Complete residential gas and electric billing data for California's investor owned utilities (PG&E, SCE, SDG&E, SoCalGas)
- 79% of all California households
- Electricity: Trimmed shortest and longest bills; drop bills with daily consumption less than 2 kWh and drop bills for solar households
- Gas: Trimmed shortest and longest bills, dropped bills whose revenues we could not credit by 95%; dropped bills whose consumption is in the tails (99th and 1st percentile).

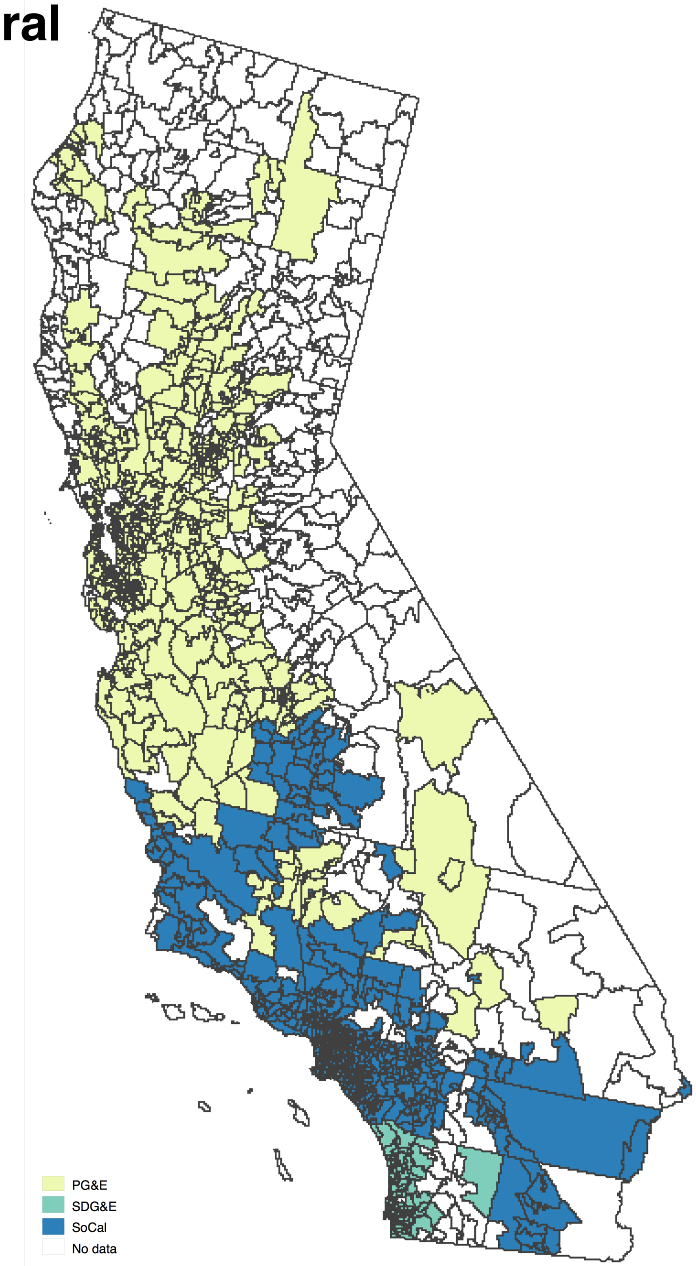
Utility	Electricity Years	# of Bills	Gas Years	# of Bills
PG&E	2003-2009	342 Million	2004-2014	587 Million
SDG&E	2000-2009	153 Million	2008-2015	74 Million
SCE	1999-2008	469 Million		
SoCalGas			2010-2015	267 Million
Total		964 Million		928 Million

The billing territory covers most of the state

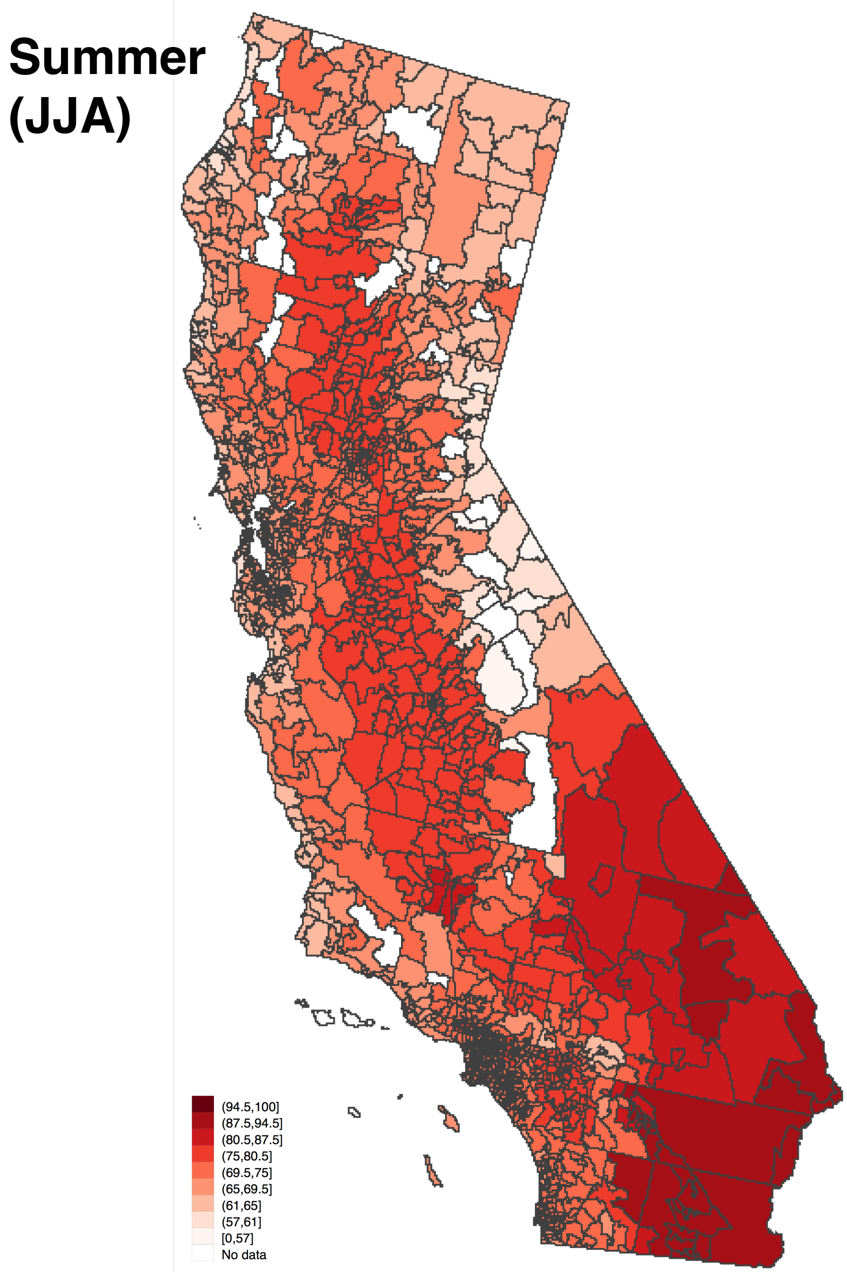
Electricity

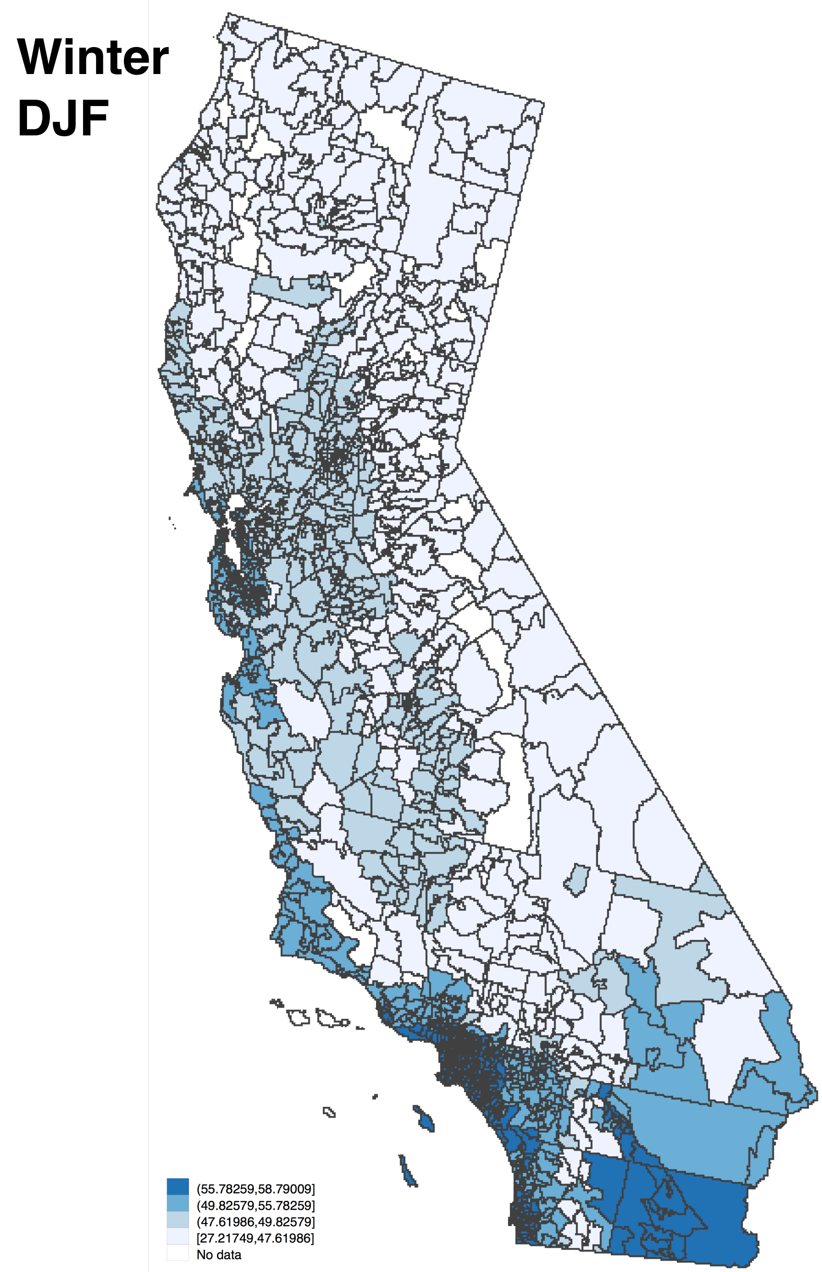


Natural Gas



California has diverse climate zones.





Electricity Estimation Strategy

First Stage: Intensive Margin Response estimated separately for each ZIP Code *j*:

$$\log(q_{it}) = \sum_{p=1}^{14} \beta_{jp} D_{pit} + \gamma Z_{it} + \alpha_i + \phi_m + \psi_y + \varepsilon_{it}$$

Second Stage: Extensive Margin Response estimated across ZIP Codes

$$\beta_{jp} = \delta_1 + \delta_2 C_{pj} + \boldsymbol{\delta_3 Z_j} + \eta_{jp}$$

Functional forms in first and second stage

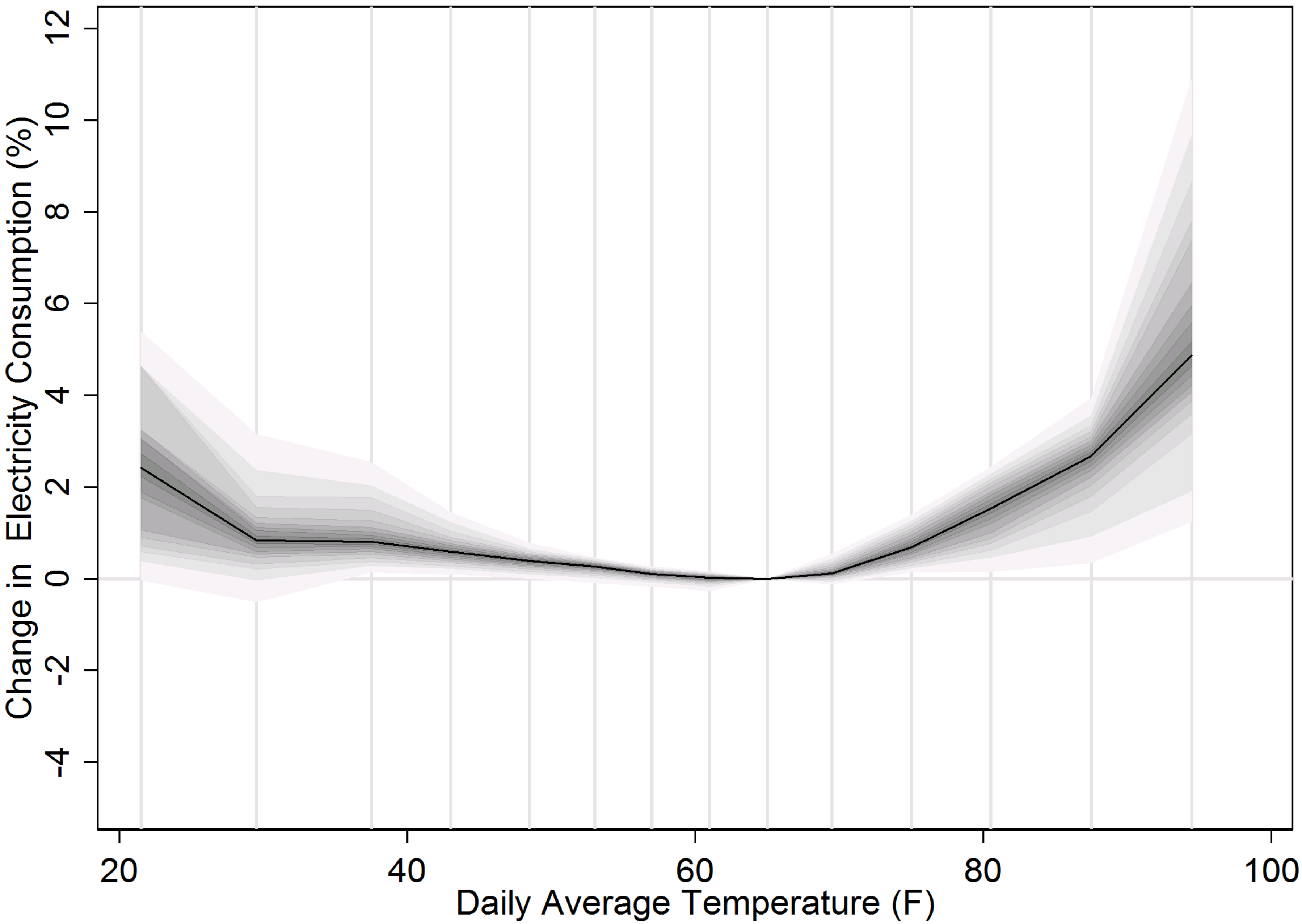
Flexible functional form for temperature in **first stage** :

- D_{pit}= number of days of an electricity bill in p^{th} temperature bin
- Percentile bins approach:
- 14 bins with cutoff at 1^{st} , 5^{th} ,10^{th} ,....,90^{th} ,95^{th},99^{th} percentile
- These translate into cutoffs of 24, 35, 40, 46, 51, 55, 59, 63, 67, 72, 78, 83 and 92 degrees Fahrenheit

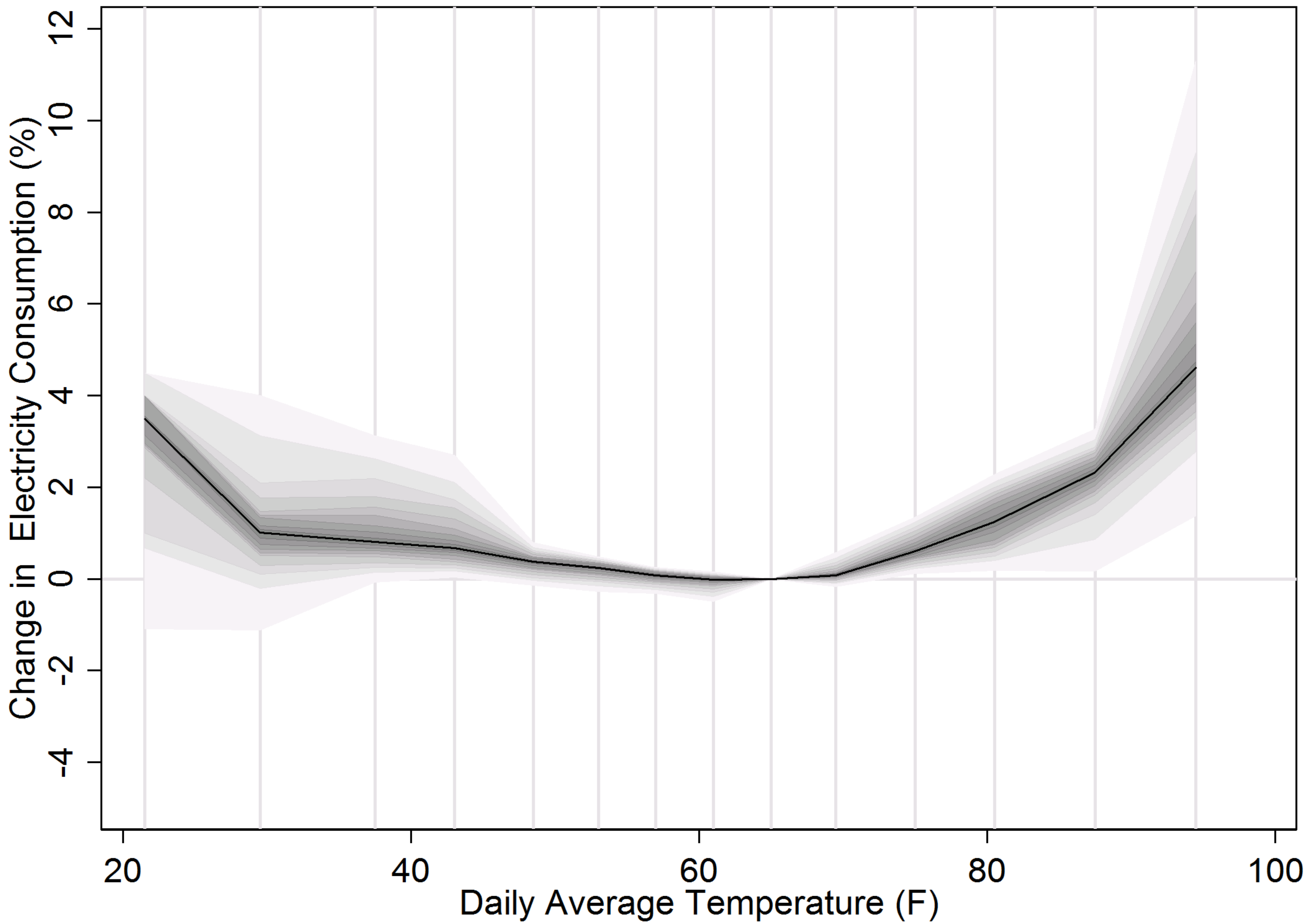
Climate impact in **second stage** :

- C_{jp}= Share of days spent in bin p during 2000-2010

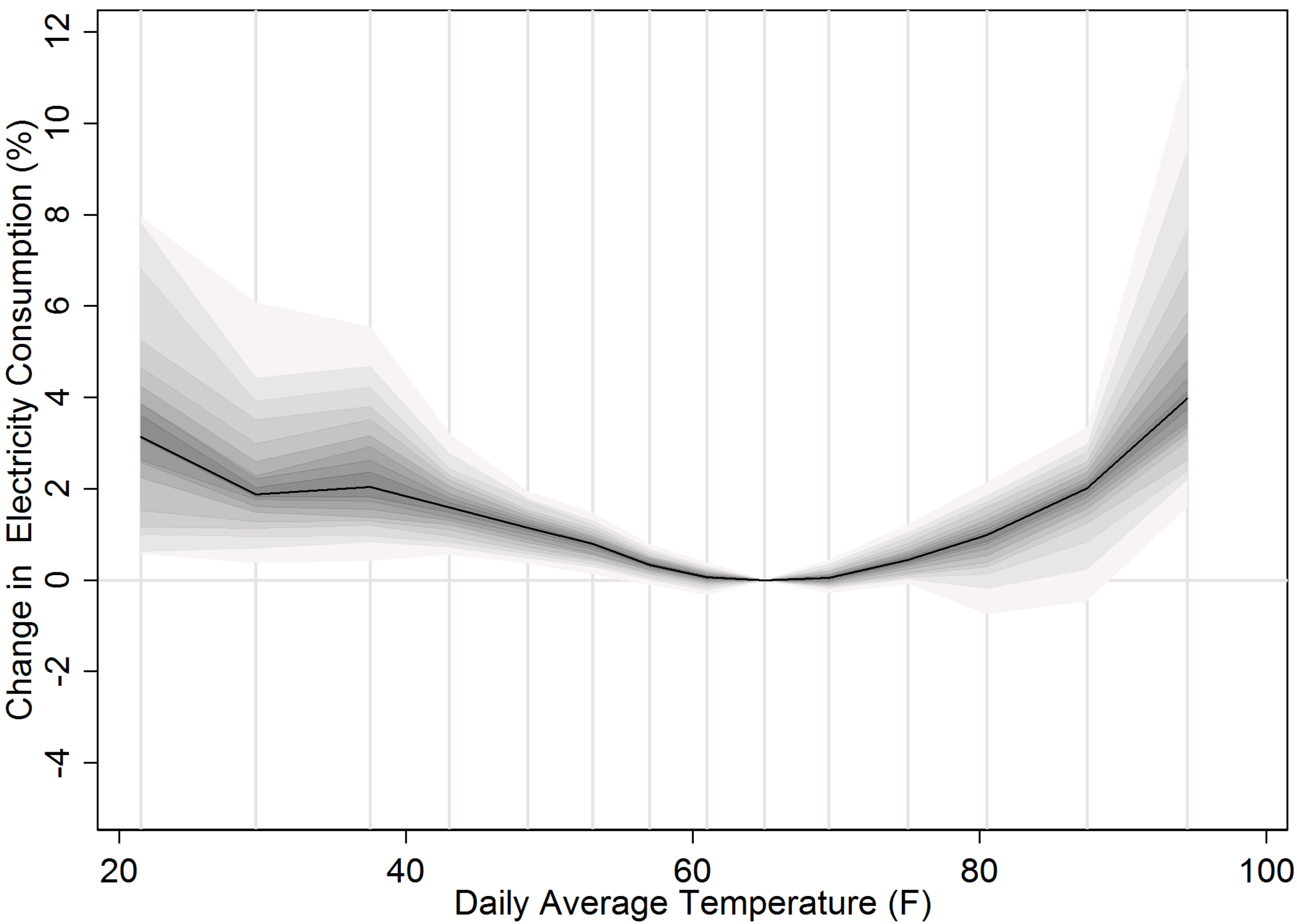
Temperature Response: "Normal households"



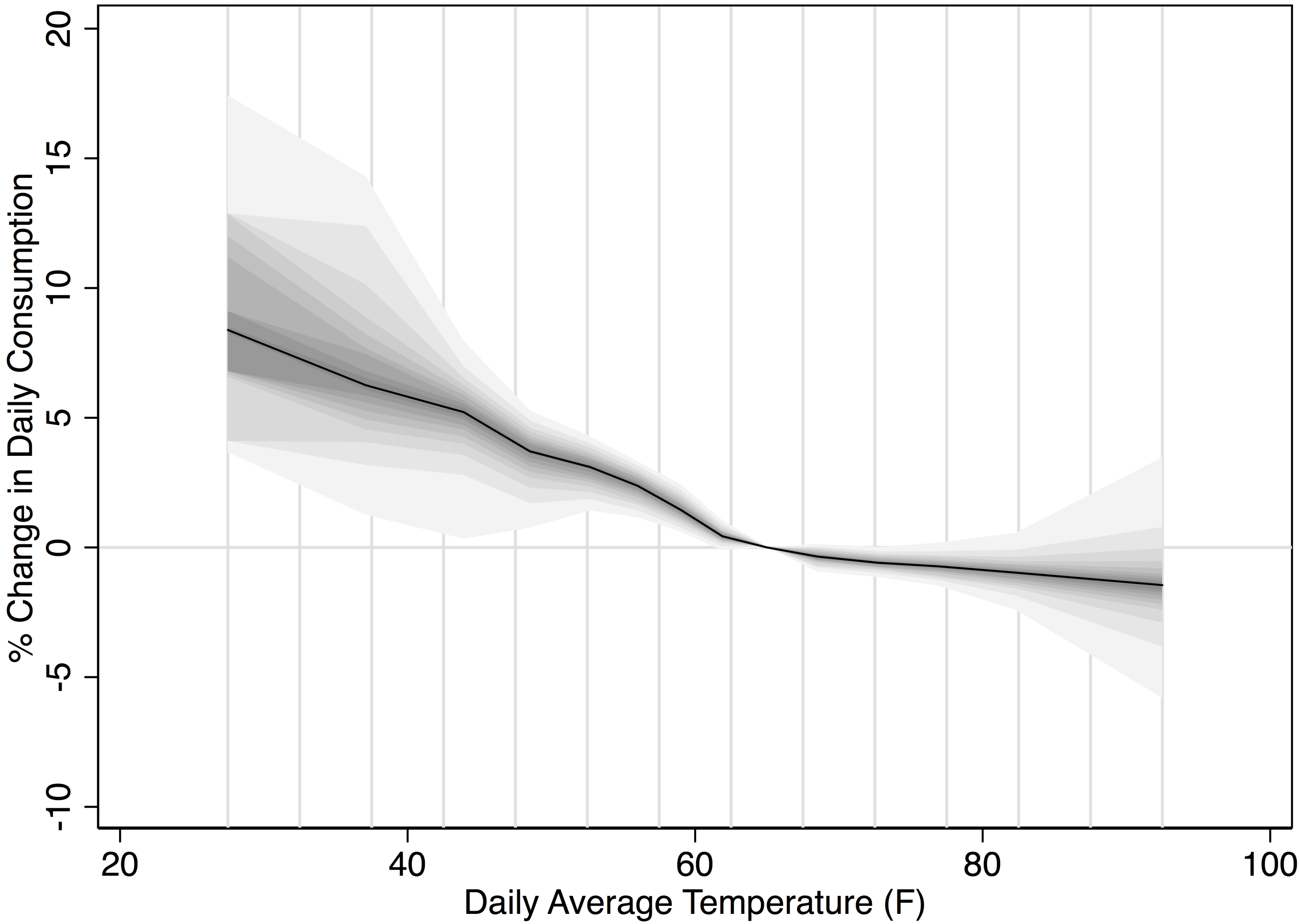
Temperature Response: “Subsidy households”



All-Electric households



Natural Gas Response



Second stage regression

Table 3: Second Stage Regressions of Temperature Response Coefficients by Temperature Bin

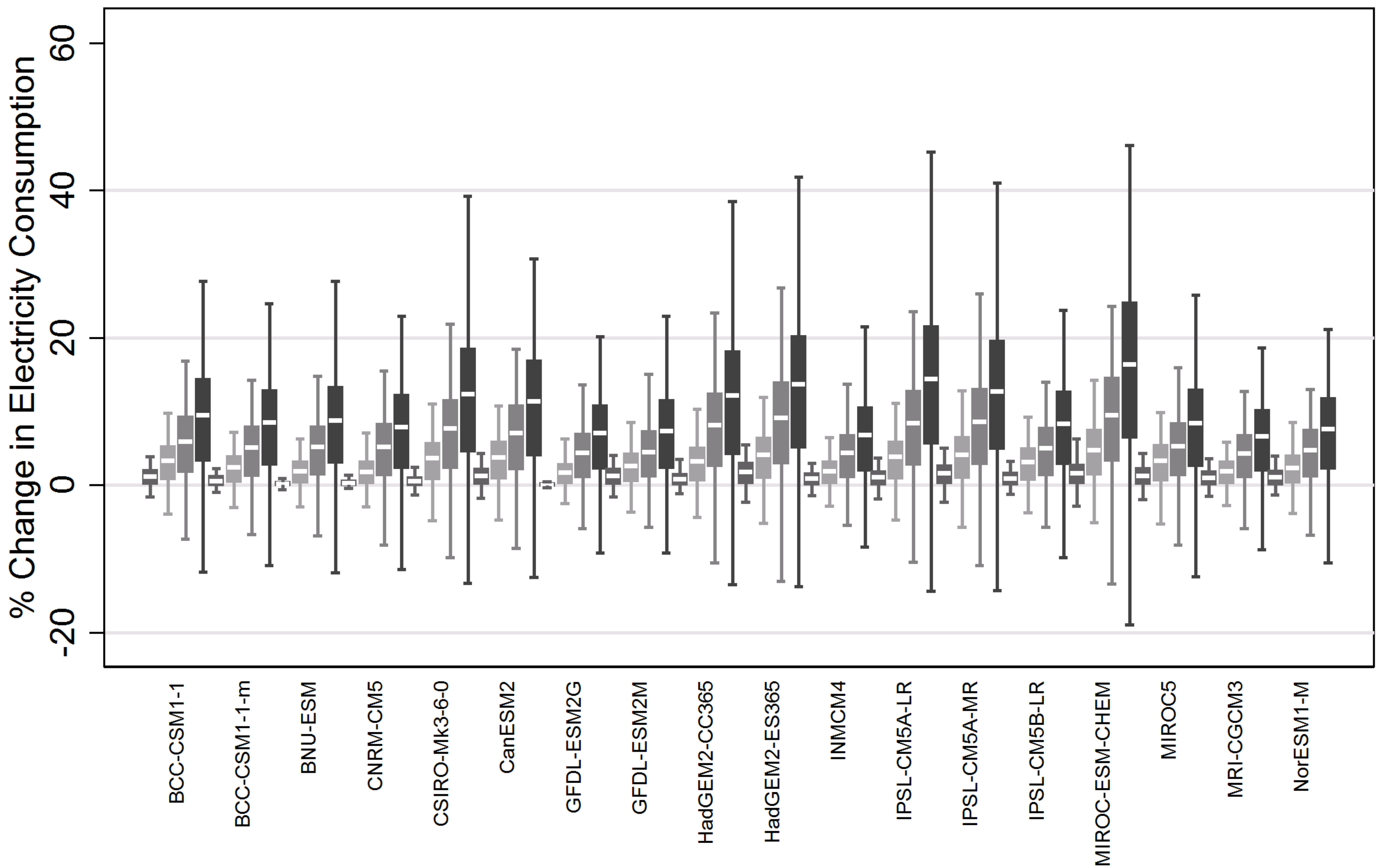
	(1)	(2)	(3)	(4)
Historical Bin	0.0254***	0.0163***	0.0205***	0.0186***
Tavg Share	(0.000)	(0.000)	(0.000)	(0.000)
Interaction		0.0360***	0.0403***	0.0373***
Bin 12+		(0.000)	(0.000)	(0.000)
Special Customer	No	No	Subsidized	All-E
Income	Yes	Yes	Yes	Yes
Population Density	Yes	Yes	Yes	Yes
Bin Fixed Effects	Yes	Yes	Yes	Yes
Observations	4,938	4,938	4,783	4,436

Notes: This table displays coefficients from a regression of the electricity slope coefficients estimated in equation (1) on the share of days in a given temperature bin the ZIP code has experienced over the period 1981-2000. The regression only includes the air conditioning relevant temperature bins 10-14. The standard errors are Huber-White. Regressions 1-2 are for “normal" households. Regression (3) is for households with subsidized energy bills. Regression (4) is for all-electric homes.

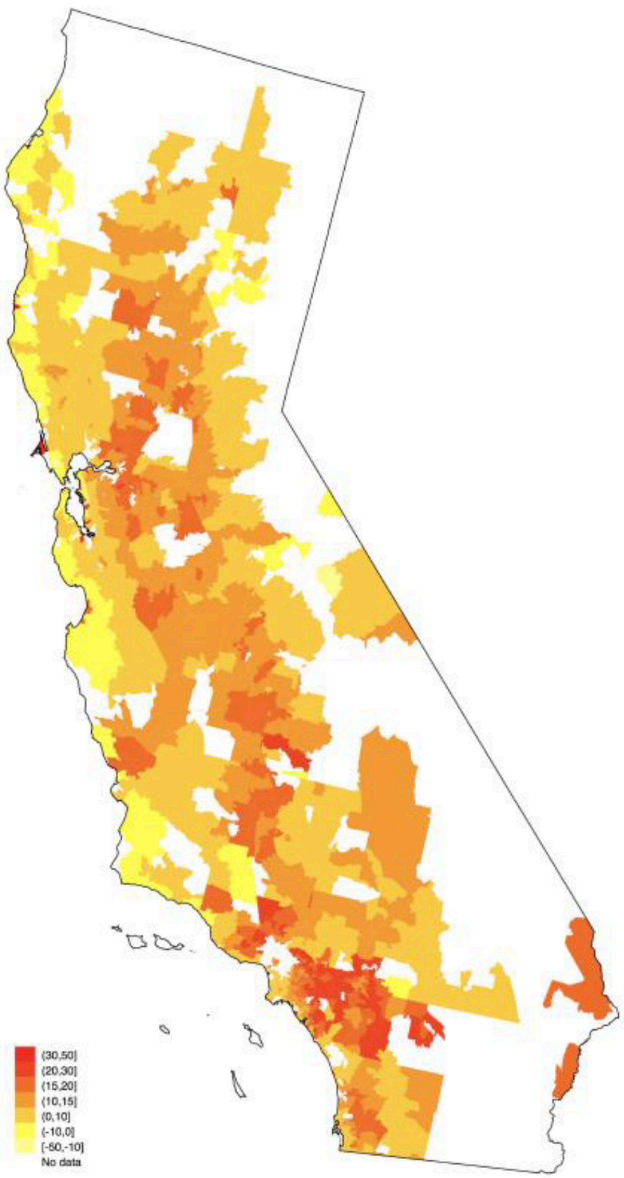
Simulated Impacts: GCM

- Output from 18 climate models from the IPCC's 5th assessment report
- Each model provided for RCP 4.5 and RCP 8.5
- Model output processed:
  - Downscaled
  - Daily
  - Rainfall, TMin, TMax
- Climate data are processed using the same algorithm used to process weather data.
- Doing this is really painful. To an economist.

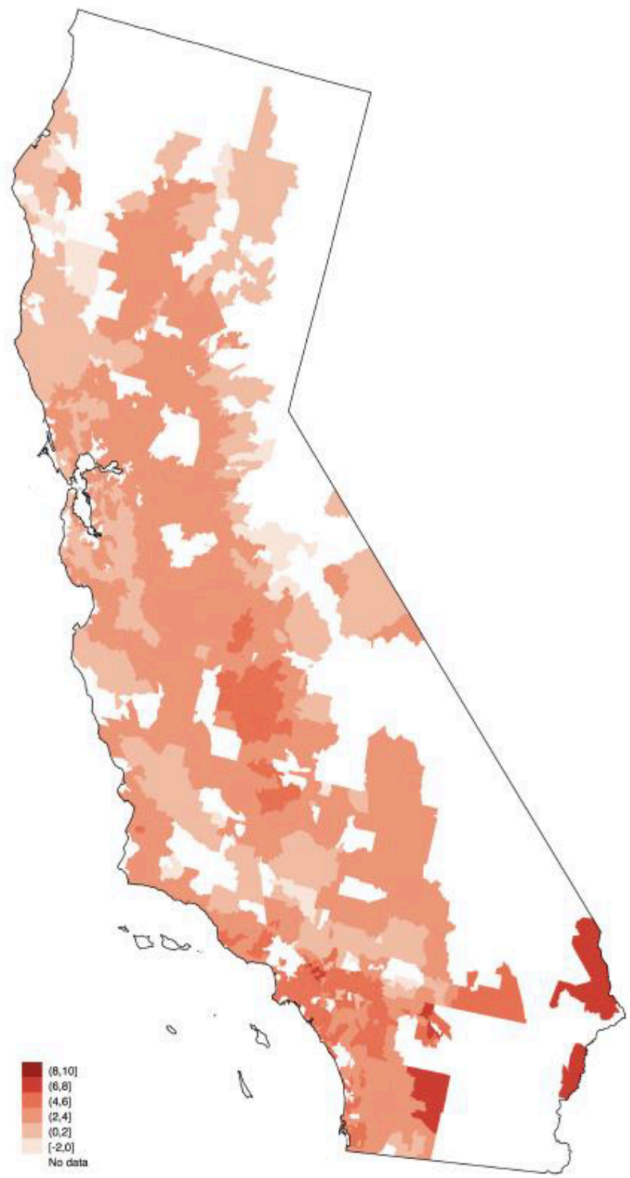
Projected intensive margin impacts (electricity)



Projected Electricity Impacts (per household)

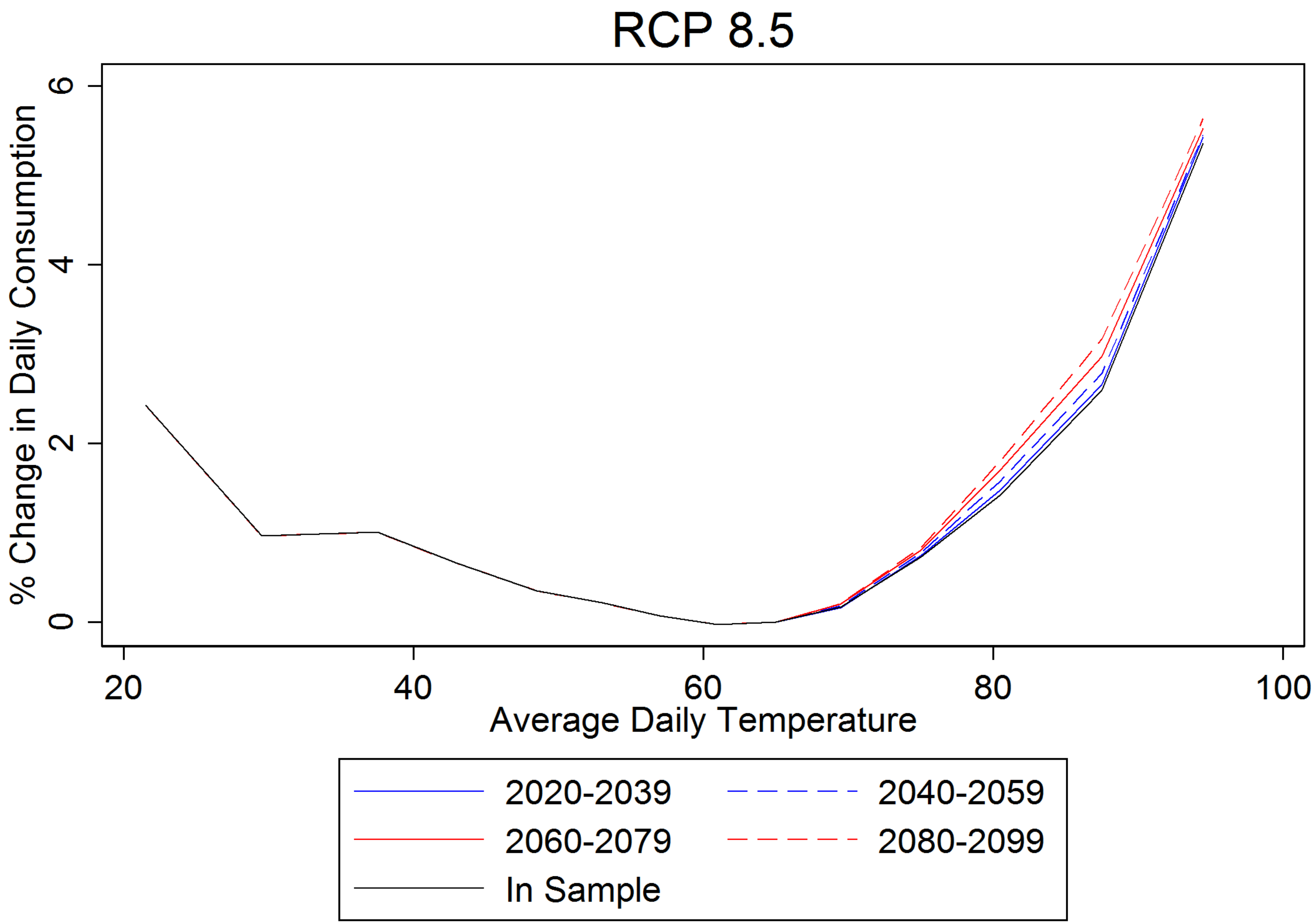


(a) Intensive Margin



(b) Extensive Margin Delta

Population weighted state-wide response function



Projected aggregate temperature impacts in %

Table 4: Projected Percent Changes in Residential Electricity Consumption

Simulation	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RCP	4.5	8.5	4.5	8.5	4.5	8.5	4.5	8.5
Special Customer	No	No	CARE	CARE	All-E	All-E	No	No
Fuel	Elec.	Elec.	Elec.	Elec.	Elec.	Elec.	Gas	Gas
Price Controls	No	No	No	No	No	No	No	No
Intensive Margin								
2020-39	1.3	1.6	1.4	1.6	0.3	0.3	-4.0	-4.9
2040-59	2.7	3.7	2.6	3.5	0.6	0.9	-7.9	-10.4
2060-79	3.7	7.2	3.5	6.7	0.8	2.5	-10.3	-16.1
2080-99	4.2	11.4	3.9	10.5	1.0	5.0	-11.3	-20.5
Extensive Margin								
2020-39	1.0	1.4	1.0	1.3	0.3	0.4	NA	NA
2040-59	2.8	4.2	2.7	4.0	0.9	1.6	NA	NA
2060-79	4.2	8.6	3.9	8.6	1.5	4.3	NA	NA
2080-99	4.9	14.7	4.6	14.1	1.9	8.0	NA	NA

Conclusions

- I know I am so out of time by now. But humor me.
- California Homes used 0.287 quadrillion BTU of electricity and 0.439 quadrillion BTU of natural gas in 2009 (EIA, RECS).
- Climate Change is simulated to lead to a **0.039 quad BTU net decrease** in energy consumption for the residential sector in California (~total non transportation energy consumption of 650,000 households)
- Technological change can push this even further!
- Of course, everywhere else is different from California
- Consumption changes are not the only costs.