Technology Adoption as Climate Adaptation: Evidence from US Air Conditioning and Implications for Energy Systems

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Plan of Talk

Climate-Change Impacts on Global Energy Demand: Intensive Margin Estimates

Amplification of Future Energy Demand Growth due to Climate Change

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How Will the Need to Adapt to Climate Change Affect Energy Systems?

- Energy is one of the human systems most directly exposed to weather
- With rising ambient temperatures, individuals' demand for thermal comfort/firms' demand for a stable thermal environment will increase demand for cooling during hot seasons, and reduce demand for heating during cold seasons, and amplify demands for irrigation during crop growing seasons
- What is the range of net impacts that we can expect these opposing forces to have on regional and global energy use?
- To assess the risks to energy systems we must confront two uncertainties:
  (a) On the decadal time-scales of climatic change, what is the character of the future "baseline" energy system—determined by the non-climatic forces of population and GDP growth, shifts in sectoral composition, and the pace of energy-saving technological progress?
  (b) What temperature stresses will the future baseline energy system be exposed to—globally, driven by radiative forcing scenarios, and regionally in different realizations of the climate simulated by earth system models (ESMs)?
- Integrated assessment models (IAMs) are increasingly being tasked with projecting climate change effects on energy demand, supply and prices, and associated welfare impacts, yet IAMs' energy system responses to temperature change are often based on engineering relationships of questionable empirical provenance.
- Ultimate goal is to integrate empirical representations of climate change impacts into IAMs, leveraging statistically estimated reduced-form responses of impact endpoints to meteorological exposures as a computationally efficient complement to process-based simulation models.

Analytical Approach

Empirical modeling of the responses of energy demand to income and weather extremes (De Cian and Sue Wing, 2019)

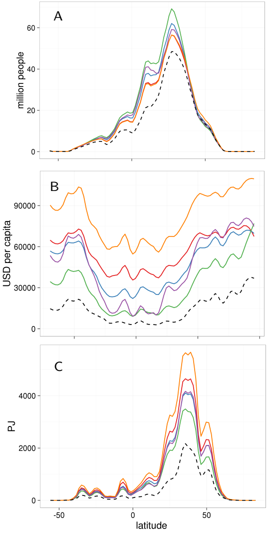
- We estimate the per-capita demand for three fuels (electricity, petroleum, natural gas) by five sectors (agriculture, industry, commerce, households, transportation) across tropical and temperate countries as a function of per capita GDP and exposure to days with extreme high ($>27.5^\circ$C) and low ($<12.5^\circ$C) average temperatures.
- Two main data sources: cross-section/time-series records of fuel consumption for 90+ countries over 39 years from IEA, matched to population-weighted 0.25° gridded 3-hr temperature and humidity fields from GDLAS-2 reanalysis.
- The model's key feature is its ability to statistically distinguish between short-run (interannual covariation, attributed to weather) and long-run (equilibrium, attributed to climate) responses. Panel regression of energy consumption (Q) response to temperature (T) for ℓ locations and t periods, controlling for $\mathbf{X}$ temporally/geographically observables and (possibly location specific) trends $\gamma(t)$:

$$\Delta Q_{\ell,t} = \sum_b \mu_b \Delta T_{b,\ell,t} + \Delta\mathbf{X}_{\ell,t}\boldsymbol{\nu} + \alpha_\ell + \varpi \left\{ Q_{\ell,t-1} - \sum_b \zeta_b T_{b,\ell,t-1} - \mathbf{X}_{\ell,t-1}\boldsymbol{\chi} \right\} + w_{\ell,t} \quad (1)$$

Projection of baseline energy use and temperature change circa 2050

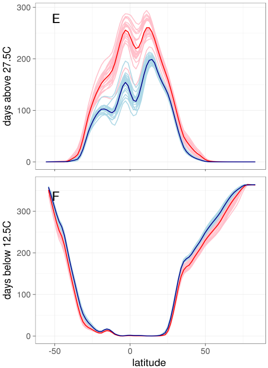
- To characterize (a) we combine estimated long-run income elasticities with projected 2010-2050 growth in per capita GDP and gridded population for 183 countries taken from the Shared Socioeconomic Pathway (SSP) scenarios.
- To characterize (b) we combine estimated long-run temperature elasticities with projected 2050-2010 change in hot and cold days for the RCP 4.5 and 8.5 climate scenarios, using 0.25° gridded realizations of daily mean temperature simulated by 21 CMIP5 ESMs from NASA NEX Global Daily Downscaled Projections.
- Superimposing the changes (a) and (b) yields mid-century projections of the future increases in the demand for energy with and without climate change.

2050 Baseline



D. 2010-2050 baseline energy demand growth (2010=1)

	SSP1	SSP2	SSP3	SSP4	SSP5
Europe	2.0	1.8	1.4	1.8	2.5
North America	2.0	1.8	1.5	1.9	2.6
Oceania	2.4	2.2	1.6	2.2	3.1
South America	2.3	2.1	2.0	2.0	2.7
Middle East & Africa	3.0	2.8	2.6	2.7	3.7
Asia	3.3	2.7	2.2	2.6	3.9
World	2.5	2.2	1.9	2.2	3.1

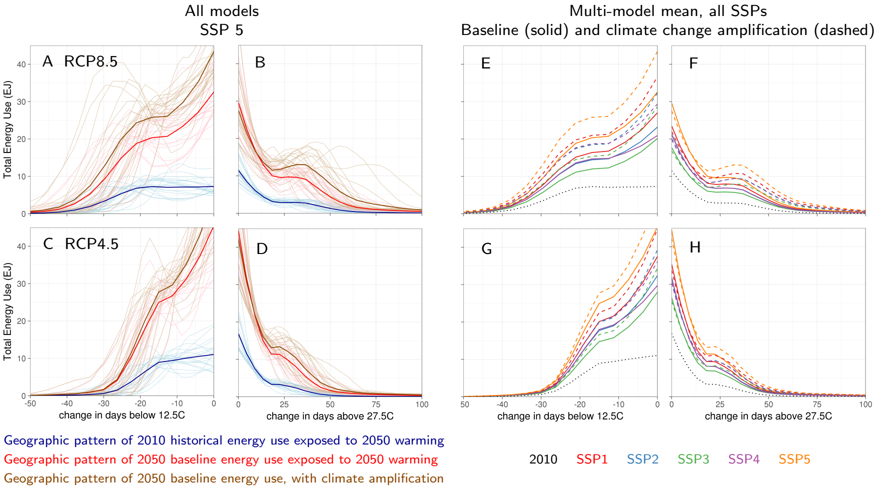


2010 SSP1 SSP2 SSP3 SSP4 SSP5

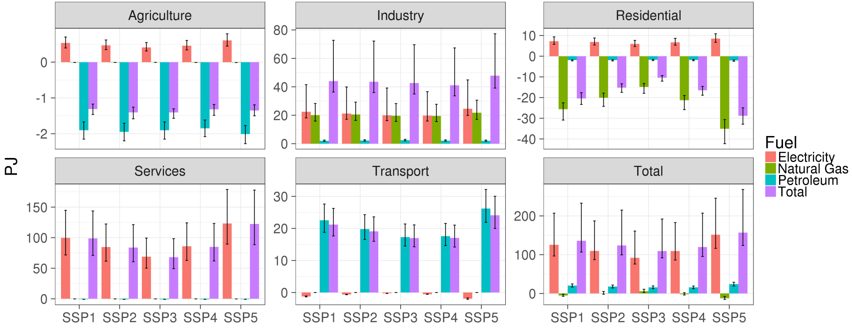
2010 historical 2050, RCP8.5

Population (A), Per Capita Income (B), Total Energy Consumption (C,D), and Hot and Cold Days (E,F)

Global Energy Consumption Exposure to Temperature Changes Circa 2050

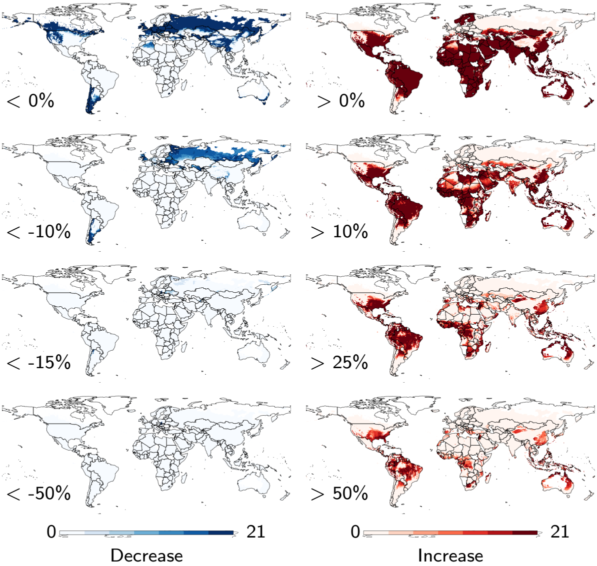


Median Fuel × Sector Global Impacts: RCP 8.5



- Previous studies have emphasized beneficial impacts on residential sector, due to reductions in heating fuel demand (oil, natural gas) that occur in mid/high latitudes where high income, high energy consumption countries dominate the global energy mix.
- Our results highlight the additional important roles of the service, industrial and transportation sectors. Industrial and tertiary increases in the demand for electricity, especially in the tropics, are a key driver of global impact.
- Error bars indicate the 95% CI of impacts across ESMs. Worst-case amplification of demand in industry and services substantially exacerbates impacts on the global energy system.
- By constrast, impacts are much less sensitive to differences in socioeconomic futures.

Geographic Hotspots of Energy Demand Impact Risk



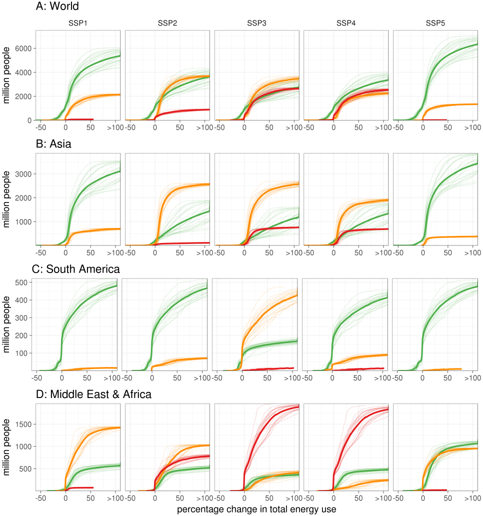
Number of earth system models projecting energy demand change

Energy Demand Change Relative to 2050 Baseline

	SSP1	SSP2	SSP3	SSP4	SSP5
A. RCP8.5 (%)*					
Europe	-2	-2	-1	-2	-3
	[-5,1]	[-4,3]	[-3,6]	[-4,3]	[-6,-1]
North America	34	34	34	34	33
	[28,44]	[29,44]	[29,44]	[28,44]	[27,43]
Oceania	14	15	15	14	14
	[10,21]	[10,21]	[10,22]	[9,21]	[9,20]
South America	30	31	33	32	28
	[24,45]	[25,48]	[27,52]	[25,49]	[22,43]
Middle East & Africa	28	29	29	29	28
	[23,41]	[23,42]	[23,41]	[23,40]	[22,40]
Asia	33	34	36	34	31
	[20,47]	[22,50]	[24,53]	[22,50]	[19,45]
World	24	25	26	24	22
	[19,35]	[20,37]	[21,38]	[19,36]	[18,33]
B. RCP4.5 (%)*					
Europe	-5	-4	-3	-4	-5
	[-5,-4]	[-5,-3]	[-4,-3]	[-5,-3]	[-6,-5]
North America	17	17	17	17	16
	[12,25]	[12,25]	[12,25]	[12,24]	[12,24]
Oceania	4	5	5	4	4
	[3,7]	[3,7]	[4,7]	[3,7]	[3,6]
South America	15	16	18	17	15
	[13,22]	[14,23]	[15,25]	[14,23]	[13,21]
Middle East & Africa	17	17	17	17	16
	[13,19]	[13,19]	[13,19]	[13,19]	[12,18]
Asia	17	18	20	18	16
	[11,24]	[13,25]	[14,26]	[12,25]	[10,22]
World	13	13	14	13	12
	[9,17]	[10,18]	[10,19]	[9,18]	[8,16]

* Multi-model median, inter-quartile range in square braces.

Why SSPs Matter: The Distribution of Impact Exposure by Adaptation Capacity Determines Welfare Cost



High adaptation challenges (Lower-middle income) Moderate adaptation challenges (Upper-middle income) Low adaptation challenges (High income)

Recapitulation

- Adaptation to higher temperatures induced by climate change will increase the demand for energy globally and in most regions.
- A key insight of our explicit consideration of uncertainty is that as early as mid-century we quantify potential energy conservation benefits of climate change mitigation. The densities of the RCP 4.5 and RCP 8.5 impact distributions diverge, with a statistically significant 14-20% difference in means.
- However, associated costs depend critically on the uncertain greenhouse gas intensity of electricity generation that satisfies anticipated increases in future demand.
- Adapting to an uncertain climate poses a monumental challenge to energy supply and infrastructure development planning: for RCP 8.5 (RCP 4.5), worst-case amplification of total final energy demand is 90% (28%) globally, and, across regions, 160% (45%), concentrated in Asia. These figures dwarf the uncertainties in percentage and absolute impacts due to compositional differences in countries energy systems under the various SSPs.
- Our projections generate a large database of 0.25° gridded fields of fuel × sector energy demand shocks circa mid-century for 10 combinations of RCP and SSP scenarios × 21 ESMs. Shocks denominated in percentage terms are explicitly designed to be representative of broad sectoral groupings, flexibly aggregated across regions, and linked to techno-economic model scenarios via the SSPs. We anticipate this will catalyze downstream IAM and energy-system model investigation of the technology and economic consequences of impacts. This is the focus of research in progress, using analytical and computational general equilibrium economic models, as well as techno-economic simulations.

Climate-Change Impacts on Electricity Demand: The Extensive Margin

Technology Adoption as Climate Adaptation:
Evidence from US Air Conditioning

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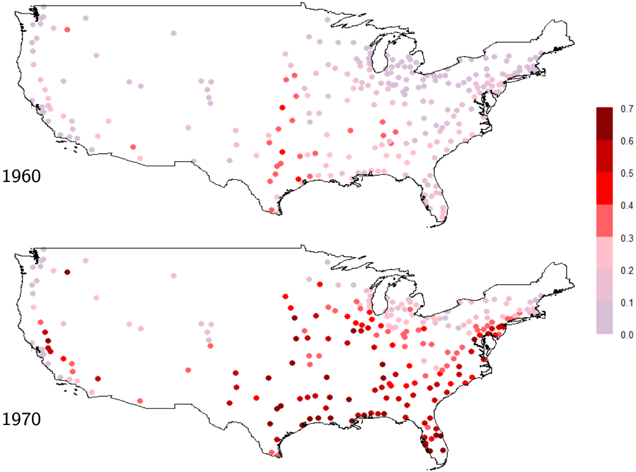
Extensive Margin Adaptation to Heat: AC Adoption and Utilization

- As the climate warms, a crucial but poorly understood pathway of energy system impact is the effect of temperature changes on economic actors' incentives to adapt by investing in space conditioning capital—especially air conditioners (AC), and, simultaneously, shifting their energy consumption by adjusting their utilization of heating/cooling capital stocks.
- A key concern is that warming will hasten the penetration of AC in developing countries, particularly those in the tropics where extreme high temperature exposures are projected to increase substantially by 2050, and thereby induce large increases in consumption of electricity, fossil fuels, and GHGs.
- Assessing the risk of a positive feedback from adaptation to warming necessitates rigorous empirical modeling of the joint decisions to adopt AC and consume electricity to maintain thermal comfort—but it is rare to find situations in which the joint decisions are observed. 1960, '70 and '80 waves of the US Census provide a rare opportunity!
  - What were the forces driving the historical penetration of residential air AC technology in the US?
  - How much of the pattern of households' AC adoption is explained by climate shocks, and in what ways?
  - What consequences did AC penetration have for residential electricity demand?
  - What do the answers to these questions portend for the impacts of future climate change on the extensive margin?
- Implications: How wrong are the results I just showed???
  - What does US historical experience suggest might be the effects of climate change on AC adoption as an adaptation to climate warming—especially in developing countries in the tropics?
  - Conditional on the resulting aggregate penetration, how much amplification of residential electricity demand is likely?

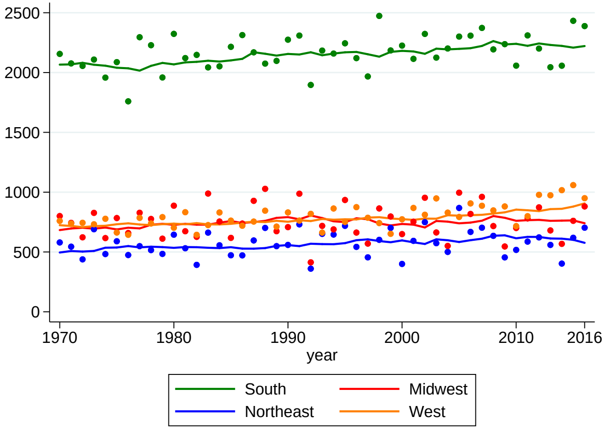
A Strong Latitudinal (Climatic) Gradient to Historical AC Adoption

In the first 4 decades of AC use in the US, penetration was primarily driven by factors other than temperature—income, education and electricity prices in the commercial sector (Biddle, 2011), and regulatory policy regarding public housing that helped create markets for residential AC (Ackermann, 2002).



Fraction of reporting households with any AC (one or more central or window systems) in 253 SMSAs, 1960 and 1970 Censuses.

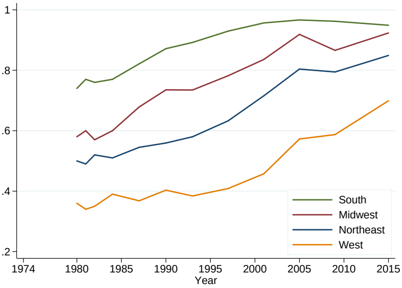
Gentle Increase in Cooling Degree Days With Climate Change



Lines: 10-year moving average annual CDDs Points: current-year annual CDDs

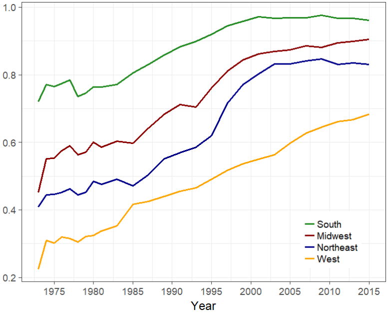
AC Has Penetrated Most Rapidly in Hot Regions

Panel A



DOE/EIA Residential Energy Consumption Survey, various years

Panel B



Annual Housing Survey/American Housing Survey, national sample

US Aggregate AC Share

1960	1970	1980
12.6%	35.8%	58.5%

US Census of Housing (Biddle, 2008)

Energy Demand as Intensive Margin Climate Adaptation

Panel regression of energy consumption (Q) response to temperature (T) for ℓ locations and t periods, controlling for $\mathbf{X}$ temporally/geographically observables and (possibly location specific) trends $\gamma(t)$:

$$Q_{\ell,t} = \sum_b \beta_b^Q T_{b,\ell,t} + \mathbf{X}_{\ell,t}\boldsymbol{\lambda}^Q + \alpha_\ell^Q + \gamma^Q(t) + u_{\ell,t} \tag{2}$$

- Semi-parametric: weather shocks discretized into b intervals with average temperature T_b and associated coefficient vector $\widehat{\boldsymbol{\beta}}^Q$ whose elements trace out the potentially nonlinear response.
- Exogeneity of T, temporal invariance of unobserved shocks jointly affecting Q and $\mathbf{X} \Rightarrow \widehat{\boldsymbol{\beta}}^Q$ = average within response across locations to weather shocks. Impact of marginal change in the distribution of weather relative to expectation = impact of analogous marginal change in the climate $\Rightarrow \widehat{\boldsymbol{\beta}}^Q$ identifies climate response.
- FE approach accounts for unobservable differences in locations, eliminating potential omitted variable bias contaminating cross-sectional regressions. Omitted variable bias still problematic if there are time-varying factors that affect Q and are correlated over time with T or $\mathbf{X}$ after conditioning on $\gamma(t)$ (Hsiang, 2016).
- Location-specific levels/shifts of heating and cooling capital are a confounder: a key driver of Q almost never directly observed in demand studies, correlated with T and observables (e.g., income, energy prices), lags of $Q \Rightarrow$ true climate response not identified!
- Few studies using fine temporal/spatial scale observations of Q in low-income countries, particularly in the tropics (De Cian and Sue Wing, 2019; Auffhammer and Mansur, 2014)

	Impact metric	Locations	Time step
Eskeland and Mideksa (2010)	Final electricity use	European countries	Annual
Deschenes and Greenstone (2011)	Total energy	US states	Annual
Auffhammer and Aroonruengsawat (2011)	Hhold electricity use	California zip codes	Monthly
Auffhammer et al (2017)	Electric load	US load balancing authorities	Hourly
Wenz et al (2017)	Electric load	European countries	Hourly
De Cian et al (2013)[a]	3 fuels	OECD countries	Annual
De Cian and Sue Wing (2019)[a]	3 fuels $\times$ 5 sectors	Countries	Annual

[a] In contrast to the static model (2), these studies employ dynamic error-correction models that distinguish between long- and short-run responses.

Response of Durables Adoption to Weather Shocks

Panel regression of AC stock (K) response to temperature:

$$\vartheta(K_{\ell,t}) = \sum_b \sum_\omega \beta_b^K T_{b,\ell,t-\omega} + \mathbf{X}_{\ell,t}\boldsymbol{\lambda}^K + \alpha_\ell^K + \gamma^K(t) + v_{\ell,t} \tag{3}$$

- Biddle (2008) employs a pooled regression specification that does not include city FEs.
- Current and lagged temperatures (ω) capture the fact that durable stock adjustments depend on climate, i.e., expected weather exposures over a long period (Auffhammer, 2014).

	Impact metric	$\vartheta(K)$	Locations	Time step
Sailor (2003)[a]	AC penetration	K	US Census regions	Annual
McNeil and Letschert (2008)[a]	AC penetration	K	US Census regions	Annual
Biddle (2008)	Hhold AC adoption	K	US cities	Annual
Auffhammer (2014)[b]	AC penetration	$\ln\left(\frac{\kappa}{K} - 1\right)$	Chinese provinces	Annual
Auffhammer and Wolfram (2014)[b,c]	Appliance penetration	$\ln\left(\frac{\kappa}{K} - 1\right)$	Chinese provinces	Annual
Rapson (2014)[d]	Hhold AC adoption	$Pr(K)$	US Census regions	Annual

[a] Engineering studies that use a nonlinear cross-sectional specification with no controls.

[b] κ is an exogenously-imposed parameter determining the shape of the diffusion S-curve.

[c] Weather covariates are not included.

[d] Different from the reduced form specification (3), Rapson estimates a full structural dynamic discrete choice model of AC purchases that accounts for cost of cooling households' floor-space given annual CDDs.

Approaches to Understanding Extensive Margin Adaptation

Stratify energy demand responses according to climate (Auffhammer, 2017)

Using observations of individual households ($\ell(j)$ is the location at which j resides), model demand using first-stage FE regression with locationally-varying responses to contemporaneous temperature shocks:

$$Q_{j,t} = \sum_b \sum_\ell \beta^Q_{b,\ell} T_{b,\ell(j),t} + \mathbf{X}_{j,t}\boldsymbol{\lambda}^Q + \alpha^Q_{\ell(j)} + \gamma^Q(t) + u_{\ell,t} \quad (4a)$$

Then model responses as a function of long-run zonal climate ($\widetilde{T}$) in second-stage OLS regression:

$$\widehat{\beta}^Q_{b,\ell} = \eta_0 + \eta_1 \widetilde{T}_{b,\ell} + \widetilde{\mathbf{X}}_z \boldsymbol{\eta}_2 + v_{b,\ell} \quad (4b)$$

Caveats: Households' AC adoption still unobserved, even long-run controls $\widetilde{\mathbf{X}}$ (e.g., population density in hot vs cold climates) are potentially endogenous, η_1 does not explicitly identify extensive margin.

Stratify energy demand responses according to AC penetration (Davis and Gertler, 2015)

Model penetration in the first stage using (3), then model demand in the second stage with responses stratified according to dummy variables indicating d levels of penetration—$I_d = 1$ if $Pr(K \neq 0) \in [\underline{\pi}_d, \overline{\pi}_d]$:

$$Q_{j,t} = \sum_b \sum_d \beta^Q_{b,d} \left(T_{b,\ell(j),t} \times I_{d,\ell(j),t} \right) + \mathbf{X}_{\ell(j),t}\boldsymbol{\lambda}^Q + \alpha^Q_j + \gamma(t) + v^Q_{j,t} \quad (5)$$

Caveats: Although (3) cleanly facilitates projection of future AC penetration, shifts in the indicators, and potential demand amplification, no correction is made for endogeneity of I_d in the second stage, only a single cross-section of data available to run the first-stage regression, different first- and second-stage samples mean individuals are assigned the average AC penetration rate of their location.

Combine (3) **and** (2) **in a Dubin-McFadden discrete-continuous selection framework (Barreca et al, 2016)**

Using household observations, model AC adoption using a first-stage logit analogue of (3), from which a selection correction term (Φ) is calculated and enters as an additional covariate in the second-stage regression (2):

$$Q_j = \sum_b \beta^Q_b T_{b,\ell(j)} + \xi\Phi_j + \mathbf{X}_j\boldsymbol{\lambda}^Q + \alpha^Q_{\ell(j)} + u_j \quad (6)$$

Caveats: Implemented on a single cross-section of microdata, as opposed to repeat cross-sections, or a panel.

Our Approach: Long Differences (after Burke and Emerick, 2016)

Fundamental challenge: model energy demand as a function of climate while also recognizing unobserved heterogeneity of locations. We measure adaptation to a changing climate and contemporaneous weather.

Estimate AC penetration for county i and decade t:

$$ACshare_{i,t} = f(\overline{DD}_{i,t}; \boldsymbol{\beta}^K) + \mathbf{X}_{i,t}\lambda^K + \alpha_i^K + \gamma_t^K + u_{i,t} \tag{7}$$

where

$$f(\overline{DD}_{i,t}; \boldsymbol{\beta}) = \beta_1 \overline{CDD}_{i,t} + \beta_2 \overline{CDD}^2_{i,t} + \beta_3 \overline{HDD}_{i,t} + \beta_4 \overline{HDD}^2_{i,t}$$

Estimate adoption and electricity demand amplification for household j and decade t:

$$AC_{j,t} = \delta ACshare_{s(j),t-1} + f(\overline{DD}_{s(j),t}; \boldsymbol{\beta}^K) + f(DD_{s(j),t}; \boldsymbol{\theta}^K) + \mathbf{X}_{j,t}\lambda^K + \alpha^K_{s(j)} + \gamma^K_t + u_{j,t} \tag{8a}$$

$$\begin{aligned} \ln Q_{j,t} = {} & \eta AC_{j,t} + f(AC_{j,t} \times \overline{DD}_{s(j),t}; \boldsymbol{\phi}^Q) + f(AC_{j,t} \times DD_{s(j),t}; \boldsymbol{\psi}^Q) \\ & + f(\overline{DD}_{s(j),t}; \boldsymbol{\beta}^Q) + f(DD_{s(j),t}; \boldsymbol{\theta}^Q) + \mathbf{X}_{j,t}\lambda^Q + \alpha^Q_{s(j)} + \gamma^Q_t + v_{j,t} \end{aligned} \tag{8b}$$

- $ACshare$ = share of households in county i or SMSA s with air conditioning of any kind
- AC = dummy indicating whether household j has air conditioning of any kind
- Q = annual houshold electricity consumption (MWh)
- $\overline{DD} = \{\overline{HDD}, \overline{CDD}\}$ prior decade average annual heating and cooling degree days (climate)
- $DD = \{HDD, CDD\}$ contemporaneous annual heating and cooling degree days (weather)
- $\mathbf{X}$ = demographic and house characteristics
- $s(j)$ = indicates individual j is resident in SMSA s
- Eq. (7) estimated by weighted least squares using county population weights
- Instrument for AC in eq. (8b) using SMSA lagged adoption

Data Sources

Households with air conditioning

County aggregate sample

- 1970 and 1980 Decennial Census waves, aggregated by county
- Number of households with central AC, one or more room ACs or no AC
- Demographics: population size, race, income, telephone adoption, vehicles available
- Home characteristics: age, size (number of rooms)

Household sample

- 1970 5% metro and 1980 1% Decennial Census public use microsamples
- Does a household have central AC, one or more room ACs, or no AC
- Annual electricity cost
- Demographics: household size, race, income, telephone adoption, vehicles available
- Home characteristics: age, size (number of rooms)

Weather shocks

- 0.25° gridded 3-hourly temperature fields from reanalysis data (NASA Global Land Data Assimilation System—GLDAS-2), aggregated to annual heating and cooling degree days (65°F base)
- Key explanatory variable: HDDs and CDDs at county/SMSA centroids, averaged over the decade prior to each Census wave

Summary Statistics of Main Variables

Panel A

Variables	All Counties 1970	All Counties 1980
Percent Households with Any AC	0.321	0.521
	(0.214)	(0.255)
Ave CDD Previous Decade	1.003	1.085
	(0.804)	(0.848)
Ave HDD Previous Decade	4.973	4.762
	(1.948)	(2.064)
Current CDD	1.090	1.242
	(0.789)	(0.923)
Current HDD	4.967	4.895
	(1.966)	(2.103)
1 automobile	0.477	0.353
	(0.065)	(0.054)
2 automobiles	0.295	0.341
	(0.088)	(0.073)
3 or more automobiles	0.056	0.177
	(0.023)	(0.064)
Share Hhld Inc 10k-15k	0.225	0.154
	(0.053)	(0.025)
Share Hhld Inc 15k-25k	0.131	0.266
	(0.059)	(0.027)
Share Hhld Income >25k	0.038	0.288
	(0.025)	(0.095)
Observations	3,042	3,047

Panel B

Variables	Households in MSAs 1970	Households in MSAs 1980
Air Conditioning	0.349	0.597
	(0.477)	(0.491)
Ave CDD Previous Decade	0.857	1.080
	(0.792)	(0.930)
Ave HDD Previous Decade	5.127	4.721
	(1.708)	(2.005)
Current CDD	0.933	1.217
	(0.780)	(0.987)
Current HDD	5.103	4.851
	(1.723)	(2.078)
1 automobile	0.499	0.446
	(0.500)	(0.497)
2 automobiles	0.171	0.328
	(0.376)	(0.470)
3 or more automobiles	0.021	0.095
	(0.145)	(0.293)
Income per Capita (10k)	2.476	2.873
	(2.403)	(2.402)
Telephone	0.833	0.952
	(0.373)	(0.214)
MSA Lagged Adoption	0.168	0.396
	(0.112)	(0.199)
MWh	5.471	8.917
	(4.177)	(6.903)
Observations	117,054	2,529,073

Note: degree days in thousand $^\circ$F

AC Adoption: Counties (Census)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ave CDD Previous Decade	0.247	0.536***	0.666***	0.610***	0.333	0.741***	0.501***
	(0.154)	(0.163)	(0.173)	(0.172)	(0.377)	(0.102)	(0.067)
Ave CDD Previous Decade Squared	-0.031	-0.071**	-0.087***	-0.077**	-0.044	-0.105***	-0.077***
	(0.029)	(0.030)	(0.034)	(0.033)	(0.068)	(0.019)	(0.016)
Ave HDD Previous Decade	-0.538***	-0.306***	-0.220**	-0.232**	-0.268	0.104**	
	(0.105)	(0.099)	(0.094)	(0.094)	(0.213)	(0.050)	
Ave HDD Previous Decade Squared	0.049***	0.017**	0.009	0.010	0.011	-0.003	
	(0.009)	(0.008)	(0.008)	(0.008)	(0.020)	(0.003)	
Demographics	N	Y	Y	Y	Y	Y	Y
House Age	N	N	Y	Y	Y	Y	Y
Durables	N	N	N	Y	Y	Y	Y
Sample	All	All	All	All	MSA	MSA	MSA
Fixed Effects	County	County	County	County	County	MSA	MSA
Observations	6,089	6,089	6,089	6,089	1,401	1,401	1,401
R-squared	0.968	0.978	0.980	0.980	0.989	0.959	0.957

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

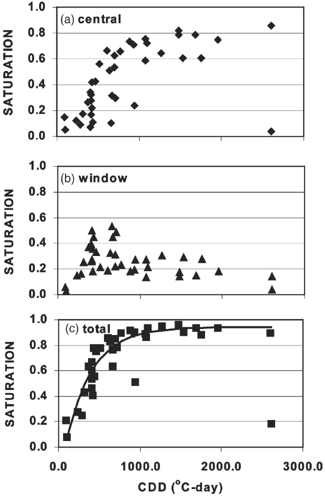
Weighted Least Squares by households. Standard errors clustered by FIPS or MSA-year

Demographic controls include number of rooms in structure, fraction of households that are white, and income. All regressions include an indicator for 1980. Other durables include telephone availability and number of automobiles available (1, 2 or $\geq$ 3). House age is a vector of dummies.

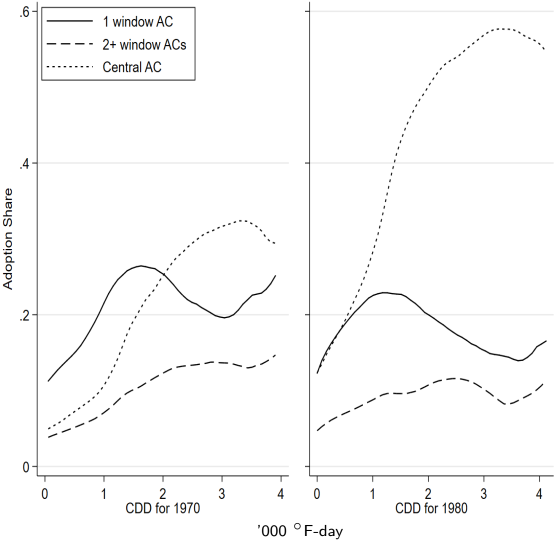
1 S.D. increase in cooling degree days $\Rightarrow$ 45-49% increase in AC penetration!

AC Adoption: Household Sample (IPUMS)

Sailor (2003) (39 cities)



This study (253 cities)



AC Adoption: IPUMS—Linear Probability Model

Dependent variable: $AC = 0$ or 1

Variables	All	Window	2+ Windows	Central
Ave CDD Previous Decade	0.872***	0.694***	0.651***	0.280
	(0.193)	(0.195)	(0.228)	(0.228)
Ave CDD Previous Decade Squared	-0.143***	-0.109***	-0.075*	-0.060
	(0.035)	(0.036)	(0.043)	(0.040)
Current CDD	-0.078	-0.067	0.166	-0.027
	(0.096)	(0.084)	(0.126)	(0.094)
Current CDD Squared	0.014	0.034	0.002	0.017
	(0.025)	(0.025)	(0.029)	(0.024)
MSA Lagged Adoption	0.175***	0.162***	0.212***	0.568***
	(0.055)	(0.049)	(0.072)	(0.063)
log Window AC Price	-0.449***	-0.217	-0.144	-0.503***
	(0.159)	(0.209)	(0.220)	(0.081)
log Electricity Price	-0.001	0.001	0.052	0.013
	(0.024)	(0.019)	(0.044)	(0.043)
Income per Capita (10k)	0.032***	0.024***	0.029***	0.033***
	(0.003)	(0.003)	(0.004)	(0.002)
Income per Capita Squared	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Indicator for 1980	0.035	0.003	-0.028	-0.027
	(0.032)	(0.036)	(0.038)	(0.021)
Observations	3,168,046	1,970,445	1,684,997	2,270,706
R-squared (All variables)	0.3275	0.1600	0.2530	0.5025
R-squared (Climate & FE only)	0.2161	0.1047	0.1588	0.3284
R-squared (FE only)	0.2074	0.1012	0.1529	0.3153

*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Standard errors clustered by MSA-year

Controls include dummies for number of persons in household, number of rooms in structure and whether respondent (head of household) is white. Other durables include telephone availability and number of automobiles available (1, 2 or ≥ 3). House age is a vector of dummies.

Electricity Demand: IPUMS—IV Approach

Dependent variable: ln Q (MWh)

Variables	All	Window	2+ Windows	Central
Air Conditioning	-1.651	-1.907	-1.957	0.073
	(1.181)	(1.613)	(1.476)	(0.301)
AC * Current CDD	0.588**	0.692*	0.533*	-0.083
	(0.259)	(0.353)	(0.301)	(0.257)
Current CDD	0.745***	0.922***	1.640**	0.313
	(0.233)	(0.236)	(0.708)	(0.476)
Current CDD Squared	-0.260**	-0.206***	-0.309**	0.091
	(0.113)	(0.076)	(0.156)	(0.232)
Current HDD	0.079	0.068	0.159	0.084
	(0.091)	(0.063)	(0.106)	(0.070)
log Electricity Price	0.164	0.208	0.216	0.193
	(0.154)	(0.179)	(0.142)	(0.165)
Income per Capita (10k)	0.057*	0.042	0.077	0.049
	(0.031)	(0.033)	(0.056)	(0.037)
Income per Capita Squared	-0.001	-0.001	-0.002	-0.001
	(0.001)	(0.002)	(0.002)	(0.001)
Indicator for 1980	0.504***	0.359***	0.416***	0.482**
	(0.154)	(0.097)	(0.113)	(0.232)
Observations	2,646,127	1,598,865	1,363,637	1,875,815

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Standard errors clustered by MSA-year

All regressions controls for number of persons in household, number of rooms in structure, house age, whether respondent (head of household) is white, telephone availability and number of automobiles available.

AC Adoption: Heterogeneity

Dependent variable: Any $AC = 0$ or 1

	(1) All	(2) Renters	(3) Low Income	(4) New Building
Ave CDD Previous Decade	0.872***	0.378**	0.463**	0.331
	(0.193)	(0.185)	(0.226)	(0.432)
Ave CDD Previous Decade Squared	-0.143***	-0.066*	-0.090**	-0.080
	(0.035)	(0.035)	(0.039)	(0.068)
Current CDD	-0.078	0.011	-0.036	-0.408**
	(0.096)	(0.100)	(0.100)	(0.171)
Current CDD Squared	0.014	0.015	0.025	0.072*
	(0.025)	(0.027)	(0.027)	(0.037)
MSA Lagged Adoption	0.175***	0.236***	0.358***	-0.035
	(0.055)	(0.049)	(0.049)	(0.082)
log Window AC Price	-0.449***	-0.495***	-0.512**	-0.792***
	(0.159)	(0.185)	(0.223)	(0.165)
log Electricity Price	-0.001	0.022	-0.029	-0.035
	(0.024)	(0.024)	(0.028)	(0.050)
Income per Capita (10k)	0.032***	0.037***	-0.020***	0.019***
	(0.003)	(0.005)	(0.005)	(0.002)
Income per Capita Squared	-0.001***	-0.001***	0.036***	-0.001***
	(0.000)	(0.000)	(0.004)	(0.000)
Indicator for 1980	0.035	0.001	-0.011	-0.010
	(0.032)	(0.036)	(0.043)	(0.034)
Observations	3,168,046	1,231,989	942,606	371,880
R-squared	0.3275	0.3692	0.3020	0.3689

*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Standard errors clustered by MSA-year

Electricity Demand: Heterogeneity

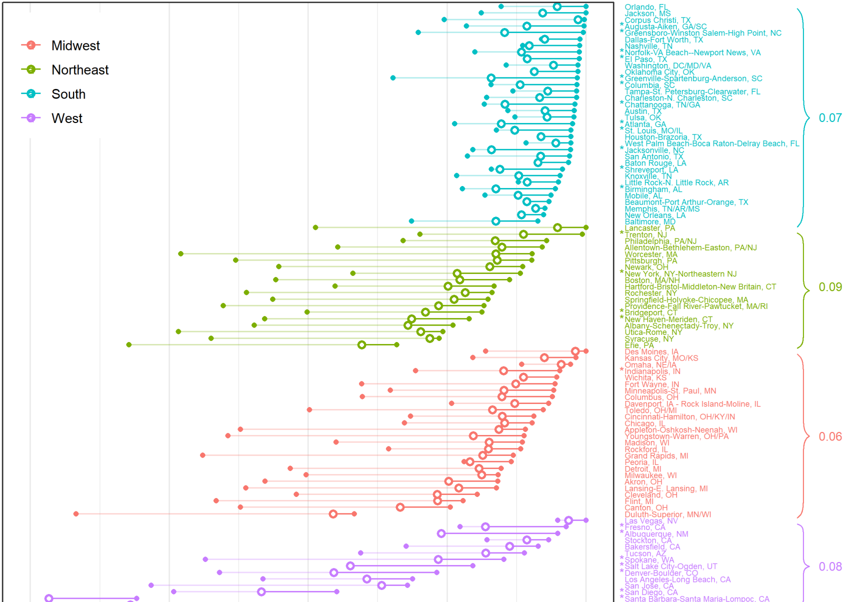
Dependent variable: ln Q (MWh)

	(1) All	(2) Renters	(3) Low Income	(4) New Building
Air Conditioning	-1.651	-1.573	-1.168	-0.198
	(1.181)	(1.278)	(0.836)	(0.885)
AC * Current CDD	0.588**	0.721**	0.528**	1.002*
	(0.259)	(0.329)	(0.208)	(0.561)
Current CDD	0.745***	0.849***	0.882***	0.442
	(0.233)	(0.249)	(0.253)	(0.625)
Current CDD Squared	-0.260**	-0.278**	-0.244***	-0.287*
	(0.113)	(0.120)	(0.093)	(0.152)
Current HDD	0.079	0.062	0.078	0.352*
	(0.091)	(0.082)	(0.058)	(0.200)
log Electricity Price	0.164	0.311**	0.145	0.135
	(0.154)	(0.152)	(0.169)	(0.199)
Income per Capita (10k)	0.057*	0.045	-0.084***	0.014
	(0.031)	(0.038)	(0.013)	(0.014)
Income per Capita Squared	-0.001	-0.001	0.059***	0.000
	(0.001)	(0.001)	(0.021)	(0.001)
Indicator for 1980	0.504***	0.337**	0.419***	0.331***
	(0.154)	(0.167)	(0.108)	(0.053)
Observations	2,646,127	961,655	747,650	315,289
R-squared	-0.1686	-0.0880	0.1190	0.2164

*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Standard errors clustered by MSA-year

Change in 10-Year Average Cooling Degree Days

Change in AC Adoption



Climate Change Impact: AC Penetration Across Cities

Percentile	City	Prior Decade Average CDD	1980 AC Share	Total AC Effect	Marginal AC Effect
1	Seattle, WA	.05	3.4%	4.5%	85.6%
10	San Jose, CA	.25	21.8%	21.1%	79.9%
20	Flint, MI	.42	33.4%	34.5%	75%
30	Boston, MA	.5	44.2%	40.4%	72.7%
40	Chicago, IL	.64	67.3%	50.4%	68.7%
50	New York, NY	.67	58.1%	52.1%	67.9%
60	Richland, WA	.79	89.3%	60.4%	64.4%
70	Greenville, SC	1.26	65.3%	87.2%	51.1%
80	Jacksonville, NC	1.7	79.6%	107.2%	38.3%
90	Beaumont, TX	2.57	89.3%	129.7%	13.6%
99	Miami, FL	4.11	88.8%	116.6%	-30.5%

Note: degree days in thousand $^{\circ}$F

- Prediction generated by applying average response to change in temperature to the contemporaneous and long-run average temperatures in different SMSAs (Slide 15, model 5)

$$\widehat{AC}_s = \widehat{\beta}_1^K \overline{CDD}_s + \widehat{\beta}_2^K \overline{CDD}_s^2 \tag{9}$$

- In the 400-1200 degree day range the marginal effect of decadal average heat exposure declines modestly, but the AC share rises from 29% to 76%.
- Over the 90-year interval 1981-2010 to 2080-2099, in a high-warming climate change scenario (RCP 8.5) Boston, MA shifts from the climate of 1980 New York, NY to that of 1980 Jacksonville, NC (Petri and Caldeira, 2015) $\Rightarrow\sim$ 50% larger AC penetration.

Climate Change Impact: Electricity Use Across Cities

Percentile	City	CDD in 1980	1980 Observed MWh	Total Effect MWh	No AC Effect MWh	AC Only Effect MWh
1	Seattle, WA	.01	15.8	.24	.23	0
10	Spokane, WA	.17	15.8	2.71	2.16	.54
20	Albuquerque, NM	.46	6	2.03	1.58	.44
30	Providence, RI	.57	4	1.82	1.2	.61
40	Chicago, IL	.68	5.9	3.1	1.82	1.27
50	New York, NY	.83	4.9	2.91	1.6	1.31
60	Philadelphia, PA	1.04	7.1	4.73	2.2	2.52
70	Greensboro, NC	1.42	11.4	9.25	2.63	6.61
80	El Paso, TX	2.06	6.8	6.11	.78	5.33
90	Las Vegas, NV	2.81	9.9	10.13	.08	10.05
99	Miami, FL	4.15	9.5	10.15	0	10.15

Note: degree days in thousand $^{\circ}$F

- Prediction generated by applying average response to change in temperature and its interaction with predicted AC penetration to the contemporaneous temperatures in different SMSAs (Slide 16, model 2)

$$\widehat{Q}_s = \exp\{\widehat{\theta}_1^Q CDD_s + \widehat{\psi}_1 \widehat{AC}_s \times CDD_s\} \tag{10}$$

  where $\widehat{AC}$ is predicted by eq. (9).
- AC-driven amplification of electricity demand is very slight below 1000 degree days, but increases approximately linearly with larger heat exposures, accounting for more than half of the pure intensive-margin adjustment in energy consumption in the hottest cities where AC penetration saturates.
- Over the 1981-2010 to 2080-2099 interval, for RCP 8.5, Chicago, IL shifts from the climate of 1980 New York, NY to that of 1980 El Paso, TX (Petri and Caldeira, 2015) $\Rightarrow\sim$ 60% increase in AC penetration, 4-fold increase in extensive margin consumption, doubling of total electricity use.

Comparison with Davis and Gertler's (2015) Results

Table 1. End-of-century predictions

Greenhouse gas concentration trajectory	Households with air conditioning, %	Change in residential electricity consumption (compared with 2010), %	Total change in annual electricity expenditure (US 2010 dollars, millions)	Total change in annual carbon dioxide emissions millions of tons
		Intensive margin only		
RCP 4.5	13	7.5	\$357	2.7
RCP 8.5	13	15.4	\$733	5.5
		Intensive and extensive margins, with 2% annual income growth		
RCP 4.5	71	64.4	\$3,065	23.1
RCP 8.5	81	83.1	\$3,955	29.8

Conclusions

- Cross-SMSA differences in cooling degree days have a large impact on households' propensity to adopt AC.
- They also strongly influence households' electricity consumption, controlling for holdings of durable goods, especially AC.
- AC adoption by itself does not affect electricity consumption, the interaction of AC with cooling degree days has a modest positive marginal effect.
- The slight increases in temperature observed post-1980 are insufficient to explain the subsequent rapid regional penetration of AC.
- However, a cross-city comparison of different climates suggests that the large increases in CDDs due to vigorous climate warming over the 21st century would substantially increase both AC adoption and concomitant amplification of electricity consumption.
- Next Steps:
  - Experiment with nonlinear probability models of the first-stage adoption decision.
  - Refine IV approach in the second stage.
  - Explore implications for energy use in developing countries, ways to introduce our degree-day elasticities into IAMs.

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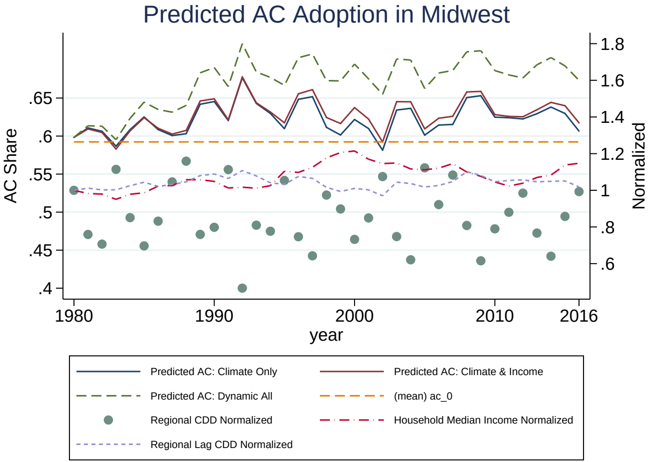
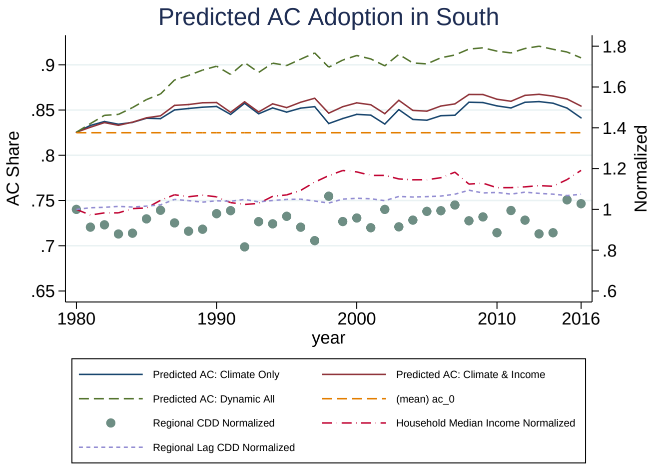
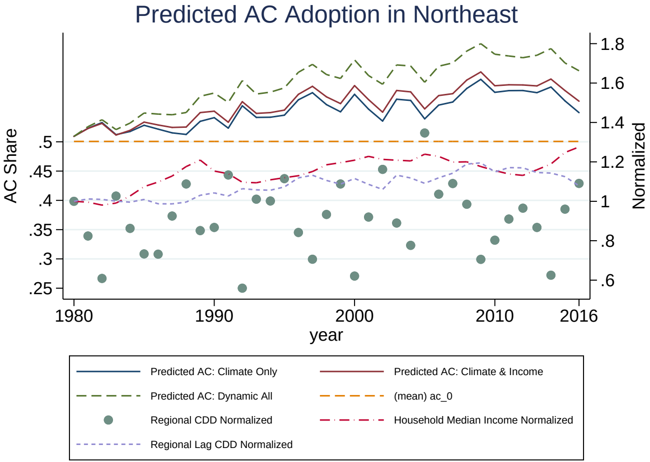
Drivers of Out of Sample Prediction: Midwest



Drivers of Out of Sample Prediction: South



Drivers of Out of Sample Prediction: Northeast



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