“Adaptation to weather shocks and household beliefs on climate: Evidence from California”

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Abstract

I show that California households exposed to heat anomalies are differentially more likely to adopt central air conditioning units than those less exposed, controlling for historical climate. This links to anticipatory adaptation through idiosyncratic beliefs about the future climate. Using this heat-induced prediction of air conditioning adoption, I show that induced adopters have a significant increase in their summer energy demand in years following anomalies, with insignificant effects on their winter electricity demand. Unlike existing work linking weather to energy demand, this presents a novel form of *ex ante* adaptation to weather, and I show that these effects are differentially concentrated in households that believe in climate change. Additionally, I present a dynamic structural framework where household belief-updating about the climate rationalizes household learning about the climate that cannot be explained by myopia or alternative channels, and I propose counterfactual policy experiments that investigate the dynamics of future adaptation.

Keywords: Climate change, Investment, Adaptation, Energy
JEL Codes: Q54, Q47, D83

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1 Introduction

Heat waves increase energy use in the short run through the use of cooling infrastructure. The IPCC documents that these heat waves have been occurring with greater frequency and duration and projects that these trends will continue as the climate changes (Allan et al., 2021). As these events are likely to increase energy use in the short run, we may expect longer-run changes in energy use as a response to heat waves. However, credible empirical estimates typically capture only short-run responses of energy use to heat events (see Deschênes and Greenstone (2011) for a review). How much and how rapidly climate change might drive investment that can increase long-run energy use is an open question.

In this paper, I provide novel evidence that investment responds to short-run weather using a novel dataset of household durable ownership and energy use in the state of California.[1] Moreover, this is because people recognize that these heat events are linked to climate change. I estimate the effect of heat exposure on differential adoption of air conditioning using within-city variation in anomalous exposure to heat events between three cross-sectional surveys in California from 2003 to 2019 relative to historical climate since 1981. I show that differential uptake of new air conditioning units is largely driven by households in ZIP codes with relatively large anomalous heat exposure across this time series. I specifically consider installations of central air conditioning (as opposed to window or standalone units) because the lag-time for installation of central air conditioning is not concurrent with contemporaneous heat exposure. Previous work has shown that air conditioning is important for avoiding heat mortality (Rey et al., 2009; Li and Gu, 2020; Auffhammer, 2022*b*), and my findings suggest that short-run heat may insulate individuals from future heat exposure through this mechanism.

Using this heat wave-induced adoption of central air conditioning, I link contemporaneous adoption of air conditioning to longer-run impacts on household-level energy demand. Using plausibly exogenous variation in exposure to past heat events, I show that the impacts of past weather shocks increase monthly summer electricity demand following this induced adoption. Average energy demand increases in summer months for induced households by about 470 kWh per month, conditional on contemporaneous heat. I find no response in long-run electricity demand for the winter, suggesting that in this particular setting, these effects are driven primarily by cooling and not by changes in heating systems (e.g., switching from natural gas to electric heating, as suggested in Auffhammer (2022*a*)).

In addition to the link to longer-run energy demand, I explore the potential mechanisms

[1] Existing literature has often used interpolations of air conditioning ownership from disaggregated data (Barreca et al., 2015). As far as I know, this is the first paper to use micro data on household investment in the US context.

by which households are induced to adopt an air conditioning unit by contemporaneous hot weather (relative to an average year). Survey evidence shows that the effect of education on belief in climate change varies by partisan identification. That is, belief is increasing for Democratic partisans with education, and decreasing with Republican partisans with education.[2] I use county-level measures of belief in climate change and precinct-level general elections returns in conjunction with household education to construct a proxy measure of household belief in climate change. I use this measure, and I am able to replicate patterns found in these survey data, whereby households that are more likely to believe in climate change via these empirical patterns are also more likely to be in the set of induced adopters of air conditioning based on extreme heat events.

Awareness of climate change may induce changes in durable investments for two separate reasons: first, this could represent learning about climate change itself, where individuals learn about the changing climate distribution for their particular location. Second, this could be about learning about the disutility of extreme heat. In my empirical specification, I find null effects from extreme winter cold, suggesting that this is learning about the disutility of extreme heat rather than about the pace of climate change itself.[3]

In ongoing work, I develop a dynamic structural choice model of air conditioning adoption that rationalizes these patterns. I model an agent who chooses whether to pay a fixed cost for air conditioning installation and has beliefs about future weather that depend on beliefs of the weather process (that is, the linkages between weather and climate). From this, I can provide novel simulations that investigate the dynamics of air conditioning adoption. For instance, to what degree will the trajectory of climate adaptation depend on idiosyncratic exposure to extreme climate events? Next, how might lack of belief in climate change slow air conditioning investment and increase heat mortality? Finally, what are the welfare benefits of improving information about climate change or the consequences of extreme heat?[4]

Existing literature has focused on identifying the short-run energy response using panel variation in realized weather (Deschênes and Greenstone, 2011; Auffhammer and Aroonruengsawat, 2011). This is *ex post* adaptation to realized weather: that is, the inframarginal demand response to heat as a result of the installed air conditioning base. A separate literature considers the extensive margin of air conditioning adoption, and this is concentrated largely

[2] https://news.gallup.com/poll/182159/college-educated-republicans-skeptical-global-warming.aspx

[3] A behavioral channel for uptake is a potential alternative. Busse et al. (2015) find investment decisions that respond to idiosyncratic weather, which is inconsistent with a fully-rational purchase decision. I cannot explicitly discount behavioral mechanisms, but projection bias would need to vary across climate beliefs to be consistent with adoption patterns I observe.

[4] There has been reduced form evidence on information provision in the context of flood and wildfire risk demonstrating increase in uptake in insurance markets for households given new information about risk fundamentals (Gibson and Mullins, 2020; Garnache and Guilfoos, 2019).

in rapidly developing country-contexts, where there is a thick margin for new adoption with increases in income (Auffhammer and Mansur, 2014; Davis, Fuchs and Gertler, 2014). I provide novel evidence of an adoption margin for air conditioning in a developed country context, suggesting a margin for adoption even in high income settings.

Investment and adaptation as a response to climate varies across different empirical contexts. In aggregate settings, financial markets seem to fully incorporate climate change projections from the scientific community (Schlenker and Taylor, 2019). However, at a more disaggregated level, there is a growing literature of differential household investment based on climate beliefs. Homeowners that are likely to underestimate flood risk in coastal areas sort into these high flood-risk markets (Bakkensen and Barrage, 2017), and flood-prone new construction starts are more likely to occur in climate-skeptic communities (Barrage and Furst, 2019).[5] I show novel evidence that durable investment in air conditioning varies with heterogeneous measures of climate change belief.

More generally, I show the importance of *ex ante* adaptation to climate change. Many have suspected that this adaptation, based on expectations over climate change and extereme events, is important, but difficult to identify. Previous empirical work has used responses to seasonal forecasts to identify *ex ante* adaptation by fishers months ahead of El Niño events (Shrader, 2017). I credibly identify *ex ante* adaptation to climate change, and I show that this adaptation occurs as an *ex post* response to realized weather events. Much of the existing literature has focused on this *ex post* margin for credible identification, however, I credibly show that *ex ante* adaptation is not only significant and important, but that this links to longer-run effects on energy demand.

The rest of the paper proceeds as follows: in section 2, I review existing literature on durable good investment as a response to climate, and discuss the novelty of beliefs and dynamics in this setting. In section 3, I present a stylized model of household adoption of cooling as a theoretical motivation for the analyses. In section 4, I discuss the data and its construction. In section 5, present the models used to estimate the effect of weather on air conditioning adoption, energy demand, and belief mechanisms for induced adoption. In section 6, I present a dynamic model of air conditioning adoption and the estimation process. In section 7, I discuss three policy experiments. Finally, in section 8, I conclude.

[5] Additionally, salience about the fundamentals of flood and wildfire risk after extreme events is important for take-up in insurance markets, suggesting relative differences in mitigation based on information (Gallagher, 2014; Bakkensen, Ding and Ma, 2019; Gibson and Mullins, 2020; Garnache and Guilfoos, 2019).

2 Literature

This paper explores the link between short-run weather shocks and longer-run outcomes via *ex ante* adaptation, specifically through induced adoption of air conditioning and the implications for energy demand. In this section, I summarize existing literature that links energy demand to local climate impacts, as well as the literature that specifically focuses on air conditioning adoption.

There is a large literature assessing energy consumption and climate relationships (see Auffhammer and Mansur (2014)). First, panel methods focus largely on local weather variation and estimate energy demand response at the intensive margin (Deschênes and Greenstone, 2011; Auffhammer and Aroonruengsawat, 2011). The disadvantage of using this intensive-margin relationship to estimate long-run projections of energy demand is the inability to account for adaptation over time. In the residential setting, fixing a household's portfolio of energy-using goods could lead to underestimates (if they buy an air conditioner) or overestimates (if they install rooftop solar) as temperatures increase.

Second, cross-sectional or time-series methods use wide spatial variation or long differences in climate to estimate the impact of long-run changes in climate. The advantage of these methods is that over large geographic or temporal dimensions, the extensive margin effects can be captured (assuming that individuals have "re-optimized" to their long-run equilibrium preferences). Albouy et al. (2016) use cross-sectional variation in the climate and estimate American's willingness to pay for climate amenities. Aside from concerns about omitted variables bias (OVB) in these methods, they have largely been unable to address shorter run fluctuations in the weather. I contribute to the synthesis of these by using short-run weather shocks to estimate adaptation at the extensive margin, and link this to longer-run implications for energy demand.

Studies focused on the extensive margin of air conditioning adoption often highlight the developing-country context, as non-linearities in the income-adoption curve imply large changes in future energy demand as incomes grow (Wolfram, Shelef and Gertler, 2012). Auffhammer (2014) uses monthly variation in temperature over a panel of provinces in China to measure the extensive effect of temperature on air conditioning adoption, and shows strong evidence that years following a hot summer see larger increases in adoption, but does not link this to realized energy demand. In a similar (but shorter) setting, Asadoorian, Eckaus and Schlosser (2008) use monthly variation in temperature over a panel of provinces in China to measure both intensive and extensive effects on energy demand through air conditioning. While they find that air conditioning adoption is highly sensitive to energy prices, they find no significant effects of monthly temperature on air conditioning in both urban and rural settings. There are two potential explanations for the different temperature/adoption relationship that I observe. First, the results from the California setting may not be externally valid to China or other developing setting. Second, both of those studies focus on monthly variation at a spatially-aggregated level. Instead, I focus on daily events that capture more information about the tails of the temperature distribution. If particularly severe events are more important to the adoption decision than mean changes, then these monthly panels may not adequately reflect the underlying temperature/adoption relationship.[6]

My findings suggest that in the California setting, severe shocks can increase adoption, even when changes in longer-run measures (such as monthly means) are modest. However, focusing on lower temporal frequencies is common in this space. Biddle (2008) shows that differences in long-run measures of climate can explain most of the differences in air conditioning penetration at the Metropolitan Statistical Area (MSA) level, with most of the residual difference explained by household income. Studies in the engineering literature document correlations between climate and air conditioning adoption to define a measure of "saturation" of air conditioning (McNeil and Letschert, 2010).[7] However, I document that short-run events can induce significant increases in medium- to long-run energy demand through air conditioning adoption, highlighting the importance of tail events.

3 A Stylized model of adoption

Let $V_{it}(AC)$ represent the value for household i having installed air conditioning prior to period t. The value of having installed by period t is equal to the flow value of cooling as a function of the realized weather, Ω_t, plus the expected net present value of the flow value of cooling for all years in the future.

$$V_{it}(AC) = f_{it}(\Omega_t) + \mathbb{E}_{it}\left(\sum_{j=t+1}^{\infty} \beta^j f_{ij}(\Omega_j)\right) \tag{1}$$

Now, consider a household that has not installed by period t. They are faced with a straightforward optimization choice: install in the current period and pay a fixed cost S, or forgo installation in the current period. Importantly, the household benefits of cooling are

[6] This could also explain differences between Auffhammer (2014) and Asadoorian, Eckaus and Schlosser (2008), the former of which uses a longer province panel (1995–2009, compared to 1995–2000)

[7] Though non-causal, this points to an important feature of the adoption margin relative to the local climate that is relevant for this paper: as adoption reaches saturation for a particular climate region, extreme heat wave can mechanically induce smaller changes in the adoption margin for air conditioning. This means that average effects from heat wave in empirical models presented below include the net effect of areas further and closer to saturation, implying heterogeneity in the potential to react to a heat wave.

not realized until future periods.[8]

$$V_{it}(0) = \max\left\{\beta V_{it+1}(0), -S + \mathbb{E}_{it}\left(\sum_{j=t+1}^{\infty} \beta^j f_{ij}(\Omega_j)\right)\right\} \tag{2}$$

In this scenario, an individual chooses to install in time t if the cost of installation plus expected future benefits exceeds the value of not having cooling the the next period, or $-S + \mathbb{E}_{it}\left(\sum_{j=t+1}^{\infty} \beta^j f_{ij}(\Omega_j)\right) > \beta V_{it+1}(0)$.

This decision hinges on the expected path of Ω in the future. Since central air conditioning has a long-lagged installation time, a household does not realize any contemporaneous benefits from the decision to install. That is, if an agent believes that weather is distributed i.i.d., then contemporaneous realizations Ω_t do not enter into the adaptation decision in Equation 2. Alternatively, if an agent expects contemporaneous realizations of Ω to be informative of future weather, then the flow utility of having adopted changes based on the belief process.

So, consider heterogenous agents, where they differ based on beliefs about the weather process. Denote V as the value function for a climate believer, and denote $\hat{V}$ as the value function for a climate skeptic. Suppose that T and $\hat{T}$ map current weather Ω_t to expected future weather, or $\mathbb{E}_{it}(\Omega_{t+1}|\Omega_t) = T\Omega_t$ for climate believers, and $\mathbb{E}_{it}(\Omega_{t+1}|\Omega_t) = \hat{T}\Omega_t$ for climate skeptics. I calibrate this process in section 6 in a stylized $AR(p)$ process.

We can see that with different choices of T affect the expected net present value of future cooling. In this scenario, the belief process about weather is critical for the *ex ante* adaptation decision to install air conditioning. Once an agent has made a fixed cost S to install, in latter periods, we can analyze the ex post flow benefits of cooling, where energy demand is an inframarginal choice with respect to installation choice.

4 Data

4.1 Household appliance and energy data

The primary data I use in the empirical analysis contain information on household appliance ownership and one year of monthly energy use from the Residential Appliance Saturation Survey (RASS), commissioned by the California Energy Commission in order to project future energy demand. This cross-sectional survey includes 21,901 California households in 2003, 25,517 households in 2009, and 39,961 households in 2019. Households were randomly drawn from the service areas of three primary independently-owned utilities (IOUs)—Pacific Gas

[8] Since the primary analysis focuses on installation of central air conditioning, it is reasonable to assume that households cannot immediately install during the current realization of the weather today, Ω_t

and Electric (PG&E), Southern California Edison (SCE), and San Diego Gas and Electric (SDG&E)—and the largest publicly-owned utility, Los Angeles Department of Water and Power, which collectively serve 87 percent of California's customers.[9] Additionally, this was expanded in 2019 to cover homes in the Sacramento Municipal Utility District (SMUD). Households are identified geographically at the ZIP-code level.

The primary outcome of interest is household ownership of central air conditioning and monthly electricity demand. In addition, the RASS includes other household characteristics including household size, home age, income, race, and education of the head of household. In addition, I use household-reported installations of other appliances including dishwashers, standalone freezers, and CFL lighting as a placebo test for the baseline estimation strategy.

Table 1 breaks down the level of central and room air conditioning each year by California utility. Percent of households owning central air conditioning increased in each utility's jurisdiction. In aggregate, central air ownership increased 8 percentage points between 2003 and 2009. In all jurisdictions aside from SDG&E, ownership of room air conditioning units (that is, window units or standalone units) decreased, suggesting substitution towards central air conditioning.

Table 1: Air conditioning saturation by utility from RASS

	Survey wave					
	2003		2009		2019	
	Central Air	N	Central Air	N	Central Air	N
PG&E	0.46	9,134	0.51	7,515	0.54	14,991
SDG&E	0.45	2,500	0.53	3,884	0.60	4,862
SCE	0.59	7,862	0.67	10,743	0.71	12,679
LADWP	0.43	1,311	0.56	2,540	0.64	2,595
SMUD					0.95	2,249
All (minus SMUD)	0.51	20,807	0.59	24,682	0.64	37,376

Note: summaries for proportion of installations of central or room-style air conditioning by utility. RASS covers the three largest IOUs and the largest POU, LADWP to represent greater than 80 percent of California households. SMUD was only covered by the 2019 RASS.

Installation of central air conditioning represents a sizable investment for a household. The 2019 national average cost of installation is reported to be typically between $4,000 and $7,000, with potentially higher costs depending on idiosyncratic home characteristics.[10] Conversely, portable room units can be purchased for only a few hundred dollars, and because of relative portability, have an active secondary market. Central units are tied to the structure,

[9]As reported for 2010 by the State of California Energy Commission.
[10]See https://www.homeadvisor.com/cost/heating-and-cooling/install-an-ac-unit/.

and represent a longer-term investment decision for the house. Because of this, I focus the primary analysis on central air-conditioning units, but report the robustness of the primary results using room air-conditioning units, and the combination of all units in Appendix A.

4.2 Temperature data

I obtain local weather data at the ZIP-code level from the Parameter elevation Regression on Independent Slopes Model (PRISM), which uses meteorological models and weather station data to interpolate daily temperatures at a four kilometer resolution (PRISM Climate Group, 2021). For each ZIP code, I take a simple mean of pixels that are bounded within a ZIP code's associated ZTRAX boundary for a daily observation; or in the case that no pixel falls within a ZIP code, I take the closest pixel observation. I winsorize these ZIP-code average daily temperatures at the top and bottom one percent, and match these to the household appliance and energy use data (identified geographically at the ZIP-code level).

4.3 Construction of historical climate and temperature anomalies

In order to relate contemporaneous weather observations to the climate of a locality, I construct a measure of local historical climate and define yearly anomalies relative to this historical climate. For a ZIP code z, I count the number of cooling degree days (CDD) in a year t, where a CDD occurs when the mean daily temperature is above 65 °Fahrenheit, as given by Equation 3. I define the historical climate for ZIP code z to be the mean number of CDD per year from 1981 to 2003 (Equation 4). I use 2003 as the upper cutoff for this historical climate and focus on the plausibly exogenous temperature shocks in subsequent years.

$$CDD_{z,t} = \sum_{\text{days } \in t} (\text{mean temp} - 65°F) \times \mathbb{1}(\text{mean temp} > 65°F) \tag{3}$$

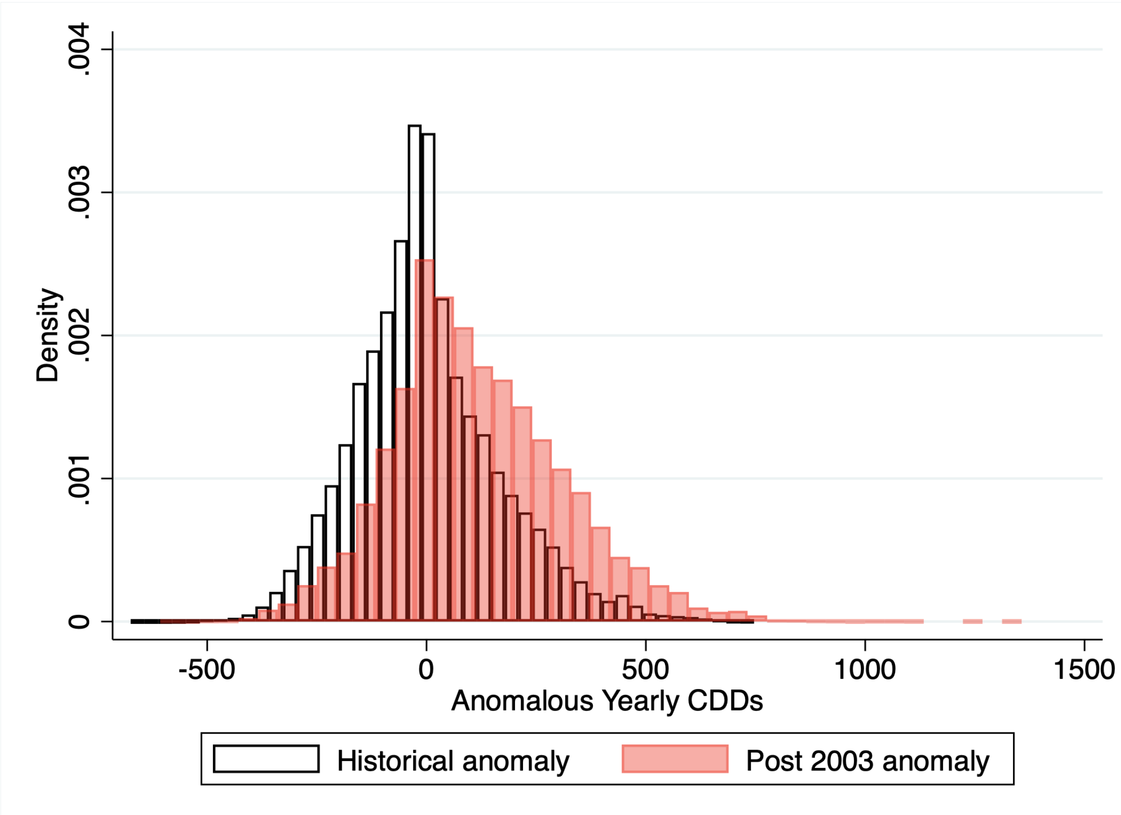
$$Climate_z \equiv \overline{CDD}_{z,t\in\{1981,\ldots,2003\}} \tag{4}$$

Then, for each ZIP code z in year t, I define the year CDD anomaly as the difference between realized year weather and the historical climate:

$$CDD\,anomaly_{z,t} \equiv CDD_{z,t} - Climate_z \tag{5}$$

The immediate concern of using the CDD anomaly as the identifying variation is whether this anomaly can be taken as plausibly exogenous. For example, one may think that the

Figure 1: Distribution of ZIP code anomalies



Note: this histogram depicts the number of extra CDD by ZIP code relative to the historical number of CDD for the ZIP code.

historical climate of a ZIP code as measured by average CDD could be correlated with a contemporaneous anomaly. That is, if historically hot ZIP codes are more likely to experience larger anomalies, this would be a concern for the identifying assumption that this CDD anomaly is orthogonal to the historical climate. Table 2 shows that the residual climate anomaly (after netting out city fixed effects) is not predicted by the historical number of CDD for a ZIP code.

Similarly, one may be concerned that ZIP codes that are more severely affected by a heat wave in a particular year may typically experience more variance in year-to-year daily temperatures. That is, if a household living in a particular ZIP code experiences severe temperature anomalies in 2006, but they were *also* likely to be more exposed in previous years, the 2006 anomaly from historical *mean* years would not capture this fact. However, I find that that past anomalies do not contemporaneously forecast anomalies at the municipal level, shown in Table 2.

I construct a balance table across the four quartiles of maximum anomalous heat exposure

Table 2: Prediction of contemporaneous anomalies on historical climate

Dep Var: Anomalous CDD	(1)
Historical CDD	0.021
	(0.015)
Constant	28.938*
	(14.648)
Observations	50466

Note: this shows anomalous CDD with respect to historical climate after including city FE. Historical climate is defined as the yearly number of CDD from 1981 to 2002 for a specific ZIP code, and anomaly is defined as the yearly deviation with respect to the historical measure. Standard errors are clustered at the county level.

and report these results in Table 3.

4.4 Beliefs about climate

Finally, I match these household data identified at the ZIP-code level to two different measures of beliefs in climate change. First, I use the 2018 Yale Climate Survey that reports county-level measures of belief in climate change. The specific series I use is any belief in climate change, regardless of belief in its severity or cause.[11] Since this is measured at the county level, using this as a measure for household-level beliefs will introduce significant measurement error.

To supplement this county level measure, I also use precinct-level elections returns data for the 2004 and 2012 presidential elections from the California Secretary of State. Partisanship is highly predictive of belief in climate change and its severity (McCright and Dunlap, 2011). I spatially match households in a particular ZIP code with percent Democratic share in the nearest election precinct, using both ZIP code and precinct centroids for geographic distance. While I use both of these measures as a very imperfect proxy for household level belief in climate change, I also use education and precinct Democratic share to instrument for belief defined at the county level.

In addition, I use a fact documented by a 2015 Gallup poll about belief heterogeneity in

[11]The specific question is: "Do you think that global warming is happening?" Howe et al. (2015)

Table 3: Balance of covariates across quartiles of heat exposure

	Q1		Q2		Q3		Q4	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Education	4.64	(1.16)	4.326	(1.20)	4.42	(1.20)	4.38	(1.28)
Household Income ($1k's)	105	(101)	82.3	(79.5)	84.6	(79.2)	88.2	(86.0)
Owner occupied	0.74	(0.43)	0.77	(0.41)	0.75	(0.43)	0.67	(0.46)
Pct. Black	0.048	(0.21)	0.029	(0.16)	0.033	(0.18)	0.067	(0.25)
Historical heat	383	(426)	1081	(505)	1091	(452.2)	1179	(685)
Dem share	0.64	(0.21)	0.43	(0.18)	0.47	(0.151)	0.55	(0.18)

Note: education is reported in 6 bins, with 4 representing some college. Income is reported in thousands of dollars divided by number of inhabitants. Democratic nearest-precinct share is reported for the 2004 presidential election.

climate change by level of education.[12] For Democrats, belief in climate change is increasing in education. However, for Republicans, belief is decreasing in education. I exploit this empirical fact in my discussion of mechanisms for induced air conditioning adoption.

5 Empirical strategy

5.1 Baseline specification

For each household in the survey, I observe individual ownership y_{zit} for household i in ZIP code z in time t. However, I do not directly observe time of installation. For each ZIP code, I construct the change in the share of adopters between periods, controlling for the share of households that have not yet adopted by period t.[13] Specifically, if s_t is the share of homes observed in a ZIP by time t, then I define

$$y_{zt} = \frac{s_t - s_{t-1}}{1 - s_{t-1}}. \tag{6}$$

[12]https://news.gallup.com/poll/182159/college-educated-republicans-skeptical-global-warming.aspx

[13]By aggregating at the ZIP-code level, a small portion of the observations have negative trends over time. I find similar estimates when I drop or bottom-code changes as 0 across periods.

In the baseline specification, I use:

$$y_{zt} = \beta_0 \max \left\{ \begin{array}{c} \text{CDD anomaly} \\ 2003-2009 \end{array} \right\} \times \mathbb{1}\{2009\}_t + \beta_1 \max \left\{ \begin{array}{c} \text{CDD anomaly} \\ 2009-2019 \end{array} \right\} \times \mathbb{1}\{2019\}_t$$
$$+ \beta_2 \max \left\{ \begin{array}{c} \text{CDD anomaly} \\ 2009-2019 \end{array} \right\} \times \mathbb{1}\{2009\}_t + \Theta X_{zt} + \gamma_k + \delta_t + \varepsilon_{zt}, \quad (7)$$

where β_0 and β_1 can be interpreted as the effect of an extra 100 CDD in the warmest year between survey waves on ZIP code on the relative share of central air conditioning in a ZIP code. X_{zt} is a vector of controls, including historical climate, demographics (education, income, and race) at the ZIP code level, and average ZIP code housing characteristics (square footage, age, number of bedrooms, and home ownership status). γ_k and δ_t are spatial and time fixed effects respectively, where in the baseline specification, γ_k is a city fixed effect. I cluster the standard errors at the county level.

The identifying variation is within-city and within-period variation in relative exposure to anomalous heat. I also run the same model on mean CDD anomaly exposure during each survey period. I report the results of this specification in Table 10. Column (2) reports the baseline specification with covariates. $\beta_0 = 0.041$ is suggests a response to the hottest year across the first wave, where 200 extra CDD can explain about 8 percent of the remaining share of non-adopting homes to adopt (in magnitudes, this could explain half of the 8 percentage point increase in total installation over the same period). $\beta_1 = 0.57$ and is statistically significant. An extra 200 CDD for a maximum exposure explains about 11 percent of the remaining share of non-adopting homes to adopt.

Columns (3) and (4) report the same specification, using within-city exposure to mean heat anomalies over the period. In this specification, the coefficient on first period exposure is positive and significant, and an average additional 70 CDD over the course of the period can explain about 6 percent of the relative uptake in cooling. The coefficient on second wave heat exposure (2009–2019) is also positive and significant, and the average exposure of 46 CDD implies about a 6 percent relative increase in the share of cooling installation. In all of the specifications, the coefficient on historical climate is negative and not significant, though the sign is in line with a thicker margin for adoption in cooler climates.

I run a placebo test of the specification in Equation 7, where I construct the same share measure for other durable goods including standalone/second freezers, dishwashers, and CFL lightbulbs (over the first period only). In each of these cases, the estimated coefficients are tightly estimated zeros, with point estimates an order of magnitude smaller than any of the estimated effects on air conditioning.

While a priori, we may expect extreme heat draws to matter more for infrastructure that mitigates against extreme heat, draws of extreme cold may also contribute to differing levels of adoption of central air conditioning. In order to test for the response to other draws from the distribution, I run the baseline specification in Equation 7 and include ZIP code level exposure to heating degree days (HDD).[14] In column (1), I only include historical HDD exposure; in columns (2) and (3), I include the CDD exposure and the interaction of both anomalies separately. These results are not suggestive of AC installation responding to cold anomalies, which will motivate the parametrization of weather in section 6.

5.2 Effects on long-run energy demand

In this section, I use disaggregated household data to look at the reduced form impact of anomalous heat exposure on longer-run household energy demand, conditional on current year weather:

$$Energy_{zit} = \beta_0 \max\left\{\begin{array}{c}\text{CDD anomaly}\\ 2003-2009\end{array}\right\} \times \mathbb{1}\{2009\}_t + \beta_1 \max\left\{\begin{array}{c}\text{CDD anomaly}\\ 2009-2019\end{array}\right\} \times \mathbb{1}\{2019\}_t$$
$$+ \beta_2 \max\left\{\begin{array}{c}\text{CDD anomaly}\\ 2009-2019\end{array}\right\} \times \mathbb{1}\{2009\}_t + \beta_2 CDD_{zt} + \Theta X_{it} + \gamma_k + \delta_t + \varepsilon_{zit} \quad (8)$$

Here, the same structure is used as the baseline model, but with household-level energy demand as the outcome. Here, I include contemporaneous weather (CDD_{zt}), since this should vary tightly with contemporaneous year heat. I use this specification both for total summer electricity demand at the household level (July through September) and for total winter electricity demand (January through March).[15] I also include the exposure to the second period anomaly interacted with an indicator for 2009, where the null hypothesis is that future weather should not affect past adoption.

The results of this specification are reported in Table 8. For the summer, max exposure is significant and positive in total kWh electric demand in the first period (column 1), and mean exposure is significant and positive for the second period. I use the point estimates from the baseline specification of about 4 percentage points of induced demand, and I combine these with the reduced form impacts on additional energy. At the mean, the additional effect of an average max anomaly is about 1400 kWh in extra demand from households induced to adopt, or about 470 kWh in increased demand per month per induced household.

Additionally, heat wave anomaly is not predictive of longer-run electricity demand for the

[14]HDD are defined as the total number of degree days that fall below 65 °F.
[15]Details for linking staggered billing cycles are found in the appendix.

winter months (columns 2 and 4).[16]

5.3 Heterogeneity and mechanism analysis

In order to explore the mechanism by which households are induced to acquire cooling through temperature anomalies, I interact proxies for measures of climate change belief with the baseline specification. In order to use household-level demographics, I use the disaggregated model used to estimate the effects of heat on propensity to own air conditioning.

$$AC_{zit} = \beta_1 belief \times \max \left\{ \begin{array}{c} \text{CDD anomaly} \\ 2003-2019 \end{array} \right\} \times \mathbb{1}\{2019\}_t + \sum_j \alpha_j \{\text{two-way interactions}\} + \Theta X_{it} + \gamma_k + \delta_t + \varepsilon_{zit} \quad (9)$$

I use three different measures of belief that the climate is changing and report the results of this estimation in Table 9. In column (1), I use differences in county level beliefs that climate change is happening, and the main coefficient of interest shows that the anomalous heat exposure effect on central air installation is increasing in this course measure of belief that climate change is happening. In column (2), I consider a difference by level of nearest-precinct democratic vote shares in the 2012 presidential election. Though the point estimate of 0.005 is positive in magnitude, it is not statistically significant. In column (3), I interact the household measure of education, and find that households headed by higher educated individuals are more likely to be amongst this group of induced adopters while controlling for observing demographic and home characteristics.

Finally, in column (4), I use the interaction of education and democratic share in 2012 as a measure of belief. I use an empirical fact documented in section 4, which documents non-monotonicity of belief in climate change when splitting by partisanship. When I introduce this proxy, I find large and significant effects of this coarse measure for household belief in climate change.

[16] Recent work suggests that air conditioning use may directly add to cities' electricity consumption for heat use due to accelerated turnover from natural gas to electric heating (Auffhammer, 2022*a*). I do not find evidence of this, suggesting that this is not a critical channel in California.

Table 4: Baseline specification of heat on air conditioning adoption

Dep Var: share-adjusted central air	(1)	(2)	(3)	(4)
Max Exposure 2003 to 2009 $\times$ $\mathbb{1}\{2009\}$	0.047	0.041		
	(0.029)	(0.027)		
Max Exposure 2009 to 2019 $\times$ $\mathbb{1}\{2019\}$	0.057***	0.057***		
	(0.019)	(0.018)		
Mean Exposure 2003 to 2009 $\times$ $\mathbb{1}\{2009\}$			0.099**	0.090**
			(0.045)	(0.040)
Mean Exposure 2009 to 2019 $\times$ $\mathbb{1}\{2019\}$			0.134***	0.131***
			(0.036)	(0.033)
Historical CDDs	-0.014	-0.015	-0.013	-0.013
	(0.020)	(0.021)	(0.019)	(0.021)
Home characteristics		✓		✓
Demographics		✓		✓
Observations	1931	1916	1931	1916

Note: standard errors clustered at the County level. Max Exposure within a period refers to the maximum experienced anomalous CDD (100s) between periods. *p<0.1, **p<0.05, ***p<0.01.

Table 5: Baseline specification of heat on air conditioning adoption

Dep Var: share-adjusted central air	(1)	(2)	(3)	(4)
Max Exposure 2003 to 2009 $\times$ $\mathbb{1}\{2009\}$	0.165**	0.158*		
	(0.084)	(0.085)		
Max Exposure 2009 to 2019 $\times$ $\mathbb{1}\{2019\}$	0.016	0.022		
	(0.115)	(0.114)		
Max Exposure 2009 to 2019 $\times$ $\mathbb{1}\{2009\}$	-0.135	-0.130		
	(0.124)	(0.122)		
Mean Exposure 2003 to 2009 $\times$ $\mathbb{1}\{2009\}$			0.292**	0.279**
			(0.130)	(0.130)
Mean Exposure 2009 to 2019 $\times$ $\mathbb{1}\{2019\}$			0.071	0.086
			(0.127)	(0.128)
Mean Exposure 2009 to 2019 $\times$ $\mathbb{1}\{2009\}$			-0.221	-0.211
			(0.162)	(0.163)
Historical CDDs	0.024	0.034	0.034	0.042
	(0.029)	(0.029)	(0.029)	(0.029)
Home characteristics		✓		✓
Demographics		✓		✓
Observations	1931	1916	1931	1916

Note: standard errors clustered at the County level. Max Exposure within a period refers to the maximum experienced anomalous CDD (100s) between periods. *p<0.1, **p<0.05, ***p<0.01.

Table 6: Placebo test of other appliances

	Freezer (1)	Washer (2)	CFLs (3)
Max Exposure 2003 to 2009 $\times$ $\mathbb{1}\{2009\}$	0.035	-0.111	-0.009
	(0.028)	(0.125)	(0.022)
Max Exposure 2009 to 2019 $\times$ $\mathbb{1}\{2019\}$	0.003	0.148	0.000
	(0.034)	(0.171)	(.)
Max Exposure 2009 to 2019 $\times$ $\mathbb{1}\{2009\}$	-0.026	0.305*	-0.019
	(0.041)	(0.176)	(0.022)
Historical CDDs	0.006	-0.093	-0.009
	(0.010)	(0.077)	(0.009)
Home characteristics	✓	✓	✓
Demographics	✓	✓	✓
Observations	2186	1867	584

Note: standard errors clustered at the County level. Max Exposure within a period refers to the maximum experienced anomalous CDD (100s) between periods. Note: CFL installation is not surveyed in the 2019 RASS. *p<0.1, **p<0.05, ***p<0.01.

Table 7: Response to heating degree days (HDDs)

Dep Var: share-adjusted central air	(1)	(2)	(3)
Max HDD Exposure 2003 to 2009 $\times$ $\mathbb{1}\{2009\}$	0.011	0.022	0.032
	(0.023)	(0.025)	(0.031)
Max HDD Exposure 2009 to 2019 $\times$ $\mathbb{1}\{2019\}$	-0.013	0.020	0.031
	(0.023)	(0.026)	(0.039)
Historical HDDs	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Max Exposure 2003 to 2009 $\times$ $\mathbb{1}\{2009\}$		0.047*	0.051
		(0.028)	(0.033)
Max Exposure 2009 to 2019 $\times$ $\mathbb{1}\{2019\}$		0.061***	0.068*
		(0.019)	(0.037)
Historical CDDs		-1.251	-1.224
		(1.760)	(2.153)
Max Exposure $\times$ Max HDD Exposure 2003 to 2009 $\times$ $\mathbb{1}\{2009\}$			-0.005
			(0.016)
Max Exposure $\times$ Max HDD Exposure 2009 to 2019 $\times$ $\mathbb{1}\{2019\}$			-0.003
			(0.010)
Constant	0.017	-0.034	-0.050
	(0.430)	(0.502)	(0.492)
Home characteristics	✓	✓	✓
Demographics	✓	✓	✓
Observations	1916	1916	1916

Note: standard errors clustered at the County level. Max Exposure within a period refers to the maximum experienced anomalous CDD (100s) or anomalous HDDs (100s) between periods. *p<0.1, **p<0.05, ***p<0.01.

Table 8: Effects of heat exposure on longer-run electricity demand

	Summer (1)	Winter (2)	Summer (3)	Winter (4)
Max Exposure 2003 to 2009 $\times$ $\mathbb{1}\{2009\}$	32.410***	9.472		
	(11.739)	(10.161)		
Max Exposure 2009 to 2019 $\times$ $\mathbb{1}\{2019\}$	11.606	-8.549		
	(7.887)	(11.526)		
Mean Exposure 2003 to 2009 $\times$ $\mathbb{1}\{2009\}$			-1.442	21.174
			(17.439)	(13.626)
Mean Exposure 2009 to 2019 $\times$ $\mathbb{1}\{2019\}$			35.911***	5.049
			(11.718)	(15.133)
Historical heat exposure	0.008	-0.028	-0.081	-0.031
	(0.154)	(0.117)	(0.151)	(0.111)
Contemp. CDD	0.204**	0.104	0.286***	0.102
	(0.089)	(0.092)	(0.081)	(0.082)
Max Exposure 2009 to 2019 $\times$ $\mathbb{1}\{2009\}$	-10.285	-17.674**		
	(19.754)	(6.825)		
Home characteristics	✓	✓	✓	✓
Demographics	✓	✓	✓	✓
Observations	54352	53589	54352	53589

Note: standard errors clustered at the County level. Max Exposure within a period refers to the maximum experienced anomalous CDD (100s) or anomalous HDDs (100s) between periods. *p<0.1, **p<0.05, ***p<0.01.

Table 9: Effects are concentrated in households that believe climate is changing

Dep Var: Central air	(1)	(2)	(3)	(4)
Happening × CDD anomaly × $\mathbb{1}\{2019\}$	0.002***			
	(0.000)			
Max Exposure 2003 to 2019 × $\mathbb{1}\{2019\}$	-0.153***	0.009***	-0.004	0.004**
	(0.031)	(0.002)	(0.003)	(0.002)
Happening	-0.134**			
	(0.058)			
Historical heat exposure	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Dem share × CDD anomaly × $\mathbb{1}\{2019\}$		0.005		
		(0.004)		
Democratic share		-0.152***	-0.138***	-0.185***
		(0.024)	(0.021)	(0.023)
Edu × CDD anomaly × $\mathbb{1}\{2019\}$			0.003***	
			(0.001)	
Educ × Dem share × CDD anomaly × $\mathbb{1}\{2019\}$				0.003***
				(0.001)
Constant	9.788**	0.487***	0.518***	0.517***
	(4.066)	(0.024)	(0.025)	(0.025)
Home characteristics	✓	✓	✓	✓
Demographics	✓	✓	✓	✓
Observations	49416	49416	49416	49416

Note: standard errors clustered at the County level. Max Exposure within a period refers to the maximum experienced anomalous CDD (100s) or anomalous HDDs (100s) between periods. *p<0.1, **p<0.05, ***p<0.01.

6 A dynamic model of air conditioning adoption

In this model, I analyze the household's choice over investment in permanent cooling technology. I focus specifically on household installation of central air conditioning for two reasons: (1) relative to portable or window units, central air conditioning represents a fixed cost of adoption on the order of other large durable investments (Biddle, 2008), and (2) the time horizon of installation to use implies some forward-looking anticipation about future heat exposure.

Households (indexed by i) have heterogenous private value of cooling in a period u_{it}. Household holdings of air conditioning are indexed by $j \in \{0, 1\}$, where cooling is a binary choice. I assume that the dynamics of cooling choice are weakly monotonic. Explicitly, households that have invested in cooling ($j = 1$) always have cooling in future periods.

Household specific utility u is a linear function of the net benefits from cooling based on household observables h_{it}, investment costs for the next period S_{it}, and an idiosyncratic household preference shock $\vec{\varepsilon}$. Flow benefits are a function of the realized weather ω_{it} from the climate distribution Ω_t.

$$v_{it}^j = \underbrace{h_{it}^j(\omega_t)}_{=b_{it}^j - c_{it}^j} + \varepsilon_{it}^j \tag{10}$$

Net benefits can be separated into benefits b and costs c. Marginal cost c can be calculated in two ways: first, c can be explicitly backed out from monthly electricity charges for some subset of households in the RASS. Second, I can construct the marginal cost of cooling for a household i covered by a particular electric utility based on household demographics. Let β be the inter-temporal discount factor, and Let $\mathbb{E}_p$ and $\mathbb{E}_{p'}$ be the expectation operator assuming different transition matrices for climate expectations in the next period Ω_{t+1}. Let V and $\hat{V}$ represent the value functions for climate believers and climate skeptics respectively. I simplify the dynamic problem by assuming that climate believers expect to be climate believers in the future (V_{it} and V_{it+1}) and that skeptics believe that they will remain skeptics ($\hat{V}_{it}$ and $\hat{V}_{it+1}$.) A household will pay a switching cost S_{it} if they decide to adopt cooling for the next period.[17]

We are left with the following value functions: Equation 11 is a climate-believing household that maximizes over the choice of existing weather and knowledge about the climate, and can pay cost S_{it} to have cooling technology in the following period.

Equation 12represents an agent that is a skeptic about the climate, but she still makes

[17]This timing decision is based on expected lag from decision to installation of central cooling, which means that the installation decision cannot affect contemporaneous utility from weather ω.

the same decision whether to adopt cooling for the following period. The import difference between this and the household described by Equation 11 is the expectations over the future climate distribution Ω_{t+1} conditional on contemporaneous experiences.

By assumption, households that are observed to have invested in cooling will always have access to cooling technology in the future, following Equation 13 and Equation 14.

$$V_{it}^0 = v_{it}^0(\omega_{it}) + \beta\mathbb{E}_p \max\left\{V_{it+1}^0(\Omega_{t+1}, \omega_{it+1}, \vec{\varepsilon}_{it+1}|\Omega_t), V_{it+1}^1(\Omega_{t+1}, \omega_{it+1}, \vec{\varepsilon}_{it+1}|\Omega_t) - S_{it}/\beta\right\} \tag{11}$$

$$\hat{V}_{it}^0 = v_{it}^0(\omega_{it}) + \beta\mathbb{E}_{p'} \max\left\{\hat{V}_{it+1}^0(\Omega_{t+1}, \omega_{it+1}, \vec{\varepsilon}_{it+1}|\Omega_t), \hat{V}_{it+1}^1(\Omega_{t+1}, \omega_{it+1}, \vec{\varepsilon}_{it+1}|\Omega_t) - S_{it}/\beta\right\} \tag{12}$$

$$V_{it}^1 = v_{it}^1(\omega_t) + \beta\mathbb{E}_p V_{it+1}^1(\Omega_{t+1}, \omega_{it+1}, \vec{\varepsilon}_{it+1}|\Omega_t) \tag{13}$$

$$\hat{V}_{it}^1 = v_{it}^1(\omega_{it}) + \beta\mathbb{E}_{p'} \hat{V}_{it+1}^1(\Omega_{t+1}, \omega_{it+1}, \vec{\varepsilon}_{it+1}|\Omega_t) \tag{14}$$

6.1 Estimation framework

In order to empirically estimate the model in section 6, I make several parametric assumptions. First, I parametrize the structure of the contemporaneous household value of current cooling investment. Assume that h_{it} is linear in household characteristics X_{it} and weather realizations ω_{it}, so that $h_{it} = X_{it}'\gamma_1 + \omega_{it}'\gamma_2$. Further, I assume that $\vec{\varepsilon}_{it}$ is distributed i.i.d. extreme value type I to allow for the value of current holdings in cooling vary across observable household heterogeneity.

Second, I assume that the fixed costs of installation S_{it} can be decomposed into capital costs (the actual air conditioning unit) and the labor cost of installation. I assume that conditional on some set of housing characteristics $\tilde{X}$, the fixed capital cost is relatively constant across space and within time.[18].

$$S_{it} = \underbrace{\tilde{X}_i k_t}_{\text{capital costs } | \text{ demographics}} + \underbrace{l_{it}}_{\text{labor costs}} + \epsilon_{it} \tag{15}$$

I use the wage estimates for workers in the air conditioning industry as a measure of labor costs

[18]That is Home Depot in San Marcos sells the same HVAC unit at the same price as in San Bernadino in a given year

of installation. The Occupational Employment and Wage Statistics office of the US. Bureau of Labor Statistics reports mean wages for workers in this industry at the year-by-metropolitan level Bureau of Labor Statistics (2021).[19] I link these to the ZIP-code level household data using the 2010 Q4 Core-Based Statistical Area (CBSA) to A ZIP code crosswalk hosted by Housing and Urban Development.[20] Since ZIP codes and CBSAs may not perfectly overlap, I assign the CBSA to a ZIP code representing the largest residential share of the ZIP code. Finally, not all ZIP codes are located within a CBSA. In this empirical setting, only 1.14% of household-level observations fall outside of this designation. In the main analysis, I omit these households.

Weather process

I use Prism daily weather data from 1981–2019 and match these to fixed 2010 ZIP codes. The challenge here is defining the total climate at a time, Ω_t and a tractable transition process.

Consider outcome y_{it} that follows an AR(p) process as in Equation 22. I specify α_i as a ZIP-code level fixed effect. Then, we can interpret the coefficients on the lags as how deviations from mean CDD in previous years forecast CDD contemporaneously. I do not include year fixed effects in this specification for the following reason: if there is an aggregate trend (likely, with the case of warming and suggested graphically in Figure 4), then year fixed effects will absorb this trend, which should be important for expectation dynamics. The full details of the calibration are in Appendix B.

$$y_{it} = \alpha_i + \sum_{k=1}^{p} \gamma_{ik}\, y_{it-k} + \varepsilon_{it} \tag{16}$$

6.2 Estimation

Given these parametric assumptions, I estimate the model via maximum likelihood. Let Pr_{it}^{01} denote the probability that household i adopts cooling in period t, and Pr_{it}^{00} be the probability that household i continues to not have cooling. Given the monotonicity assumptions above, I assume no dynamics for households that have already invested in cooling.

Since climate type for a household is not observed, let p_{it} be the probability that a household is a climate believer, and p'_{it} be the probability that a household is a climate skeptic. Expectations $\mathbb{E}_p$ and $\mathbb{E}_{p'}$ are the expectation functions for climate believers and skeptics, respectively. In the estimation, I take these as exogenously given by a linear

[19] Occupational Employment and Wage Statistics occupational code 49-9021 Heating, Air Conditioning, and Refrigeration Mechanics and Installers.

[20] https://www.huduser.gov/portal/datasets/usps_crosswalk.html

combination of household observables. Equation 17 is the probability that a household adopts, conditional on not having cooling. Equation 18 is the probability that a household does not adopt, conditional on not having cooling.

$$
\begin{aligned}
&(Pr_{it}^{01}|j=0) = \\
&p_{it} \cdot \frac{\exp\left(h_{it} + \beta \mathbb{E}_p\left[V_{it+1}^1(\Omega_{t+1}, \omega_{it+1}, \vec{\varepsilon}_{it+1}|\Omega_t) - S_{it}/\beta\right]\right)}{\exp\left(h_{it} + \beta \mathbb{E}_p\left[V_{it+1}^1(\Omega_{t+1}, \omega_{it+1}, \vec{\varepsilon}_{it+1}|\Omega_t)\right] - S_{it}/\beta\right) + \exp\left(h_{it} + \beta \mathbb{E}_p\left[V_{it+1}^0(\Omega_{t+1}, \omega_{it+1}, \vec{\varepsilon}_{it+1}|\Omega_t)\right]\right)} \\
&+p'_{it} \cdot \frac{\exp\left(h_{it} + \beta \mathbb{E}_{p'}\left[\hat{V}_{it+1}^1(\Omega_{t+1}, \omega_{it+1}, \vec{\varepsilon}_{it+1}|\Omega_t) - S_{it}/\beta\right]\right)}{\exp\left(h_{it} + \beta \mathbb{E}_{p'}\left[\hat{V}_{it+1}^1(\Omega_{t+1}, \omega_{it+1}, \vec{\varepsilon}_{it+1}|\Omega_t) - S_{it}/\beta\right]\right) + \exp\left(h_{it} + \beta \mathbb{E}_{p'}\left[\hat{V}_{it+1}^0(\Omega_{t+1}, \omega_{it+1}, \vec{\varepsilon}_{it+1}|\Omega_t)\right]\right)}
\end{aligned} \tag{17}
$$

$$
\begin{aligned}
&(Pr_{it}^{00}|j=0) = \\
&p_{it} \cdot \frac{\exp\left(h_{it} + \beta \mathbb{E}_p\left[V_{it+1}^0(\Omega_{t+1}, \omega_{it+1}, \vec{\varepsilon}_{it+1}|\Omega_t)\right]\right)}{\exp\left(h_{it} + \beta \mathbb{E}_p\left[V_{it+1}^1(\Omega_{t+1}, \omega_{it+1}, \vec{\varepsilon}_{it+1}|\Omega_t) - S_{it}/\beta\right]\right) + \exp\left(h_{it} + \beta \mathbb{E}_p\left[V_{it+1}^0(\Omega_{t+1}, \omega_{it+1}, \vec{\varepsilon}_{it+1}|\Omega_t)\right]\right)} \\
&+p'_{it} \cdot \frac{\exp\left(h_{it} + \beta \mathbb{E}_{p'}\left[\hat{V}_{it+1}^0(\Omega_{t+1}, \omega_{it+1}, \vec{\varepsilon}_{it+1}|\Omega_t)\right]\right)}{\exp\left(h_{it} + \beta \mathbb{E}_{p'}\left[\hat{V}_{it+1}^1(\Omega_{t+1}, \omega_{it+1}, \vec{\varepsilon}_{it+1}|\Omega_t) - S_{it}/\beta\right]\right) + \exp\left(h_{it} + \beta \mathbb{E}_{p'}\left[\hat{V}_{it+1}^0(\Omega_{t+1}, \omega_{it+1}, \vec{\varepsilon}_{it+1}|\Omega_t)\right]\right)}
\end{aligned} \tag{18}
$$

Let $\tilde{\mathcal{I}} \subset \mathcal{I}$ be the subset of households in a period that have the opportunity to adopt cooling. The conditional likelihood that we observe the transition in a given period t is given by Equation 19, and I maximize the log-likelihood Equation 20.

$$
\mathcal{L}_t = \prod_{i \in \tilde{\mathcal{I}}} (Pr_{it}^{01}|j=0)^{\mathbb{1}\{i \text{ adopts in } t\}} (Pr_{it}^{00}|j=0)^{\mathbb{1}\{i \text{ does not adopt in } t\}} \tag{19}
$$

$$
\ell_t = \log(\mathcal{L}_t) \tag{20}
$$

Households have a discount factor corresponding to an annualized rate of 12 percent, in line with other literature on household durable good purchases (Busse, Knittel and Zettelmeyer, 2013; De Groote and Verboven, 2019; Langer and Lemoine, 2022).

7 Policy experiments [21]

In section 6, I present a basis for a framework to conduct three important counterfactual experiments.

[21] Please see Most recent version for any updates.

First, to what degree will the trajectory of climate adaptation depend on idiosyncratic exposure to extreme climate events? Next, how might lack of belief in climate change slow air conditioning investment and increase heat mortality? Finally, what are the welfare benefits of improving information about climate change or the consequences of extreme heat?

These are works in progress, and any public versions will be posted.[22]

8 Conclusion

In this paper, I provide causal evidence that households respond to short-run weather shocks by making investment decisions with long-run implications. Particularly, California households differentially to anomalous heat wave increased their propensity to own central air conditioning, and these events can account for nearly half of the total increase from 2003 to 2019. Through this induced adoption channel, households significantly increase their summer energy demand by about 470 kWh in a summer month, controlling for contemporaneous weather. Exploring this link between short-run weather and long-run energy demand is immediately important for forecasting exercises, but also exposes an important question about how households make investment decisions.

This has direct implications for forecasting air conditioning ownership and long-run energy demand as households are exposed to extreme weather. Previous studies define air conditioning penetration as a function of a fixed climate and other state variables (Deschênes and Greenstone, 2011). However, here I provide evidence of the dynamic adoption of air conditioning depending at least in part on tail events (heterogeneity in exposure to a severe heat wave). The total effect on energy demand is still an open question, as I cannot identify whether, on the low end, this is simply a timing decision where the effect on energy demand would be some amount of "pull-forward," or, on the high end, whether this short-run weather realization induces adoption for a household that otherwise would never purchase air conditioning without exposure excess heat.

In addition to these baseline results, I also explore the heterogeneity in response to anomalous heat exposure in order to provide suggestive evidence for a household belief-updating framework. When differencing the baseline difference-in-difference model by measures of household belief in climate change, I show that households that are more likely to believe the climate is changing are also more likely to be induced into adopting an air conditioner in response to anomalous events. This effect is strong enough to be detected when using even very imperfect measures of household level belief in climate change. This behavior can be rationalized by a belief-updating framework, where households that believe in climate change

[22]Most recent version.

take contemporaneous weather as a signal of the future path of their local climate, which changes the household problem for purchasing air conditioning. Conversely, a household that does not believe that their climate is changing does not change their dynamic calculation of the expected benefits of air conditioning.

Furthermore, I exploit the non-monotonicity of belief in climate change with education to test this belief-updating framework. College-educated individuals are not necessarily more likely to believe in climate change, but conditional on partisanship, college education increases belief for democrats, but *decreases* belief for republicans. I show that while differencing the main specification against college education yields significant estimates, interacting with partisan identification implies that the induced-adopter effect differentially applies to college educated democrats, who are most likely to believe in climate change.

Beyond the environmental literature, the novelty of household investment responding to a short-run weather event is important, since such decisions are generally determined by long-run dynamics. In this paper, I provide novel suggestive evidence that households take contemporaneous events to form beliefs over longer-run state variables in the climate, which in turn has the potential to affect a multitude of investment decisions beyond the scope of this setting. I propose a discrete choice framework with heterogeneity in the belief over the weather process in order to test different counterfactual climate events and social planner policies.

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A Robustness

Please see the updated draft here for most recent version with updated robustness results.

Table 10: Staggered difference in difference

Dep Var: Central air	(1)	(2)	(3)	(4)
Max Exposure 2003 to 2009 × $\mathbb{1}\{2009\}$	0.009**	0.010**		
	(0.004)	(0.004)		
Max Exposure 2009 to 2019 × $\mathbb{1}\{2019\}$	0.008*	0.007*		
	(0.004)	(0.004)		
Max Exposure 2009 to 2019 × $\mathbb{1}\{2009\}$	-0.003	-0.003		
	(0.004)	(0.003)		
Mean Exposure 2003 to 2009 × $\mathbb{1}\{2009\}$			0.009	0.008
			(0.011)	(0.009)
Mean Exposure 2009 to 2019 × $\mathbb{1}\{2019\}$			0.003	0.001
			(0.006)	(0.006)
Mean Exposure 2009 to 2019 × $\mathbb{1}\{2019\}$			-0.005	-0.003
			(0.009)	(0.007)
Historical heat exposure	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Home characteristics		✓		
Demographics		✓		
Observations	82774	73792	82774	73792

Note: standard errors clustered at the County level. Max Exposure within a period refers to the maximum experienced anomalous CDD (100s) between periods. *p<0.1, **p<0.05, ***p<0.01.

B Weather appendix

In simulating the weather process for the dynamic model, assume that climate Ω_t follows an AR(p) process. In the estimation, assume $p = 1$. I use the output in Table 12 to simulate a transition matrix across 4 states, with cuts at the 60th, 75th, and 90th percentiles of the CDD anomaly distribution. Let T be the transition matrix that represents the transition

Table 11: AR(1) Output

Dep Var: Period CDD anomaly	(1)
L.Period CDD anomaly	0.339***
	(0.005)
Constant	38.248***
	(1.850)
History based on pre-2000	✓
Observations	33212
R^2	0.121

Note: L*i*.*variable* denotes the *i*th lag of *variable*. Includes 1453 ZIP-codes covered by RASS over 9 2-year periods from 2001–2019 (2003 indicating period 1). Historical CDD constructed based on average yearly CDD at the ZIP-code level.

probability of moving between states, where element t_{ij} represents the probability of moving from state i to j.

$$T = \begin{bmatrix} .61 & .10 & .20 & .10 \\ .54 & .18 & .20 & .08 \\ .52 & .10 & .31 & .07 \\ .51 & .08 & .15 & .27 \end{bmatrix} \tag{21}$$

$$\Omega_t = \alpha_0 + \sum_{j=1}^{J} \alpha_j \Omega_{t-j} + \varepsilon_t \tag{22}$$

Table 12: Testing Equation 22 for different specifications

Dep Var: Annual CDDs	(1)	(2)	(3)	(4)	(5)
L.Annual CDDs	0.356***	0.356***	0.022	0.363***	0.244***
	(0.022)	(0.021)	(0.038)	(0.040)	(0.027)
L2.Annual CDDs		0.086***	-0.072***	0.062**	
		(0.008)	(0.018)	(0.019)	
L3.Annual CDDs		0.062**	-0.180***	0.196***	
		(0.020)	(0.036)	(0.024)	
L4.Annual CDDs		-0.069	0.082	-0.338***	
		(0.050)	(0.071)	(0.019)	
L5.Annual CDDs		0.054**	-0.007	0.103**	
		(0.019)	(0.031)	(0.032)	
L.CDDs × post-2000					0.078***
					(0.005)
Pre-2000	✓	✓	✓		✓
Post-2000	✓	✓		✓	✓
Observations	49172	43996	19410	24586	49172
R^2	0.923	0.931	0.950	0.941	0.927

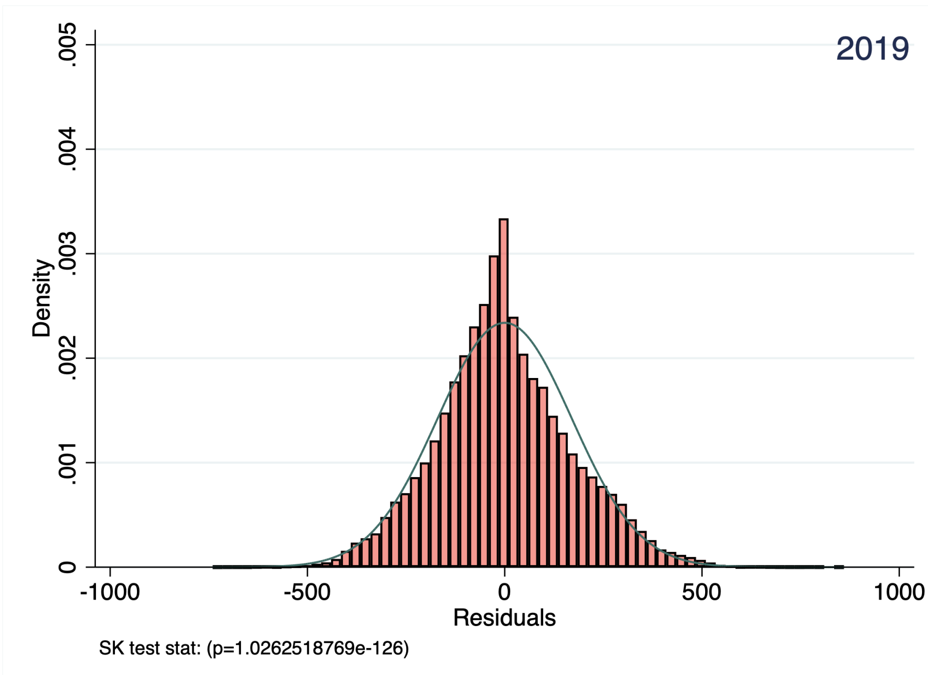
Note: Li.*variable* denotes the ith lag of *variable*. All specifications include ZIP-code fixed effects. Testing Equation 22 for different specifications. Standard errors clustered at the county level.

Table 13: Normalized CDD by ZIP code

Dep Var: Norm. Annual CDDs	(1)	(2)	(3)	(4)	(5)
L.Norm. CDDs	0.283***	0.280***	0.064	0.234***	0.209***
	(0.034)	(0.034)	(0.034)	(0.057)	(0.023)
L2.Norm. CDDs		0.102***	-0.089***	0.149***	
		(0.013)	(0.016)	(0.033)	
L3.Norm. CDDs		0.012	-0.194***	0.119**	
		(0.024)	(0.025)	(0.037)	
L4.Norm. CDDs		-0.005	0.156**	-0.303***	
		(0.043)	(0.054)	(0.021)	
L5.Norm. CDDs		0.058**	-0.034	0.111***	
		(0.017)	(0.028)	(0.024)	
L.CDDs × post-2000					0.143**
					(0.041)
Pre-2000	✓	✓	✓		✓
Post-2000	✓	✓		✓	✓
Observations	49172	43996	19410	24586	49172
R^2	0.081	0.121	0.182	0.219	0.085

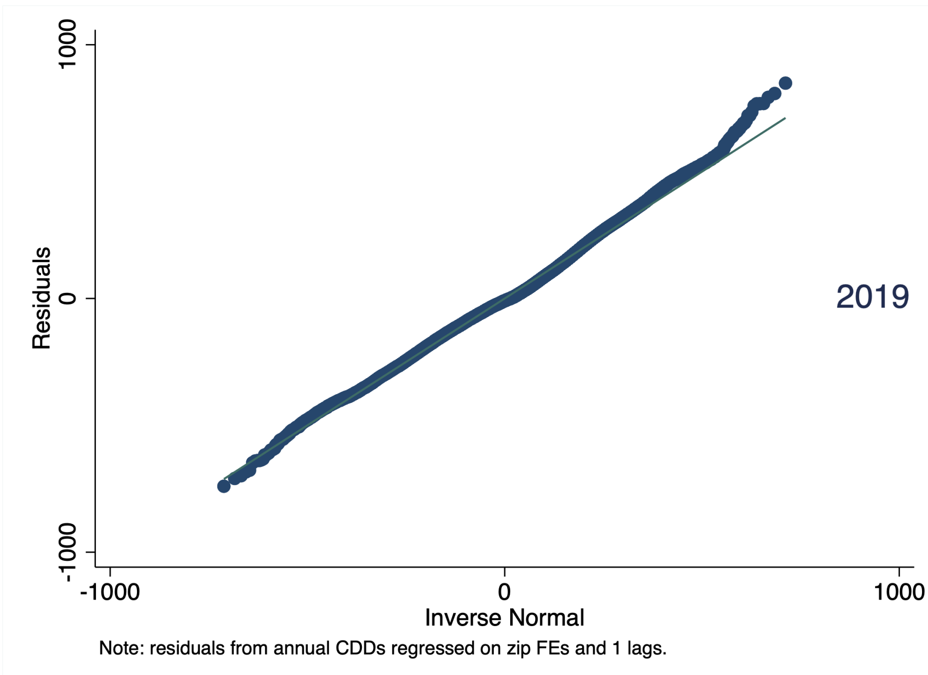
Note: CDD are normalized at the ZIP-code level by demeaning and dividing by the SE of ZIP-code observations for the entire series. L*i.variable* denotes the *i*th lag of *variable*. All specifications include ZIP-code fixed effects. Testing Equation 22 for different specifications. Standard errors clustered at the county level.

Figure 2: Distribution of residuals from Equation 22 with $p = 1$.



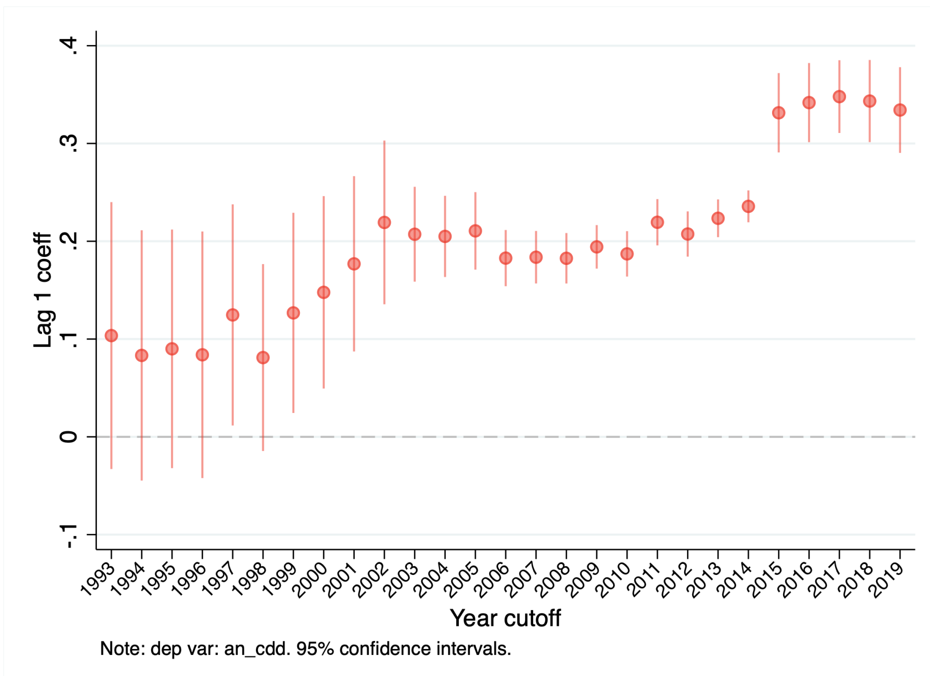
Note: this shows the distribution of residuals from Equation 22 across RASS ZIP codes in California following specification (1) in Table 12. Link to animation.

Figure 3: Residual quantile-normal plot following Equation 22 with $p = 1$.



Note: this shows distribution of residuals from Equation 22 plotted against the quantiles of a normal distribution across RASS ZIP codes in California following specification (1) in Table 12. Link to animation.

Figure 4: Ending cutoffs following Equation 22 with $p = 1$.



Note: Each coefficient is a plot of the point estimate on the first lag of annual CDD at the ZIP code level. Year refers to the latest year included in the regression. 95% confidence intervals shown.

C Data

C.1 RASS

First, I construct a variable for age of central air unit. If a household reports an age for their central air conditioning unit, but reports a missing value on if they own a central air unit, I redefine them as having central air. However, if a household reports that they do not have central air, and report an age of a unit, I do not define this household as owning AC. This increases central air ownership by approximately 1% in the 2003 survey year from the raw count.

In linking to the billing data, I considered households to have complete summer and winter information if they report kWh for all three summer months (July through September, N=20448) and all three winter months (January through March, N=20824). I also include a broader sample of households that report kWh for July and January changed from February, but only for consistency in choosing the middle of the season and a month with 31 days. I also drop 0.01 % of observations that are duplicated on unique household identifier and year by month data.

Given the heterogeneity in billing month cycles, I construct summer electricity demand in the following way: I shift forward the meter reading for a particular date by 15 days. Then, I assign that to household-level monthly demand. This ensures that a majority of a reading will fall within a particular month. This leaves us with 19882 households with summer data and 18801 with winter data.

Given that I have the data on the meter reading, including day of reading, it may make more sense to construct individually per household the number of CDD for a particular period, and assign weather in the same manner. Unfortunately, the billing data is not as complete for 2003. I should think about whether this is important for consistency later. Note: I can go back to the file 02_process_RASS.do later to generate a series that reasonably could be matched in this way. It may be worth it if I think there's stuff going on with wildfires later in the sample.

Identified the problem with many missing matches: LADWP is essentially on 2 month billing cycles. This means for a particular household, I probably will want to match the cooling degree days to electricity demand during a particular period. Finally, there is an inconsistency between billing data for 2003 and the billing data for 2009 and 2019, since 2003 in interpolated at a standard monthly level, rather than showing us specific billing cycles.

Linking prism to RASS PRISM weather data matched to zctas in 2010, which gives the highest match rate for ZIP codes across years.

Note: downloaded crosswalk to link ZIP to zcta areas. Zcta's are used to construct weather data, since ZIP codes don't have a particular shape. downloaded the 2010 UDS https://udsmapper.org/ZIP-code-to-zcta-crosswalk/. Crosswalk to counties here: https://www.huduser.gov/portal/datasets/usps_crosswalk.html#codebook. Assumption in construction: assign to county with the highest residential share in a ZIP code as primary county.