Adaptation to Weather Shocks and Household Beliefs on Climate: Evidence from California

Wesley Howden*

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Using a difference in differences framework, I show that California households exposed to a severe heat wave are differentially more likely to adopt central air conditioning units than those less exposed, controlling for historical climate. Using these "induced adopters" to predict take-up, I show that induced adopters have a significant increase in their summer energy demand 3 years following the heat wave, with insignificant effects on their winter electricity demand. In addition, I present a theoretical framework where household belief-updating about the climate rationalizes household learning about the climate that cannot be explained by myopia or alternative channels.

*Department of Economics, University of California San Diego. 9500 Gilman Drive Dept 508, La Jolla, CA 92093-0508. Email: whowden@ucsd.edu. Thanks to Mark Jacobsen, Judd Boomhower, Richard Carson, Max Auffhammer, and participants at the UC San Diego Environmental Lunch and the UC San Diego Interdisciplinary Forum for Environmental Research for helpful comments. I appreciate conversations with Jan Tabazynski for developing a narrative for a general audience. I am also grateful to Glen Sharp and the California Energy Commission for sharing data from the Residential Appliance Saturation Survey (RASS). All errors are my own.

1 Introduction

Household demand for energy responds to local climate and weather characteristics. Longer-run decisions, such as location choice or portfolio of appliances (or other energy-using durables), may reflect the state of the long-run climate for a location. Typically, we think that short-run changes to energy demand respond to short-run variations in the weather. For instance, on hotter days, households that own an air conditioner can increase their energy demand at the intensive margin by cooling their home. Using a traditional framework of household investment, extensive entry into air conditioning adoption seems unlikely to respond to a short-run increase in the number of hot days.

In this paper, I show novel evidence that households adjust their medium- to long-run capital holdings (in the form of air conditioner ownership) in response to a short-run weather shock, particularly, a severe heat wave. During the summer of 2006, a series of extreme heat waves affected regions across the Pacific and Southwest. According to reports by the California Department of Public Health, emergency room visits and hospitalizations related to heat increased significantly, and there were more than 140 heat-related deaths (Knowlton et al., 2009).

Using this heat wave-induced adoption of central air conditioning, I link this to longer-run impacts on household-level summer energy demand. Using plausibly exogenous variation in exposure to this heat wave, I show that 100 extra cooling degree days (CDDs) relative to the historical average increases the propensity for a household to own central air conditioning by about 1 percentage point. Then, estimating the reduced form impact of these weather shocks on monthly summer electricity demand 3 years following this heat wave, I show that 100 extra CDDs is associated with an average increase in energy demand by 6 kWh per household during the month of July.

This extensive entry into air conditioning adoption as a response to hot weather (as opposed to average weather, or climate, at a geographic level) is consistent with previous studies of similar phenomena. Auffhammer (2014) shows evidence for extensive entry into air-conditioning adoption in China induced by preceding hot years. One novel contribution of this paper is the link between short-run weather and long-run energy demand, as well as a qualitative replication of these Chinese results using weather data with both higher spatial and time resolution.

In addition to the link to longer-run energy demand, I explore the potential mechanisms by which households are induced to adopt an air conditioning unit by contemporaneous hot weather (relative to an average year). I use county-level measures of belief in climate change and precinct-level general elections returns to construct a proxy measure of household belief in climate change. I use this measure and introduce a third difference to the baseline specification. In this specification, I show that households that are more likely to believe that the climate is changing are also more likely to exhibit heat-wave induced adoption of air conditioning. This heterogeneity by belief in climate change is consistent with other observed empirical patterns in belief in climate change, including diverging beliefs in climate change for higher-educated Democrats (more likely to believe in climate change than lower-educated Democrats) and Republicans (less likely to believe in climate change than lower-educated Republicans).

Consistent with these patterns of heterogeneity in induced air conditioning adoption, I propose a simple framework that rationalizes these observations: households that do not believe in climate change take short-run weather anomalies (a contemporaneous heat wave) as a draw from a fixed climate distribution. Conversely, households that believe that their local climate is changing take the same weather anomaly as being informative of the future path of climate for their local ZIP code. Alternate mechanisms cannot explain this heterogeneity. This does not rule out alternative channels, such consumer myopia or contemporaneous disutility from heat, but it does suggest a role for households learning about the path of local climate.

California is a unique case for studying these events within the United States, given the high propensity of mild climates. Because of this, there is likely a large margin of households that exist near a threshold for adoption that does not exist in other United States settings. While the initial estimates may seem large, 100 extra CDDs could mean 10 nights of 80 degree Fahrenheit nights instead of 70 degree nights, contextualizing the potential impact of a marginal heat wave. And as other developed European countries are exposed to heat waves, it will become more policy relevant to think about how households make investment decisions in energy-using durable goods.[1] Further, as incomes grow in the developed world and households broach the adoption margin, these dynamics may become more relevant, with implications for the dynamic path of aggregate energy demand.

The rest of the paper proceeds as follows: Section 2 reviews past literature on climate change and energy consumption and discusses why this particular study is novel. Section 3 discusses the data and empirical strategy. Section 4 presents the models used to estimate the effect of weather on AC adoption and energy demand. Section 5 contains the model estimates. In Section 6, I discuss these results and their implications for household behavior. Finally, Section 7 concludes.

2 Literature

This paper explores the link between short-run weather shocks and longer-run outcomes, specifically through induced adoption of air conditioning and the implications for energy demand. In this section, I first summarize the literature that links energy demand to local climate impacts, as well as the literature that specifically focuses on air conditioning adoption. In addition, I discuss the literature on household and market-wide beliefs in climate change. I contribute to a new but growing literature that finds heterogeneity in household investment decisions based on beliefs about the climate.

[1] See the 2019 European heat wave: https://www.nytimes.com/2019/07/25/world/europe/heatwave-record-temperatures.html.

2.1 Energy demand and climate impacts

The first major contribution of this paper is to explore the link between short-run weather shocks on longer-run outcomes for energy demand. Auffhammer and Mansur (2014) review the literature on energy consumption and climate trends and delineate between two general methods of estimating this relationship. 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 the China or other developing setting. Second, both of these studies focus on monthly variation. 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.[2]

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. In an engineering paper, McNeil and Letschert (2010) document correlations between climate and air conditioning adoption to define a measure they call "saturation" for air conditioning, and suggest this as a statistic in energy demand forecasts.[3] However, I document that, even in the absence of changing climate, a one-off shock can induce significant increases in medium- to long-run energy demand through air conditioning adoption, highlighting the importance of tail events.

[2]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)

[3]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.

2.2 Beliefs

What is the mechanism that links short-run weather shocks to long-run air conditioning holdings and energy consumption? I provide suggestive evidence for a household learning model. Using proxies for household belief in climate change, I show that households that believe in climate change are significantly more likely to be induced into adopting air conditioning following a 2006 heat wave. This is in line with a model of households updating their beliefs about their local climate when a weather shock (heat wave) provides them with new information about their local climate.

In some market settings, equilibria may be more likely to appear as fully incorporating information about the climate. For instance, Schlenker and Taylor (2019) show that aggregate financial markets for weather futures in the United States reflect consensus climate change projections from the scientific community. In other instances, there are significant frictions where we observe large deviations from the equilibrium outcomes we might expect if individuals had perfect information about the climate.

Given significant household-level heterogeneity in climate change belief, there is a growing literature that explores how this affects investment decisions. Bakkensen and Barrage (2017) show that Rhode Island households that own coastal property are systematically more likely to underestimate flood risk, leading to housing prices that exceed their fundamentals. Barrage and Furst (2019) show further that new construction starts are more likely to occur in climate-skeptic communities. I consider similar household-level heterogeneity in belief, and use this to explain diverging adoption patterns in air conditioning based on beliefs about climate change. While this heterogeneity is consistent with a model of household learning about the climate, there are other potential channels that could drive adoption in this setting.

First, salience about the risk and frequency of climate events affects how individuals mitigate or insure against such risk. For example, households in flood-prone regions are more likely to purchase flood insurance after a flood event (Gallagher, 2014; Bakkensen, Ding and Ma, 2019). Additionally, information provision of both flood and wildfire risk maps affects equilibrium housing prices, even if the fundamental risk is unchanged (Gibson and Mullins, 2020; Garnache and Guilfoos, 2019). There are plausible salience mechanisms that could explain a link between heat waves and air conditioning adoption: disutility of heat, for example.

Second, behavioral channels could rationalize weather-induced adoption of air conditioning. Busse et al. (2015) study household purchases of vehicles in the presence of idiosyncratic weather phenomena. They find that the investment decision responds to idiosyncratic weather, which is inconsistent with a fully-rational purchase decision. Instead, they provide evidence of projection bias from current weather, where future utility is a convex combination of utility based on the current idiosyncratic state and the realized state. To this extent, households may exhibit similar behavioral biases as a response to an unexpected heat wave.

Finally, a simple rationalization of weather-induced adoption of air conditioning would be highly convex costs of temperature imposed by a heat wave. Contemporaneous costs imposed by a severe heat wave could rationalize contemporaneous adoption of air conditioning regardless of the net present value of ownership in future periods. High contemporaneous costs are consistent with results from Albouy et al. (2016), where households are willing to pay significantly more to avoid extreme high temperatures than to avoid similarly extreme low temperatures in a cross-sectional hedonic analysis. This follows the same pattern as impacts on crop yields in Schlenker and Roberts (2009), suggesting a similar physiological aversion to extreme temperatures.

However, in each of these alternative channels, unless the mechanism is systematically correlated with belief in climate change, it cannot fully explain the patterns in air conditioning adoption in this setting. Additionally, the significance of the belief channel suggests that it is not negligible relative to alternative mechanisms. I discuss the contribution of alternative mechanisms further in Section 6.

3 Data

3.1 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 21,920 and 24,464 California households in 2003 and 2009, respectively. These households were randomly drawn from the service areas of three primary independently-owned utilities (IOUs)—Pacific Gas 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.[4] Households are identified geographically at the ZIP-code level.

The primary outcome of interest is household ownership of central or room air conditioning units and monthly electricity demand. In addition, the RASS includes other household characteristics including household size, home age, income, 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.

Installation of central air conditioning represents a sizable investment for a household.

[4]As reported for 2010 by the State of California Energy Commission.

Table 1: Air conditioning saturation by utility from RASS

	Survey wave					
	2003			2009		
	Central Air	Room Air	N	Central Air	Room Air	N
PG&E	.39	.14	6,265	.44	.11	6,458
SDG&E	.35	.09	5,445	.43	.13	5,970
SCE	.48	.20	6,102	.58	.18	6,444
LADWP	.29	.25	4,071	.41	.24	5,538

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.

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.[5] Conversely, portable room units can be purchased for only a few hundred dollars, and because of relative portability, have an active secondary market.[6] Central units are tied to the structure, 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.

3.2 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 for a daily observation; or in the case that no pixel falls within a ZIP code, I take the closest pixel observation. I winsorize the ZIP-code average daily temperatures at the top and bottom one percent, and match these to the household appliance and energy use data

[5] See https://www.homeadvisor.com/cost/heating-and-cooling/install-an-ac-unit/.

[6] For example, Figure B.2 depicts results from an August 13, 2019 search for air conditioning on an online resale website in San Diego.

(identified geographically at the ZIP-code level).

3.3 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 1. I define the historical climate for ZIP code z to be the mean number of CDDs per year from 1981 to 2005 (Equation 2). I use 2005 as the upper cutoff for this historical climate and focus on the plausibly exogenous temperature shock during the summer of 2006—a particularly hot year for California.

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

$$Climate_z \equiv \overline{CDD}_{z,t\in\{1981,\ldots,2005\}} \tag{2}$$

Figure 1 depicts the distribution of relative anomalies by ZIP code, where the large mass of this distribution lies to the right of zero. This can be interpreted as saying that most California ZIP codes (covered by the RASS) experienced more CDDs during 2006 than during a typical year leading up to that point. I use this 2006 heat wave as an event between the two RASS survey waves (2003 and 2009), and consider the ZIP-code level heterogeneity in exposure to this heat wave as a source of identifying variation. I define the *CDD anomaly* as the difference between the number of CDDs in 2006 and the historical climate, enumerated by Equation 3.

$$CDD\,anomaly_z \equiv CDD_{z,2006} - Climate_z \tag{3}$$

One alternative formulation would be to define the CDD anomaly as the number of extra

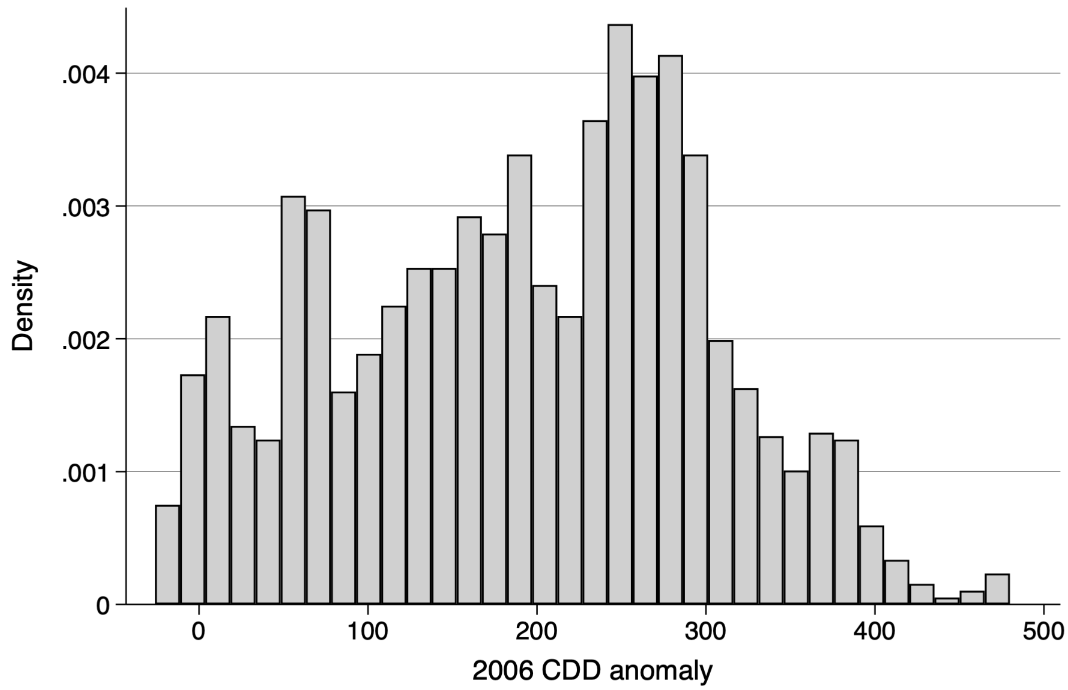

Figure 1: Heat wave anomaly for 2006

Note: this histogram depicts the number of extra CDDs in 2006 by ZIP code relative to the historical number of CDDs for the ZIP code.

CDDs compared to an average for all years between the two survey waves, that is, construct the CDD anomaly for 2004 through 2008. I report the results of this exercise in Appendix A and estimate qualitatively similar estimates for the baseline empirical specification, but with less precision.

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 historical climate of a ZIP code as measured by average CDDs could be correlated with the 2006 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. Figure 2 shows that the residual climate anomaly (after netting out city fixed effects) is not predicted by the historical number of CDDs for a ZIP code.

Similarly, one may be concerned that ZIP codes that are more severely affected by a heat wave in 2006 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 the 2006 anomaly is not predictive of past daily temperature variance. Figure 3 plots the 2006 CDD anomaly against the historical CDD variance from 1981 to 2005 after netting out city fixed effects, and shows that the extreme heat wave in 2006 is not predictive of past variability in average number of CDDs.

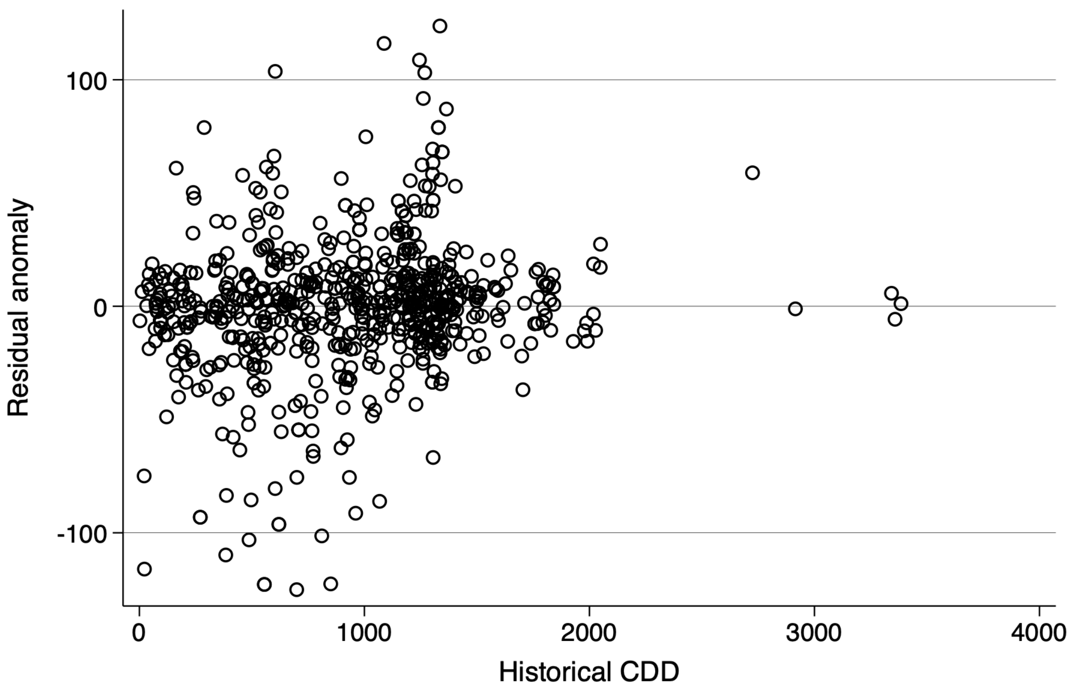

Figure 2: Orthogonality of residual anomaly

Note: the plot shows the residual climate anomaly after netting out city fixed effects. This depicts the fact that historical number of CDD is not predictive of the residual 2006 CDD anomaly.

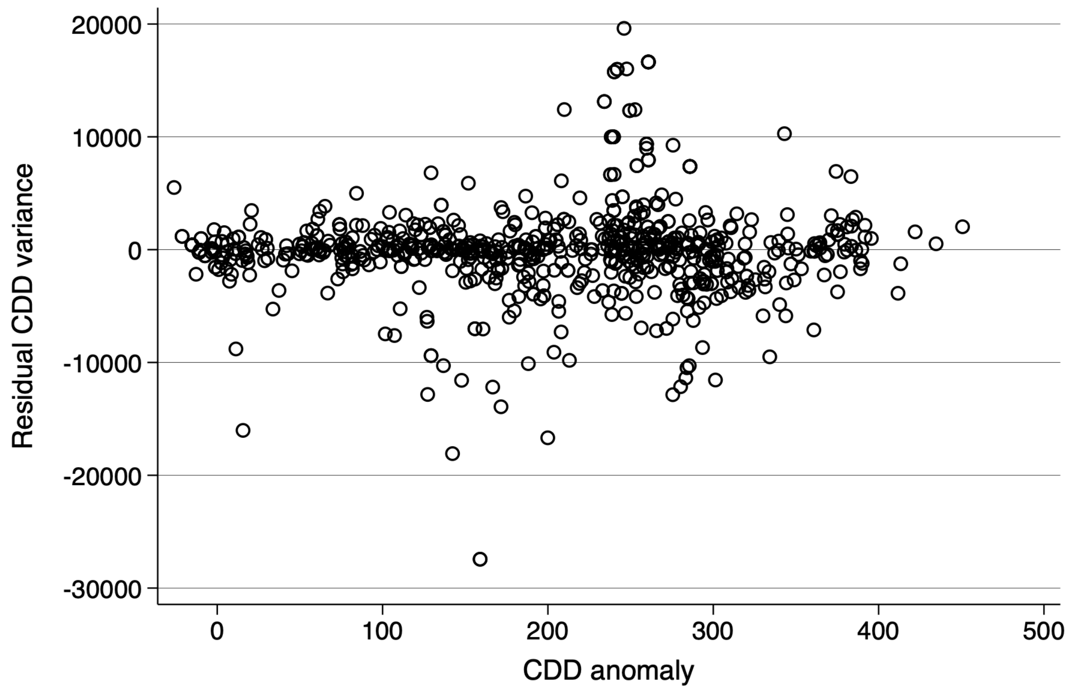

Figure 3: Contemporaneous anomaly and historical climate variance

Note: the plot shows the residual CDD variance after netting out city fixed effects. The variance of CDD for ZIP code z is defined as the variance of the yearly number of CDD for a ZIP code from 1981 to 2005. The CDD anomaly in 2006, on the horizontal axis, is not predictive of past variability in the number of CDD in a given year.

3.4 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.[7] 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 presidential election from the California Secretary of State. Partisanship is highly predictive of belief in climate change and its severity (McCright and Dunlap, 2011). I

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

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 climate change by level of education.[8] 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.

4 Empirical Strategy

In this section, I discuss the identification strategy that I use in order to measure the effect of short-run temperature anomalies on household ownership of air conditioning and longer-run energy demand.

In an ideal laboratory experiment, I would randomly expose ZIP codes to an extreme heat wave indicator and observe air conditioning penetration pre- and post-treatment. Assuming households are geographically fixed, a regression of post-treatment air conditioning penetration on the randomized heat wave and pre-treatment penetration will identify the average take-up in air conditioning induced by the heat wave. Assuming that penetration is diminishing in average temperature, it is important to note that ZIP codes with penetration near saturation levels will minimize potential contribution through this channel, and that the specific parameter identified will be the average effect over the distribution of households.

In reality, heat waves are not binary, and heat wave severity will be correlated with mean climate characteristics, so I use the CDD anomaly measure as defined in the previous section by Equation 3 as the source of identifying variation. Above, I discussed some of the potential threats to identification and why these would not be a problem for the estimation. However,

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

another concern would be if CDD anomaly were correlated with observed or unobservable household characteristics. To this effect, I compare observables for households located in the fourth quarter of the CDD anomaly to a random sample of 100 ZIP codes covered by the RASS and report the summary statistics in Table 2. Households particularly affected by the CDD anomaly do not appear noticeably different from randomly chosen households, which is reassuring for the estimation.

Table 2: Testing the orthogonality of the heat wave using simulated weather shocks

	(1) Q4 anomaly		(2) Random sample	
	mean	sd	mean	sd
Climate (avg yearly CDDs)	1001.64	410.90	901.98	41.84
Central air installation	0.42	0.49	0.44	0.03
Dem presidential vote share 2004	0.55	0.22	0.54	0.02
College educated	0.41	0.48	0.44	0.02
HH income ($1000s of 2009 USD)	52.53	40.55	60.21	2.19
Owner occupied	0.58	0.49	0.62	0.02
Number of bedrooms	2.52	1.14	2.61	0.06
Home age (years)	35.79	17.84	33.24	0.84
Observations	5713		100	

Note: this reports a test of selecting a random sample of ZIP codes to the fourth quartile of 100 ZIP codes as affected by the heat wave anomaly. Households are sampled with equal probabilities from the ZIP codes covered by the four utilities in the RASS.

4.1 Baseline specification

The baseline model is a difference in differences (DD) linear probability model in air conditioning ownership, where I compare the probability that a household in a ZIP code in 2009 owns an air conditioning unit compared to a household in the same ZIP code in 2003. This is differenced by CDD anomaly for that specific ZIP code. City fixed effects imply that the identifying variation is differential ZIP-code exposure to the CDD anomaly within a city. I use the same estimation strategy for measuring household-level summer electricity demand, and interpret this as the longer-run effect of the CDD anomaly on monthly electricity demand in kilowatt hours (kWh).

Since the RASS reports two cross sections, I am unable to test for parallel trends in ZIP-code level air conditioning penetration. However, due to the nature of the CDD anomaly and its credible exogeneity (discussed above), this does not pose the same identification problem that may exist in other DD designs.

The baseline estimating equation is:

$$y_{zit} = \beta_0 \, (CDD\, anomaly)_z \times \mathbb{1}\{2009\}_t + \beta_1 \mathbb{1}\{2009\}_t + \Theta X_i + \gamma_k + \delta_t + \varepsilon_{zit}, \qquad (4)$$

where y_{zit} is the outcome for a household i in ZIP code z in year t. X_i is a vector of housing and homeowner characteristics including a dummy for college education for head of household, household income, home age, and number of residents. γ_k and δ_t are spatial and year fixed effects.

When household central air ownership is the dependent variable, β_0 is interpreted as the effect of one extra CDD in 2006 relative to the historical local climate on a household's propensity to own a central air conditioner. The identifying variation is differential exposure to the 2006 temperature anomaly within a city. The standard errors are clustered at the ZIP code, which is the level of the treatment (CDD anomaly in 2006).[9] In different specifications of the linear probability model, I use household ownership of other types of appliances—dishwashers, standalone freezers, and CFLs—as a placebo test for the baseline model. The implicit assumption is that ownership of these items is unlikely to covary with the weather.

When July electricity demand is the dependent variable, β_0 is interpreted as the effect of one extra CDD in 2006 relative to the historical ZIP code climate on household electricity demand in 2009. I interpret this reduced-form estimate as the combined effect of induced air conditioning adoption and choosing to run the air conditioner during July 2009. The

[9]When clustering the standard errors at a higher geographic level, such as city or climate zone, the point estimates are still measured precisely. See Appendix A

analogous placebo test to the linear probability model above is electricity demand in the winter (specifically, February).

4.2 Heterogeneity and mechanism analysis

In order to explore the mechanism through which households are induced into acquiring air conditioners by temperature anomalies, I interact specific variables with the DD in the baseline specification.

First, I consider a triple difference model, where I difference the baseline specification against household-level belief in climate change. The estimating equation is:

$$\begin{aligned} AC_i = \beta_0\, belief_k \times (CDDanomaly)_z \times (2009)_i + \sum_j \beta_j [\text{two-way interactions}] \\ + \Theta X_i + \gamma_k + \delta_t + \varepsilon_i, \quad (5) \end{aligned}$$

where the right-hand side variables are as defined above, and the two-way interactions are all combinations of the three variables in the triple difference. When using belief as defined at the county level, I drop the city fixed effects that would otherwise absorb county-level belief in climate change.

Because the estimate of β_0 will be attenuated by mis-measurement of household-level belief in climate change, I also use precinct-level Democratic share in the 2004 presidential election as a proxy for household belief in climate change. In addition, I use a measure of predicted belief in Equation 5, where the first stage regresses county belief on household education and precinct Democratic share, as well as the interaction of the two.

In addition to measures of belief, I also consider a triple-differenced model with education of head-of-household as follows:

$$AC_i = \beta_0 \, College_i \times (CDDanomaly)_z \times (2009)_i + \sum_j \beta_j [\text{two-way interactions}] + \Theta X_i + \gamma_k + \delta_t + \varepsilon_i. \quad (6)$$

I also consider a fourth-differenced model, where we can difference across precinct Democratic share:

$$AC_i = \beta_0 \, College_i \times Demshare_p \times (CDDanomaly)_z \times (2009)_i + \sum_j \beta_j [\text{two-way interactions}] + \sum_l \beta_l [\text{three-way interactions}] + \Theta X_i + \gamma_k + \delta_t + \varepsilon_i. \quad (7)$$

A recent Gallup poll of Americans indicates that belief in climate change is not strictly increasing in education.[10] Instead, belief differs by partisanship. Conditional on identifying as a Democrat, belief in climate change is increasing in education. Conversely, conditional on Republican identification, belief in climate change decreases with education.

Because of this, the *ex ante* expectation of the sign on the estimate of β_0 in Equation 6 is unclear. If one of the mechanisms for induced adoption is belief that the climate is changing, higher levels of education could be associated with a higher or lower propensity of belief depending on partisan identification. However, when differencing this again by a proxy for partisanship, as in Equation 7, β_0 is interpreted as the propensity for college-educated households in a more Democratically-leaning ZIP code to have been induced into adopting an air conditioning unit by the 2006 CDD anomaly.

In addition to informing these third- and fourth-differenced models, this non-monotonic relationship between education and belief in climate change implies the importance of the interaction with education for the predicted household belief, which I use for the preferred estimate for the model defined by Equation 5 when using a predicted measure for household

[10] See Appendix B. Source: Gallup poll available here.

belief.

5 Results

In this section, I report the main results of the estimated models defined in the previous section.

5.1 Baseline results of weather on air conditioning adoption

Table 3 reports the model estimates for the baseline models of temperature-anomaly induced adoption of central air conditioning (columns 1 and 2) and long-run household electricity demand in kWh. Column 1 is the preferred specification, and the coefficient on "Anomaly $\times$ 2009" can be interpreted as follows: the mean effect of an extra 100 CDDs in 2006 relative to the historical average from 1981–2005 increases the propensity for a household to own central air conditioning by one percentage point. The identifying variation is differential ZIP code exposure to the 2006 heat wave within a city. Utility fixed effects and year fixed effects absorb variation induced by differential utility structures and variables common to households within a year respectively.

In addition to the average effect across households, column 2 in Table 3 separates this effect across quartiles of the historical climate distribution. That is, "Q1" refers to ZIP codes where the historical climate lies in the first quartile of the California distribution (defined by average number of CDDs in a year from 1981–2005). Similarly, "Q4" refers to the quartile of ZIP codes where households historically experience the highest number of CDDs within a given year (based on the daily temperature data from 1981–2005). Households in the third quartile of this climate distribution have the largest and most precise point estimate—for every 100 CDDs of anomaly, households are 2 percentage points more likely to be induced into adopting central air conditioning. Column 2 also provides suggestive evidence that households in the second quartile of California climate are more likely to be induced into air

Table 3: Baseline model

	(1) Central air b/se	(2) Central air b/se	(3) Electricity b/se	(4) Electricity winter b/se
Anomaly X 2009	0.0001***		0.06023***	0.00867
	(0.00005)		(0.010253)	(0.006725)
Q1 interaction		-0.0000		
		(0.00018)		
Q2 interaction		0.0001		
		(0.00008)		
Q3 interaction		0.0002***		
		(0.00006)		
Q4 interaction		-0.0000		
		(0.00006)		
Controls	X	X	X	X
UtilityFE	X	X	X	X
CityFE	X	X	X	X
N	38581	38581	35734	33503

Note: standard errors clustered at the ZIP-code level. In column 3, electricity corresponds to household electricity demand for the billing cycle covering mostly July in kWh. In column 4, this corresponds to electric billing cycle covering most of February. "Most coverage" is necessary because of the staggered billing cycles across households. *p< 0.1, **p< 0.05, ***p< 0.01.

Table 4: Placebo tests

	(1) Dishwasher b/se	(2) Freezer b/se	(3) CFLs b/se
Anomaly × 2009	-0.0000	0.0001	-0.0000
	(0.00004)	(0.00004)	(0.00004)
Controls	X	X	X
Utility FE	X	X	X
City FE	X	X	X
N	38581	37209	36756

Note: standard errors clustered at the ZIP-code level. In column 2, freezer refers to household ownership of a standalone freezer. CFLs refer to household ownership of compact fluorescent lamps, the energy efficient lightbulb at the time of the RASS. N varies by specification due to different household response rates to ownership of the various appliances. N falls for the electricity demand models as billing data is not fully populated in the RASS. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

conditioning adoption than either the top or bottom quartiles.

Table 4 reports the results of three separate placebo tests following Equation 4, where the outcome variable is household ownership of a dishwasher (column 1), a standalone freezer (column 2), or installation of fluorescent light bulbs (column 3). These precisely estimated zeroes for each of these specifications imply 95 percent confidence intervals that do not include any response larger than one one-hundredth of a percent in order of magnitude. Though this response is unsurprising, this lends credibility to the assumption that the model only captures household investment decisions that should be directly affected by temperature anomalies. One could imagine that a negative and significant coefficient on any of these appliances could arise if households substitute purchases of one appliance for another, but this does not seem to be the case.

5.2 Baseline results of weather on energy demand

Column 3 of Table 3 reports the baseline results of household-level electricity demand for July following Equation 4. The point estimate is interpreted as the following: for every 100 CDDs of anomaly, households on average increase their electricity demand by approximately 6 kWh.

Finally, column 4 of Table 3 shows the similar placebo results for household energy demand during the month of February. The coefficient can be interpreted as a precisely-estimated zero estimate. For every 100 CDDs of anomaly, I can rule out an increase in household electricity demand by more than 2 kWh at the 95 percent confidence interval.[11] Of course, there is no *ex ante* reason to think that induced adoption of central air conditioning does not affect winter energy demand. For instance, HVAC installation may correlate with installation of heating units, insulation, or other homeowner investments.

5.3 Heterogeneity in climate change belief and education

Table 5 reports the estimation results following Equation 5, the linear model differencing the baseline specification across different proxies for household-level belief in climate change. Column 1 of Table 5 uses county level belief in climate change. Since "belief" is the county share of adults that believe in climate change, there exists a large amount of household level measurement error for belief in climate change. The lowest proportion of county-level belief in California is 61 percent of adults, with the highest proportion being 79 percent of adults believing in climate change. The estimate in column 1 implies that the induced adoption effect is stronger in counties where people are more likely to believe in climate change.

Column 2 of Table 5 instead uses the Democratic share from the 2004 presidential general election from the nearest precinct closest to a ZIP code to difference across the baseline specification. Again, this will measure household-level belief in climate change with a large

[11] Note that the differing number of household observations in each specification is due differential response to the RASS.

Table 5: Differencing over belief in climate change

	(1) Central Air b/se	(2) Central Air b/se	(3) Central Air b/se
Belief × CDD anomaly × 2009	0.0001*** (0.00002)		
Dem share × CDD anomaly × 2009		0.0004*** (0.00013)	
$\widehat{\text{Belief}}$ × CDD anomaly × 2009			0.00064*** (0.000194)
Two-way interactions	X	X	X
Controls	X	X	X
Utility FE	X	X	X
City FE		X	X
N	38674	38581	41491

Note: standard errors clustered at the ZIP-code level. Education is an indicator for college education for head of household. Democratic share is precinct-level Democratic share in the 2004 presidential election. *p< 0.1, **p< 0.05, ***p< 0.01.

degree of error, but the point estimate may still be interpreted as saying that households that are more likely to be Democratic identifying (more likely to believe in climate change) are more likely to have been induced into adopting air conditioning.

In order to try to correct for this measurement error, I use head of household education and closest precinct Democratic share to predict household-level belief in climate change. Recalling the non-monotonicity of belief in education, discussed above, I also include the interaction in the preferred specification. Table 6 reports the results of this first stage, where both columns 1 and 2 have R-squared of about 0.3. College education, Democratic precinct share in the 2004 presidential election, and being both college educated and living in a more Democratic ZIP code are all positively correlated with belief in climate change in this first stage.

When using this predicted measure for belief, column 3 of Table 5 reports my preferred specification of the triple difference. Since county level of belief ranges from 61 to 79 percent belief, moving from households that are least likely to most likely to believe in climate change

Table 6: First stage for belief in climate change

	(1) Belief b/se	(2) Belief b/se
Education	0.0089***	0.0029***
	(0.00027)	(0.00077)
Democratic share	0.0879***	0.0823***
	(0.00068)	(0.00095)
Education × democratic share		0.0114***
		(0.00136)
Controls		
Utility FE		
City FE		
N	42312	42312

Note: standard errors clustered at the ZIP-code level. Belief is a county-level report of the percentage of adults that believe that the climate is changing. Twoways refers to the two-way interactions necessary for the triple difference model. *p< 0.1, **p< 0.05, ***p< 0.01.

increases the induced propensity by about one half of one percentage point per 10 CDD anomaly.

Table 7 reports the estimation results following the models specified in Equation 6 and Equation 7. Column 1 differences the main specification against an indicator for college education for the head of household. Though not significant at the 5 percent level, the coefficient provides some suggestive evidence that college educated households are more likely to be induced into adopting air conditioning.

Column 2 of Table 7 indicates that college educated household in the most Democratic ZIP codes are significantly more likely to be induced into air conditioning adoption than college educated households in the least Democratic ZIP codes. The negative (but insignificant) coefficient on the first row is in line with a small negative or zero effect for households located in comparatively non-Democratic ZIP codes.

Because households may choose to endogenously relocate based on weather shocks, I run all of these specifications restricted to homeowners that have lived in their homes since prior

Table 7: Heterogeneity of effects by education

	(1) Central Air b/se	(2) Central Air b/se
College × CDD anomaly × 2009	0.0001	-0.0002
	(0.00005)	(0.00010)
College × Dem share × CDD anomaly × 2009		0.0005**
		(0.00019)
Two-way interactions	X	X
Three-way interactions		X
Controls	X	X
Utility FE	X	X
City FE	X	X
N	38581	38581

Note: standard errors clustered at the ZIP-code level. Twoways (threeways) refers to the two-way (three-way) interactions necessary for the triple difference model. *p< 0.1, **p< 0.05, ***p< 0.01.

to the 2006 heat wave, and I report these results in Appendix A. Here, I also report the results of all models run using room air conditioning or any air conditioning as the outcome variable, with qualitatively similar results.

6 Discussion

In this section, I discuss the empirical results and some of the implied mechanisms for induced air conditioning adoption. I first summarize the baseline results and their implications, and move towards the suggestive evidence about the role of household beliefs in climate change.

I provide strong causal evidence that households respond to a CDD anomaly in 2006 by increasing their propensity to own air conditioning units. Following the results reported in Table 3, we can observe that the households most likely to be induced to adopt air conditioning live in the third quarter of the climate distribution in California, followed by the second quartile. This is unsurprising if ZIP codes in the top quartile of the climate distribution are fully saturated with air conditioning, and if if households in the first quartile never need air conditioning.

Using the preferred estimate from the baseline model, and using the median CDD anomaly of about 200 CDDs, the model can explain about 2 percentage points of increase in the propensity for these California households to own an air conditioner. From Table 1, this means that response to this severe heat wave can explain about one quarter of the overall increase in central air conditioning ownership from 2003 to 2009 (an increase of about 8 percent). Using the same baseline model and median CDDs, this translates to about a 12 kWh increase in monthly demand for all California households covered by the survey.

The total increase in energy demand depends on the behavior of counterfactual households in the absence of the 2006 heat wave. If these households were to eventually adopt air conditioners, but waited for a particularly hot year, this might amount to energy "pull-forward." In this case, the net effect on energy demand depends on the timing of a counterfactual shock—from earlier to the shock of interest to far in the future. However, if the 2006 heat wave actually permanently changed the stock of installed air conditioners, the total effect on energy demand would be significantly larger.

6.1 Alternative mechanisms

Prior to discussing the climate-change belief channel for air conditioning adoption, I discuss several other channels for this induced adoption. For context, consider an extremely stylized model of a household making the decision about air conditioning ownership. Formally, suppose an air conditioner lasts for T periods, weather in period t is given by ω_t from a climate distribution Ω, and household preferences over the AC decision are given by u, then a household invests in air conditioning in year t if $\mathrm{E}\sum_{\tau=t}^{t+T} u(AC, \omega_\tau) > 0$. That is, they purchase an air conditioner if the expected utility over the lifetime of the air conditioner is positive (net of all costs—fixed and flow costs, and any other associated utility costs).

First, if the contemporaneous heat wave is bad enough to cause extreme household disutility, it could be rational to install an air conditioner to assuage these high short-term costs, even if the expected net benefit for the following periods were negative. In the context of the simple model of household investment in air conditioning, this could be the case if $u(AC, \omega_t) > 0$ even if the expected utility from ownership $\mathrm{E} \sum_{\tau=t+1}^{t+T} u(AC, \omega_\tau) < 0$. However, qualitative reports of HVAC installation imply that the time horizon for central air installation would make it difficult to believe that households are responding simply because of contemporaneous disutility.

A second mechanism discussed above would simply be a shift in timing. If a weather realization in t changed the timing decision for a household acquiring air conditioning based on static expectations about the weather, this would amount to pull-forward in energy demand for some number of periods. If this were the case, we may expect to see smaller effects for induced adoption with increasing duration of home ownership. Appendix A shows that effects are not decreasing when restricting to homeowners with substantial tenure.

Other alternative mechanisms for adoption could include behavioral channels. One potential behavioral channel would be myopia or projection bias on the part of the household. This would be the case if the future utility of air conditioning ownership is a convex combination of ownership today and the actual realized utility of air conditioning ownership. Busse et al. (2015) provide strong evidence for projection bias in the automobile purchase decision, where consumers buy more convertibles on sunny days, the analogous phenomenon in this setting would be buying more air conditioning units during hot years.

6.2 Beliefs about the climate

While I cannot rule out the contribution of alternative mechanisms for weather-induced adoption of air conditioning, I propose a simple framework that rationalizes the heterogeneity in the induced adoption observed in patterns of adoption by belief in climate change, education, and partisanship.

Consider again a household that is posed with the choice to buy an air conditioner if $\mathrm{E} \sum_{\tau=t}^{t+T} u(AC, \omega_\tau) > 0$. While the above mechanisms focused on the expected utility calculation given a series of weather draws ω_t from a fixed climate distribution Ω, consider instead two types of households: those that believe that the climate distribution Ω is fixed, and those that believe that the climate distribution is actually changing—"updaters." In this setting, the updaters observe the weather today, take this as a signal of the future path of weather, and update their beliefs of the climate based on the contemporaneous weather. If nothing in the consumer's choice changes except for expectations over the climate, this can rationalize investment in central air conditioning.

This framework is consistent with the heterogeneity results discussed in subsection 5.3. We can observe that when interacted with the baseline model, both county-level survey data about belief in climate change and a proxy using precinct-level election returns suggest that households that are more likely to believe in climate change (measured with large error) are more likely to be induced adopters. And when using the predicted belief using the first stage reported in column 2 of Table 6, the coefficient of interest indicating induced adoption is larger, since this mitigates attenuation caused by mismeasurement in columns 1 and 2.

Further, the results in Table 7 qualitatively follow what would be predicted in this framework. Since higher education contributes to divergent beliefs about climate by partisanship, it is not immediately clear what the expected estimated coefficient of the triple difference following Equation 6 would be. Rather, it should depend on the relative partisan share of the population. For instance, if all households identified as Republicans, I would expect the difference across education to be negative if households are changing their investment behavior after updating their beliefs about climate. Again, this follows the empirical facts about belief in climate change and partisanship discussed in subsection 3.4. However, when I introduce a *fourth* difference by Democratic share, the coefficient of interest (differential induced adoption by educated Democratic households) is positive and significant. This is consistent with the fact that college educated Democrats are the most likely to believe in climate change and are induced into adoption differentially by the 2006 heat wave.

Though most of these heterogeneity analyses are identified imprecisely with imperfect measures of household-level belief in climate change, I find the preponderance of evidence consistent with this framework to be highly suggestive that there is some role for a belief-updating channel with respect to the climate. That is, this induced adoption of air conditioning cannot be fully rationalized by alternative channels. I take this as novel evidence that households change their investment behavior as a response to updating beliefs about the climate when it comes to household investment decisions. In this context, this has implications for the dynamics of air conditioning ownership and the path of energy demand over time. More expansively, it is likely similar mechanisms may affect a variety of dynamic consumer problems that are related to a changing climate.

7 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 exposed to a 2006 heat wave increased their propensity to own a central air conditioning unit, and this event can explain nearly 2 percentage points of the increase in central air conditioner ownership—or about one quarter of the total increase—from 2003 to 2009. Through this induced adoption channel, households also increased their July energy demand three years following the heat wave. Exploring this link between short-run weather and long-run energy demand is immediately important for forecasting exercises, but also exposes an important mechanism by which 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, if 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 absent of the heat wave.

In addition to these baseline results, I also explore the heterogeneity in response to the 2006 heat wave and provide suggestive evidence for a household belief-updating framework. When differencing the baseline DD model by measures of household belief in climate change, I show that households that are more likely to believe that the climate is changing are also more likely to be induced into adopting air conditioning in response to the 2006 heat wave. 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 take contemporaneous weather as a signal of the future path of their local climate, which changes the household decision for purchasing air conditioning. Conversely, a household that does *not* believe that the climate is changing may not update their expected upside of adopting air conditioning.

Finally, I exploit the non-monotonicity of partisan belief in climate change with respect to 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 and *decreases* belief for Republicans. In a triple- and fourth- difference specification, I show that the induced-adopter effect differentially applies to college educated Democrats, who are most most likely to believe in climate change.

This evidence that long-run household investment decisions responds to short-run weather phenomena is important, since the prevailing literature links such decisions to long-run dynamics. In this paper, I provide novel, suggestive evidence that households take contemporaneous weather events and form beliefs over longer-run state variables in the climate. This suggests implications for household decision-making both within the environmental setting and more broadly.

8 Acknowledgements

Chapter 1 is currently being prepared for submission for publication. The dissertation author is the sole author on this chapter.

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A Alternative Specifications

Table A.1: Central and standalone unit specification

	(1) All units b/se	(2) All units b/se	(3) Electricity b/se	(4) Electricity winter b/se
Anomaly × 2009	0.0001*		0.0404**	0.0152
	(0.00006)		(0.02017)	(0.01256)
Q1 interaction		-0.0000		
		(0.00017)		
Q2 interaction		0.0000		
		(0.00006)		
Q3 interaction		0.0001*		
		(0.00004)		
Q4 interaction		0.0001		
		(0.00007)		
Controls	X	X	X	X
Utility FE	X	X	X	X
City FE	X	X	X	X
N	38581	38581	35734	33503

Note: standard errors clustered at the ZIP-code level. In column 3, electricity corresponds to household electricity demand for the billing cycle covering mostly July in kWh. In column 4, this corresponds to electric billing cycle covering most of February. "Most coverage" is necessary because of the staggered billing cycles across households. *p< 0.1, **p< 0.05, ***p< 0.01.

Table A.2: Clustering at the city level

	(1) Central air b/se	(2) Central air b/se	(3) Electricity b/se	(4) Electricity winter b/se
Anomaly × 2009	0.0001***		0.0602**	0.0214
	(0.00007)		(0.03059)	(0.01999)
Q1 interaction		-0.0000		
		(0.00036)		
Q2 interaction		0.0001		
		(0.00001)		
Q3 interaction		0.0002**		
		(0.00009)		
Q4 interaction		-0.0000		
		(0.00019)		
Controls	X	X	X	X
UtilityFE	X	X	X	X
CityFE	X	X	X	X
N	38581	38581	35734	33503

Note: standard errors clustered at the municipal level. In column 3, electricity corresponds to household electricity demand for the billing cycle covering mostly July in kWh. In column 4, this corresponds to electric billing cycle covering most of February. "Most coverage" is necessary because of the staggered billing cycles across households. *p< 0.1, **p< 0.05, ***p< 0.01.

Table A.3: Clustering at the county level

	(1) Central air b/se	(2) Central air b/se	(3) Electricity b/se	(4) Electricity winter b/se
Anomaly × 2009	0.0001**		0.0602*	0.0214
	(0.00002)		(0.0356)	(0.02867)
Q1 interaction		-0.0000		
		(0.00022)		
Q2 interaction		0.0001		
		(0.00011)		
Q3 interaction		0.0002*		
		(0.0001)		
Q4 interaction		-0.0000		
		(0.00021)		
Controls	X	X	X	X
UtilityFE	X	X	X	X
CityFE	X	X	X	X
N	38581	38581	35734	33503

Note: standard errors clustered at the county level. In column 3, electricity corresponds to household electricity demand for the billing cycle covering mostly July in kWh. In column 4, this corresponds to electric billing cycle covering most of February. "Most coverage" is necessary because of the staggered billing cycles across households. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table A.4: Homeowner restricted specification

	(1) Central air b/se	(2) Central air b/se	(3) Electricity b/se	(4) Electricity winter b/se
Anomaly × 2009	0.0001*		0.0612***	0.0214*
	(0.00006)		(0.00952)	(0.01281)
Q1 interaction		-0.0001		
		(0.00026)		
Q2 interaction		0.0002		
		(0.00014)		
Q3 interaction		0.0002*		
		(0.00011)		
Q4 interaction		0.0001		
		(0.00007)		
Controls	X	X	X	X
Utility FE	X	X	X	X
City FE	X	X	X	X
N	30118	30118	28444	26826

Note: standard errors clustered at the ZIP-code level. In column 3, electricity corresponds to household electricity demand for the billing cycle covering mostly July in kWh. In column 4, this corresponds to electric billing cycle covering most of February. "Most coverage" is necessary because of the staggered billing cycles across households. *p< 0.1, **p< 0.05, ***p< 0.01.

Table A.5: Varying Fixed Effects

	(1) Central air b/se	(2) Central air b/se	(3) Central air b/se
Anomaly × 2009	5.2e-5	0.0001***	6.5e-5*
		(0.0003)	(3.4e-5)
Controls	X	X	X
UtilityFE	X	X	X
CityFE		X	
CountyFE			X
N	38581	38581	38581

Note: standard errors clustered at the ZIP-code level. *p< 0.1, **p< 0.05, ***p< 0.01.

B Supplementary Figures

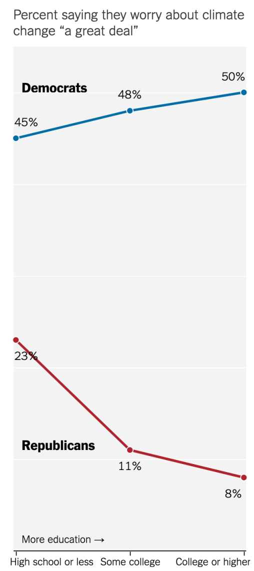

Figure B.1: Age by partisan climate change attitudes

Note: retrieved from:
https://news.gallup.com/poll/182159/college-educated-republicans-skeptical-global-warming.aspx on August 23, 2019.

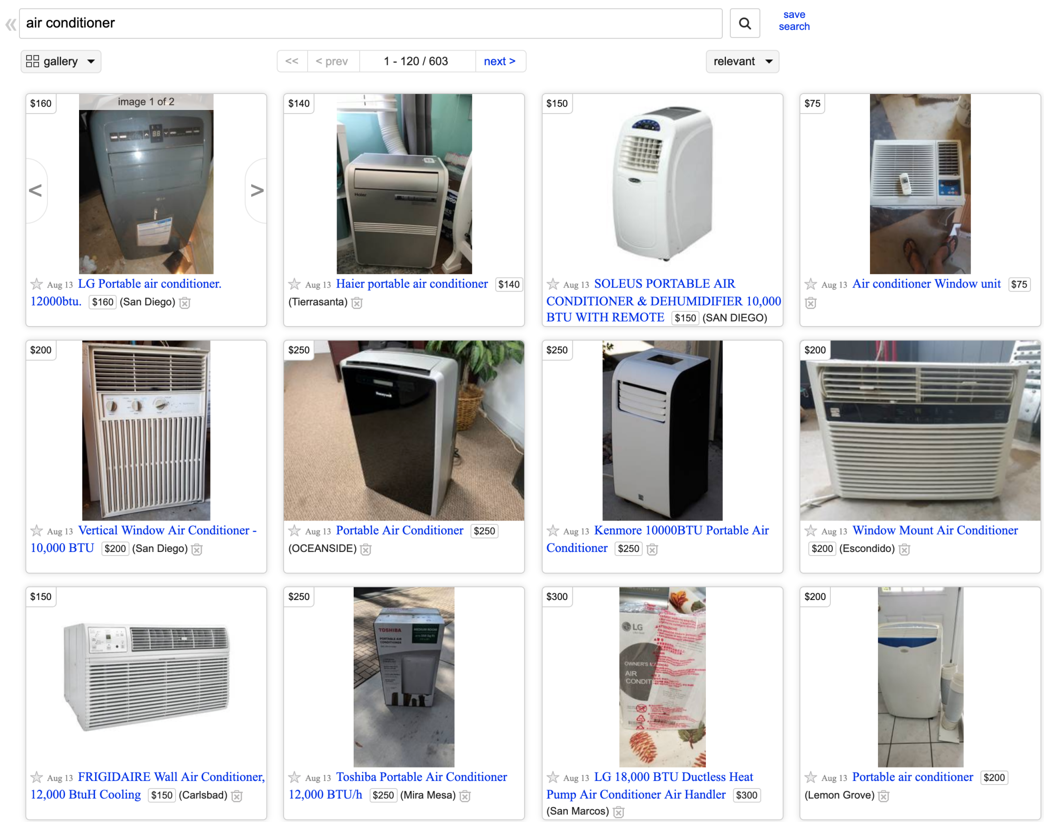

Figure B.2: Secondary market for portable air conditioners

Note: an example of the secondary market for portable air conditioners on an online resale website in San Diego. This displays a screenshot of a popular American classifieds website accessed on August 13, 2019.

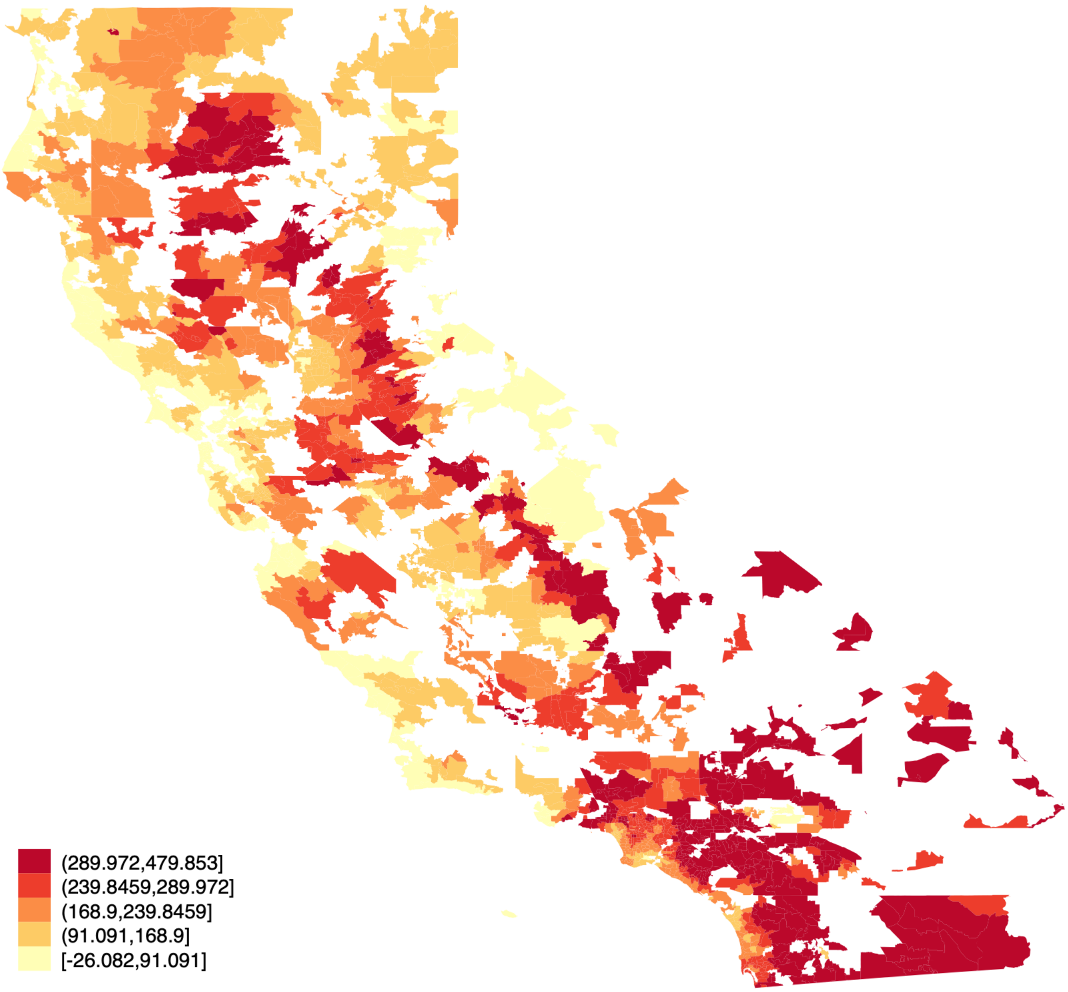

Figure B.3: 2006 CDD anomaly plot

Note: this shows the the CDD anomaly for each ZIP code in 2006. Reported ZIP codes are from SDG&E, PG&E, SCE, and LADWP.