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Abstract: Using minute-by-minute data from over 60,000 smart thermostats in households distributed across the United States, we analyze the persistence of energy consumption behaviors in response to external weather shocks. The analysis examines habitual behavior and provides insight into what affects long term change and what triggers the decision to reconsider one's passive choices. Our preferences for indoor temperatures demonstrate habituation to outdoor temperatures. This habituation is asymmetrical between positive and negative changes and non-linear at the extremes. While our indoor temperature preferences habituate to match small outdoor changes, our preferences revert to long term means in response to extreme temperature change. We also find people are more likely to make active choices when outdoor temperature is salient. Finally, we show there is heterogeneity in how preferences respond as a function of social norms, political preferences, and change costs. Results provide guidance on how conservation policies impact energy use–failure to understand the influence of habit on decision making can lead us to over-estimate the impact of short term policy nudges but underestimate the long run impact of small changes. Our results also inform how changing average temperatures and changing cultural attitudes may affect energy conservation behaviors.

Keywords: smart thermostat; energy consumption; habituation

JEL Classification Numbers: C55 D03 Q4.

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1 Introduction

Economics typically presumes that people make active and conscious decisions toward the goal of some utility maximizing outcome. However, many of our daily decisions are made implicitly, following habitual rules. Active choice requires effort and attention, therefore many of our choices are made passively. While this category of habitual consumption includes many aspects of our routine, one particularly good example is the temperature setting on our home thermostats. We tend to not give much thought to the indoor temperature even though Americans spend over $86 billion annually on household heating and cooling, accounting for more than half of the residential energy use in the U.S.[1]

Smart thermostats offer a unique opportunity to understand how consumers make active versus passive choice. Such thermostats have programmable temperature settings to control the heating and cooling in a home. They have become increasingly popular particularly in newer and remodeled homes. Smart thermostats also allow users to use their smartphone to adjust their program settings or to temporarily override the current program. In this paper, we utilize high-frequency (minute-by-minute) data obtained from a smart thermostat company of over 60,000 smart thermostats in households distributed across the United States to study the persistence of habits in consumers' temperature setting behavior. We show that implicitly made decision are a key determinant of home heating and cooling consumption and expenditures.

Our study seeks to ask three questions related to habit formation, 1) is there persistence in consumers' thermostat setting habits; 2) what triggers consumers to make an active choice in indoor temperature settings, rather than to passively continue with an implicit one; and 3) how does the relationship between set points and environment differ between households and how can this heterogeneity be explained by cultural attitudes toward the environment.

Our analysis of habituation provides direct policy implications on how conservation policies impact energy use because most policy analyses rely on static assumptions about de-

[1]Source: U.S. Energy Information Administration (EIA), Residential Energy Consumption Survey.

mand. As a result, they may overestimate the short-term impact of policy interventions to change consumption behavior, but underestimate the long-term impact of small behavior shifts. For example, it may be hard to shift behavior in the short run, but small shifts (such as turning off the lights, or changing light bulbs) may lead to long run changes in habit.

Recent empirical work on habit formation has focused primarily on small scale laboratory based psychology studies. What has remained largely unstudied is the evidence of habit formation in an economic decision made in the field, particularly one that is often made passively. Exceptions include Royer et al. (2015) which find that a short term (one month) behavioral nudge to exercise has minimal effect on long term exercise; Meer (2013) which finds that a sports related shock to alumni donations has lasting effects on donations along the extrinsic margin, and Allcott and Rogers (2014) that find small but lasting energy consumption effects from a nudge involving messages on electricity bills that can persist for years.

Consumer thermostat temperature setting behavior provides a unique empirical testing ground for the study of habit formation for two reasons. The first is that habit models (e.g. Becker and Murphy (1988) and Rozen (2010)) are based on the idea that consumption preferences are serially correlated in response to external shock: the more I consume on one day increases the marginal utility of consumption on the next. Indeed, we expect people will habituate to unexpectedly warmer temperatures on day one and therefore prefer warmer temperatures on day two. However, biological models and evidence suggest the opposite is also possible: people may seek homeostasis (Brager and deDear, 1998). Animals (and humans) exposed to extreme heat seek out cooler environments to compensate, generating negative serially correlated preferences.

The second feature of temperature preferences is that it allows us to test models of active versus passive choice. Bernheim and Rangel (2004) develop a model of how habitual behavior can be triggered by external cues in the environment that shifts consumers between a hot and cold state. More recently, Landry (2013) develops a model of how decision making is costly and develops an endogenous model of when decision points arise for habit-forming goods. Both models emphasize how both environmental cues and the history of past consumption can impact triggers for active choices. We will seek environmental triggers for active choices in temperature settings.

Our empirical findings first confirm that habits create persistence in consumers' home energy consumption behavior as proxied by thermostat settings. Households' indoor temperature settings are highly correlated with their previous settings. We also find that temperature choices respond to external temperature shocks and that the degree of response varies by household, and by cultural awareness. We find evidence for both *habituation*–small increases in outdoor temperatures lead to increases in our preferred indoor set points–but also for mean reversion or *homeostasis*–our immediate response to an extremely warm day is to lower our indoor set points. We find that the *salience* of the weather shock matters. We respond more to extreme temperatures (e.g. in the 99th percentile). In terms of when we make active versus passive choices, we find mixed evidence for the idea of *choice satiation*–the idea that making a choice today satiates my urge to make changes. Instead, we find that people are more likely to make active choices after having already made an active choice, a finding consistent with time inconsistency (e.g. I may change thermostats settings today without accounting for the fact that my preferences may be different tomorrow).

The paper is organized as follows. Section 2 provides a brief background on smart thermostats. Section 3 presents the conceptual framework. Section 4 discusses the data used in the study, followed by a series of descriptive analyses in Section 5. Section 6 outlines the empirical strategy in this study. Section 7 presents the main estimation results and discusses policy implications. Concluding remarks are offered in Section 8.

2 Smart Thermostats

The data consist of minute-by-minute thermostat and external weather readings for over 60,000 households across the country from February 2012 to March 2014, totaling approximately 50 billion observations. Thermostats work based on a set point. When the thermostat is on, it will turn on the air conditioning unit to cool the house until the set point is reached during summer months, or heat the house until the desired set point is reached in winter months. Programmable smart thermostats adjust these set points automatically, allowing users to, for example, raise or lower the set points when people are asleep or away in order to save energy. Units typically have different programs for weekdays and weekends. At any time, if users are unhappy with the temperature, they can either change the program, or override the program temporarily. The override setting will disappear after the specified temperature (under override) is reached.[2] In our data, despite the automatic nature of the smart thermostats once programmed, overrides still occur - the median user overrides once every 9 days.

The smart thermostats in question are Wi-Fi enabled programmable thermostats, capable of either four or seven unique temperature set points per day. The thermostat can be easily programmed via its companion web and mobile applications, which can also be used to make remote adjustments to the thermostat settings when the user is not at home. These thermostats report a significant amount of data related to their operation to their remote management platform (approximately 50,000 data points per thermostat per month).

Past research on smart thermostats and smart electricity metering in general have shown that providing users greater information about their usage tends to reduce demand (Faruqui and Sergici (2010); Dulleck and Kaufmann (2000)). Such programs reduced long run demand by 7% though they had little impact in the short run. Smart thermostats are popular with utility companies as they give utility companies more control for Demand Side Management

[2] Most smart thermostats also have a "hold" setting, where one needs to actively press a corresponding button and can override the programmed settings permanently until the user actively cancels. In our data, "hold" settings are rarely observed so we dropped such observations.

(DSM)-reducing energy usage at times of peak demand-and to help meet federal guidelines.

3 Conceptual Framework

We propose and test a number of competing behavioral hypotheses to guide our discussion about the persistence of habits and the factors that trigger active choices. We then consider the role of heterogeneity in explaining habits that are suggestive for future work.

3.1 Habit Formation

The standard model of rational addiction in Becker and Murphy (1988) has time consistent consumers making consumption decisions over a good characterized by reinforcement - more consumption in the past increases the marginal utility for consumption today - and tolerance - more consumption in the past decreases the absolute utility from consuming today. In other words, given a utility defined over the time path of consumption of an addictive good $c(t)$, the "addictive stock of past consumption" $S(t)$ is increasing in past consumption, and consumption over a non-addictive good $y(t)$, such that $U(t) = u[c(t), S(t), y(t)]$, tolerance is defined as $\frac{\partial u}{\partial S} < 0$, and reinforcement is defined as $\frac{\partial c}{\partial S} > 0$.

Building on Becker-Murphy, Rozen (2010) axiomatizes the class of time consistent linear models of intrinsic habit formation and derives the following representation:

$$U_h(c) = \sum_{t=0}^{\infty} \delta^t u \left(c_t - \sum_{k=1}^{\infty} \lambda_k h_k^{(t)} \right) \tag{1}$$

where $h_k^{(t)}$ represents different histories of consumption, and $\lambda_k \in (0, 1)$ represents the weights of past consumption on the addictive capital stock. In the smart thermostat setting, this implies that current temperature settings reflect past set points. Thus, our first testable hypothesis regarding the persistence of habits is as follows

Hypothesis 1 *Habit Persistence Hypothesis: Today's set point is positively correlated with yesterday's set point.*

When considering deviations of today's set point from yesterday's, the *Habit Persistence Hypothesis* implies that such deviations should be at or close to zero since most households will rely on habitual routines for their indoor temperature settings.

We then seek to uncover the factors that make consumers depart from their persistent habitual routines and seek to test hypotheses that help explain consumers' responses to external weather shocks as well as the underlying heterogeneity. The general predictions on how set points are related to weather shocks can be ambiguous due to the competing forces at work. Specifically, we propose the following two (competing) hypotheses:

Hypothesis 2 *Habituation Hypothesis: Exposure to warmer (cooler) outdoor temperatures will make consumers choose warmer (cooler) indoor temperatures.*

And

Hypothesis 3 *Homeostasis Hypothesis: Exposure to extreme hot (or cold) outdoor temperatures will make consumers change their indoor set point in the opposite direction: i.e. lower (or higher) set points.*

Our analysis, however, departs from the typical models of habit in that most studies of habit focus on positive reinforcement (i.e. habituation with $\lambda_k > 0$). We argue that temperature preferences may also be negatively autocorrelated (i.e. $\lambda_k < 0$), particularly when facing strong weather shocks.[3] Studies on thermal comfort and indoor energy consumption, such as Brager and deDear (1998), document survey evidence that shows that people experience *homeostasis* when it comes to ambient temperature. That is, our *Homeostasis Hypothesis* implies that the body has a preferred internal average temperature, and prolonged exposure

[3] Extreme weather shocks could be in terms of day-to-day changes or levels. And we will explore the implications of each.

to hotter (cooler) outside environments, can increase the desire to seek out cooler (hotter) indoor environments to compensate.

Furthermore, Becker-Murphy and Rozen, like most economic models, presume that an active choice is made once (and only once) for every time period. However, in our data, households do not make active choices regarding their indoor temperatures on a daily basis, and we are thus interested in how external cues (e.g. Bernheim and Rangel 2004) and past consumption affects choice. Conceptually, our notion of habitual choice is inspired by Landry (2013) in which the interval between when we make choices varies endogenously. Making a choice temporarily *satiates* the desire to make more choices, but the longer the waiting interval between the choices, the greater the desire to make more choices increases. However, it is also possible that strong cues can activate more desire to make an active choice. Therefore, in terms of active choices of temperature settings, we have two competing theories:

Hypothesis 4 *Choice Satiation Hypothesis: Consumer's desire to make decisions is subject to choice satiation; the likelihood of active choices on any given day is negatively autocorrelated.*

And

Hypothesis 5 *Cue Salience Hypothesis: Consumers tend to make more active choices when encountering salient external shocks; active choices should be positively autocorrelated if cues are positively autocorrelated.*

In the simplest version of the framework, people have finite attention. Making an active choice has significant transaction costs, e.g. Peffer et al. (2011) find that a big determinant of how smart thermostats are used depends on the ease of use of the design. Therefore, changes in thermostat settings are only made when the benefits outweigh the costs of the choice. The benefits to making a choice increase as the capital stock of habit accumulates. If making a choice today temporarily satiates the desire to make future choices, then we would expect an active choice today to decrease the likelihood of active choices in the near future, which generates the *Choice Satiation Hypothesis*.

On the other hand, both the Landry (2013) and the Bernheim and Rangel (2004) models allow for cues to trigger choices as well. Therefore, we will look for whether a model choice based on cues serves as a better fit for the data. Outside temperature will be the primary cue of interest, but the *salience* of the cue will be of particular importance (e.g. Mullainathan 2002).

Another potential reason the data may reject *Choice Satiation* could be due to time inconsistency. When users of a smart thermostat make changes, they can either temporarily override their settings or make change that persist into the future. One relevant form of time inconsistency is projection-bias (Loewenstein et al., 2003) where people assume their set point preferences on an unusually warm day should apply to all future days as well. If people insufficiently appreciate that their preferences today will differ from their preferences in the future, then an active today may lead to more active choice tomorrow.

3.2 Heterogeneity

While heterogeneity can arise from many sources, we are focused on two types of household-specific heterogeneity: heterogeneity due to differences in the cost of adjusting thermostat settings and heterogeneity in cultural attitudes.[4] The former can be inferred from households' frequency of thermostat change while the latter can be proxied by monthly and state variation in Google search frequency for topics related to the environment.

In order to compare household-level heterogeneity with geographic level heterogeneity, we first ask whether one type of heterogeneity dominates the other. As a back of the envelope exercise, we formulate a simple linear probability model that estimates the probability that the target indoor temperature today changes from yesterday's and test the relative explanatory power of different types of heterogeneity by comparing the R^2s of each specification.

[4]In Appendix B, we also explore additional sources of heterogeneity based on seasonality, time of the day, day of the week, time of the year, departure from the mean temperature, and political affiliations.

The R^2 statistic is admittedly a crude measure, although Gronau (1998) argues that R^2 can be appropriate for linear probability models.

Consider the following specification:

$$C_{it} = \alpha_0 + \theta_1 \cdot \Delta T_{it} \cdot \mathbf{1}(\Delta T_{it} > 0) + \theta_2 \cdot \Delta T_{it} \cdot \mathbf{1}(\Delta T_{it} < 0) + \tau_t + \xi_i + \mu_{it} \tag{2}$$

where C_t is a dichotomous variable that captures whether there are changes in the set point in either direction relative to the day before; T_t represents the outdoor temperature and ΔT_{it} is the change in outdoor temperatures relative to the day before; $\mathbf{1}(\Delta T_{it} > 0)$ and $\mathbf{1}(\Delta T_{it} < 0)$ are indicator functions that decompose the outdoor temperature changes into positive and negative components; τ_t is the day fixed effect, captured by dummies for year, month and day of the week; and ξ_i is the household fixed effects.

We estimate Equation 2 using a linear probability model that captures the household fixed effects and obtain a R^2 of 0.1278.[5] We then estimate a similar specification except we exclude the household fixed effects and rely only on the differences in weather patterns (due to geographic locations) to explain the changes in indoor temperature set points. We obtain a corresponding R^2 is 0.0197. Hence, there is evidence that household fixed effects provide much stronger explanatory power than differences in weather conditions that households face across different geographic locations. We will thus focus on the role of this kind of heterogeneity in explaining set point reactions to weather shocks.[6]

Within the realm of household fixed effects, households can differ in their costs of changing target indoor temperatures as well as their temperature preferences. Hence, we propose the following testable hypotheses regarding the role of each:

Hypothesis 6 *Change Cost Hypothesis: Households with a lower cost of changing thermostat settings will respond more to external weather shocks.*

[5] Detailed estimated coefficients will be presented in the empirical results section.

[6] We also tried other specifications with different controls for weather conditions but the dominance of the household fixed effects in explaining variations in set point changes does not change.

Households with lower cost of changing thermostat settings will tend to pay more attention to their thermostat settings and change the set points more frequently. We would expect these households to respond more to external weather stimuli compared to those with relatively high costs of changing target set points.

On the other hand, if we proxy households' temperature preferences by the cultural attitudes that they have toward topics related to weather and environment, we can then formulate the following hypothesis:

Hypothesis 7 *Awareness Hypothesis: Households living in areas with higher environmental awareness will habituate more while those in higher weather awareness regions will respond more to external weather shocks.*

If a household lives in a region during a month when more people are searching online for terms related to the environment or related to the weather, they are more likely to be aware of the environment or of the weather when they make their set point choices. That awareness may affect how they may make different set point and energy consumption decisions. Awareness about the environment is about weighing the social cost against the private cost of energy consumption decisions, whereas awareness about the weather concerns the role of attention. We thus hypothesize that more attention paid to the weather will make the household respond more to outdoor temperature shocks while more attention to "green" issues will make a household habituate more to the outdoor temperature.

4 Data

The data for this study come from multiple sources. In addition to proprietary minute-by-minute smart thermostat usage data from a major smart thermostat producer in the U.S., we utilize weather data from the National Oceanic and Atmospheric Administration (NOAA) and data from Google Adwords on internet search intensity for keywords related to economy, environment, energy, weather and thermostat in order to capture cultural attitudes around these topics.

4.1 Thermostat Usage Data

The proprietary smart thermostat data provide extremely detailed minute-by-minute panel observations on households' thermostat set points, ambient temperature readings, outdoor temperature readings, and actual utilization of different HVAC modes, such as heating and cooling as well as a combination of different fan modes. We consider a two-year sample period from February 2012 to March 2014. The raw dataset contains more than 50 billion minute-level observations for over 60,000 households across the country. Due to computational burdens, we restrict Statistical Areas (MSA) around the country with population over 500,000 people. We aggregate the minute-by-minute observations to the daily level, resulting in over 25 million daily-level observations. We then perform the following data trimming procedures: 1) we focus on households with only one thermostat in their residences;[7] 2) we drop observations with missing or inconsistent outdoor temperature and set point readings; 3) we drop households with less than 25 observations in the sample period. The thermostat usage data also contain the 5-digit zip codes of households' residences. This allows us to conveniently match the thermostat data with data on external weather shocks as well as data from google search trends in the neighborhood. Our final sample contains approximately 27,000 households and 10.5 million observations.

Table 1 outlines the main descriptive statistics of our assembled dataset. The average daily ambient temperature reading is very close to the average set point temperature, suggesting that the average HVAC units are effective in maintaining the target temperature. The small variations of ambient and target temperatures also imply a relatively stable zone of comfortable indoor temperatures that do not vary a lot with respect to outdoor conditions. We divide the sample based on the four Census Regions and find 35% of the sample

[7] This represents over 80% of all the households in the sample.

lives in the South while the rest of the sample is distributed fairly evenly across the Northeast, Midwest and West. Climate and weather conditions are understandably highly variable across the country, which underscores the importance of distinguishing the heterogeneity due to household preferences from geographic locations. The average daily duration of running heating or cooling units is approximately 100 and 125 minutes (when these units are turned on), respectively, though as suggested by the standard deviations, there are large variations of how and when consumers operate these units.[8]

Table 1: Summary statistics

Variable	**Mean**	**S.D.**
Outdoor temp	58.46	20.43
Ambient temp	71.15	5.73
Set point temp	70.70	7.25
Daily heating duration(minutes)	98.35	183.03
Daily cooling duration(minutes)	123.82	222.52
Daily morning target change freq	1.54	3.32
Daily afternoon target change freq	1.33	3.25
Daily evening target change freq	1.59	3.23
Daily midnight target change freq	1.13	3.27
Daily precipitation ($\frac{1}{10}$th of mm)	24.61	82.18
Daily snowfall (mm)	1.91	15.56
Daily snow depth (mm)	9.59	46.95
Forecast outdoor temp	55.69	18.99
Northeast	0.18	0.39
Midwest	0.22	0.42
West	0.23	0.42
South	0.36	0.48
Program set point change freq	3.97	1.08
Daily user target change freq	5.59	12.30
Days since last override	15.92	23.29
Number of Observations	10,665,178	
Number of Households	26,963	

In addition, since the smart thermostats in this study are programmable, we have information on the programmed operations of thermostat at different times of the day. This

[8]In the regression analyses, we include cooling and heating minutes in order to control for variation in household insulation.

allows us to deduce whether consumers choose to override existing thermostat settings by comparing the actual number of set point changes against the programmed number of set point changes. Table 1 suggests that a household in the sample would on average override its thermostat setting approximately every two weeks, and an average household changes the thermostat set points more frequently than the programmed changes. This suggests that consumers may not always have the patience to wait for the programmed adjustments from the smart thermostats, and will choose to adjust the temperature set points themselves if the room temperatures are not ideal. Unsurprisingly, thermostat users tend to be at home when making set point adjustments - we note in Table 1 that mornings and evenings see higher frequencies of changes in thermostat settings, implying that the majority of the overriding takes place during the hours when consumers are presumably at home.[9]

4.2 Weather and Google Adwords Data

The weather data from NOAA contains daily precipitation, snowfall and snow depths from the airport weather station closest to the MSA of interest.[10] The data are then matched to the thermostat usage data by the MSA of residence. As expected, the weather data contain large variations as suggested in Table 1.

Besides the heterogeneity due to differences in the cost of adjusting optimal indoor temperatures, another dimension of heterogeneity we explore stems from consumers' different cultural attitudes toward topics that may in turn affect their energy consumption decisions. For example, if consumers are more environmentally aware and more "green", then they could be more attentive to their temperature settings compared to those who are less aware, which can result in a different responses to external weather shocks. In our study, we follow the approach of recent studies like Stephens-Davidowitz (2014) which utilize search data

[9] It is also possible that consumers tend to override the programmed temperature settings when their routine work and leisure schedules change, e.g. when one has to unexpectedly come home early from work or stay up late.

[10] Precipitation is measured in tenths of a millimeter while snowfall and snow depths are measured in millimeters. In the case of multiple weather stations in the same MSA, we selected the weather station that is closest to the center of the MSA.

from Google as a measure for (aggregate) cultural attitudes. Stephens-Davidowitz (2014) argues that keyword searches, at least at aggregate levels, reveal what different people truly care about.

Google Adwords is an online advertising service that allows advertisers to present their advertisement to internet users based on the keywords previously searched by the users. The Adwords data allows us to track internet search traffic based on specific keywords entered. Unlike Google Trends data, which have recently been heavily utilized in behavioral studies (e.g. Stephens-Davidowitz 2014; Edelman 2012), the Adwords data have the advantage of providing the actual frequency of keyword searches instead of a scaled search intensity index.[11] We then utilize Google Adwords to track inquiries related to the economy, environment and disasters, energy, weather, and thermostat and group monthly inquiry volumes on different topics based on the states where the searches originated.[12]

The Adwords data in our study range from July 2012 to March 2014, covering most of the sample period for our thermostat data. The data are aggregated at the state-month level allowing us to capture variation over time, while controlling for household level fixed effects. We expect environmental awareness and worries about global warming to lead to "greener" energy consumption behavior, e.g. habituate one's indoor temperature settings to outdoor temperatures. On the other hand, awareness of weather can lead to more attention to one's thermostat settings, which in turn may result in larger responses to external weather shocks.

[11] We scale the search frequency by the population of each state.

[12] We use Google Correlate to identify a set of keywords related to a common theme. Google Coorelate identifies keywords that are often searched for together. Keywords related to the economy include "job search", "unemployment", and "economy". Environment related keywords include "pollution", "coral", "BP", "dolphin", "crisis", "oil", "disaster", "environment", "EPA", and "global warming". Keywords related to energy include "solar", "energy", and "electric". Weather keywords include "sunny", "temperature", "heat", "rain", and "forecast". Keywords related to thermostat usage include "Honeywell", "thermometer", "thermostat", and "Nestlabs".

5 Descriptive Statistics

We begin by providing some descriptive statistics to demonstrate the habitual persistence in how people set target temperature and to gain intuition about the heterogeneous responses to weather shocks. Our main results from multivariate analysis follow in Section 7.

5.1 Persistence of Temperature Settings

We examine the persistence in thermostat setting habits via two channels. The first channel is through intertemporal changes in set points. If behaviors are habitual and active choice is costly, then the household will rely on the indoor temperature setting from the previous day. Figure 1 plots the distribution of intertemporal set point changes, i.e. the difference between today's and yesterday's set points, with an incremental interval of 0.1 degree. Most of the intertemporal set point changes are within one degree from yesterday, with close to 50% of the distribution at or within 0.1 degree neighborhood from zero.[13] Today's set point closely resembles yesterday's set point, implying persistent habits in setting indoor temperatures.

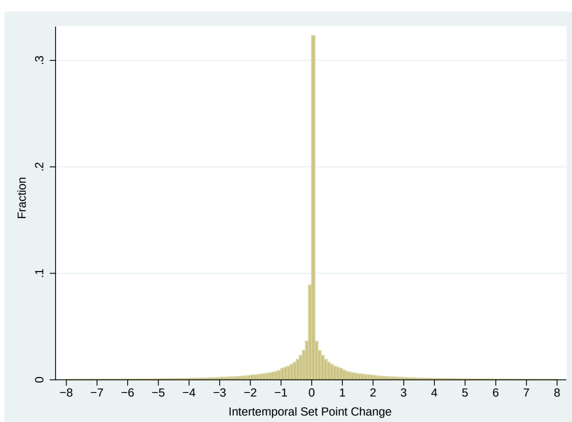
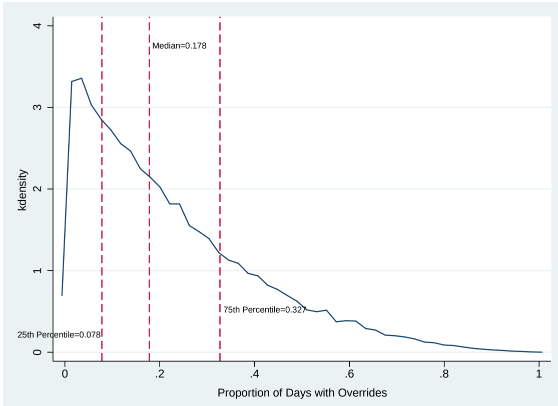


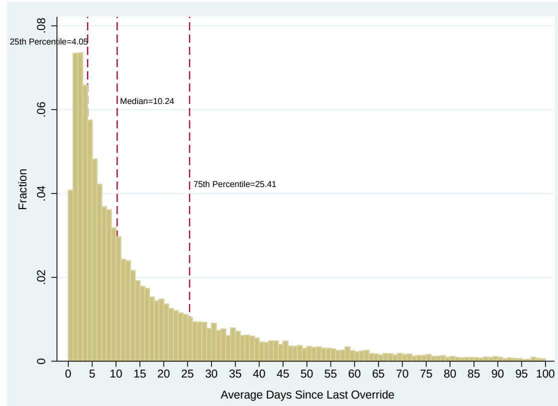
Figure 1: Distribution of Intertemporal Set Point Changes

Next, we consider the pattern of active choices made by households by plotting the frequency of manual overrides of set point settings. Panel (a) of Figure 2 plots the distribution

[13]We also experimented with separating distributions by summer and winter seasons, but the overall distribution did not change.



(a)



(b)

Figure 2: Distributions of Override Status

Note: Panel (a) plots the distribution of the proportion of sample days with overrides per household. Panel (b) plots the interval between overrides and presents the distribution of the average number of days since the last override (by households).

of the proportion of sample days with overrides per household, effectively this is the distribution of the average probability of override. The distribution is clearly skewed to the right with the 25th percentile, median and 75 percentile of probability of overriding being approximately 8%, 18% and 33%, respectively. Panel (b) of Figure 2 plots the interval between overrides and presents the distribution of the average number of days since the last override (by households). We observe a similar distribution where the median override interval for most households is over ten days. In our heterogeneity analysis we will compare the set point response of households who make frequent overrides with those who do not.

5.2 Responses to Weather Shocks

Figure 3 plots the average daily outdoor temperature along with the average daily thermostat target temperature (set point). From the plot we can see that they are correlated, lending support for the *Habituation Hypothesis*. Table 2 shows the probability of override and the average magnitude of the set point change in response to outdoor temperature. For example, the first row shows how people respond when the outdoor temperature is hotter than 99 percent of other days for a given MSA in a given year. The table shows override probability and magnitude of change increases as the outdoor temperature becomes more extreme (either extremely cold or extremely hot) supporting the *Choice Salience Hypothesis*. The table also suggests an asymmetry between the hottest days and the coldest days suggesting evidence for *Homeostasis*. We will formally test the asymmetric response using an event study described in Section 6.2.

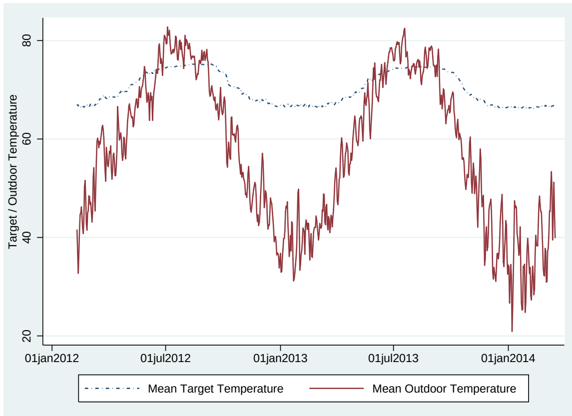


Figure 3: Average Outdoor Temperature vs. Average Set Point

Table 2: Responses to Weather Shocks

	Prob. of Override	**ΔSet Point | Override**
99th percentile temperature	0.273	-0.059
(hottest)	(0.306)	(1.233)
90th percentile temperature	0.252	0.016
	(0.225)	(0.617)
75th percentile temperature	0.246	0.014
	(0.215)	(0.464)
25th percentile temperature	0.269	-0.057
	(0.229)	(0.586)
10th percentile temperature	0.291	-0.076
	(0.249)	(0.687)
1st percentile temperature	0.322	-0.148
(coldest)	(0.319)	(1.589)

Prob. of Override is the probability of overriding. Δ*Set Point* | *Override* is the average intertemporal set point difference conditional on overriding.

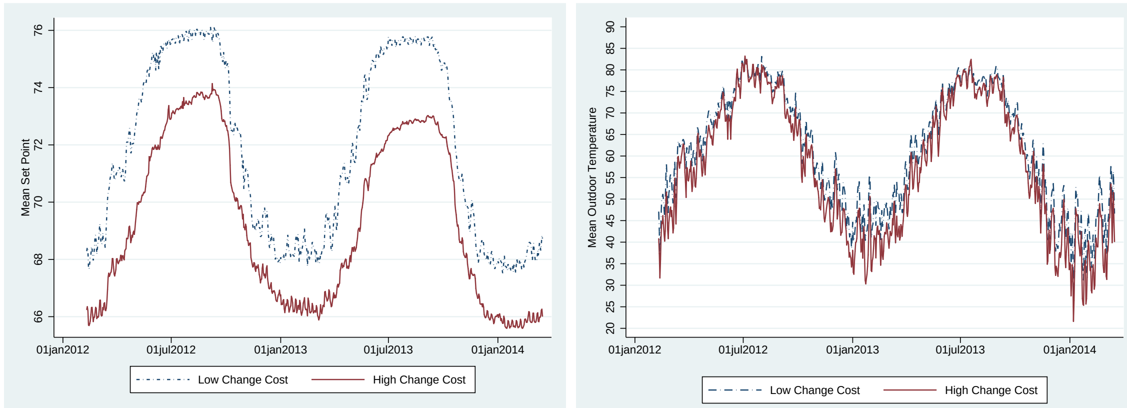
The fact that temperature settings respond to temperature could be driven by more traditional market mechanisms such as price which also responds to temperatures. On the other hand, for most households, prices change infrequently and most households are largely unaware of recent price changes. Therefore it is unlikely that prices are driving the observed behavior. More formal regression analysis and the use of energy prices as controls (both for electricity but also for gasoline which is more salient) support the idea that prices have little explanatory power over high frequency shifts in behavior.[14]

5.3 Heterogeneity

The two types of heterogeneity we focus on is the household level variation in the transaction costs associated with changing indoor temperatures and the variation due to monthly state level changes in cultural awareness. To study the former, we divide households based on their percentile ranking in the distribution of the average number of days since the last override.[15] We classify a household with an override interval of three days or less (approximately the 25th percentile or below in the distribution) as a "low change cost" household while households with an override interval of 20 days or more (approximately the 75th percentile or above in the distribution) we classify as a "high change cost" household, under the assumption that a higher overriding frequency implies a lower cost of changing set points. Panels (a) and (b) of Figure 4 plot the average set points and outdoor temperatures, respectively, based on the heterogeneity in the propensity to override temperature settings. The figures suggest that while the two groups experience identical outdoor temperature patterns, they have noticeable difference in set point patterns - the low cost households have a higher average set point than the high cost households year around. The empirical section will investigate formally how response to external weather shocks differs between households with different implied transaction costs.

[14]It is possible that households are sensitive to *cost* minimization even if they are not sensitive to prices. We explore this possible channel in the appendix by testing household set point decisions against a 7 day moving average of outdoor temperatures.

[15]Alternatively, we can divide households based on the estimated household fixed effects after controlling for weather as it is possible that one could live in an area that encourages more or fewer changes in set points, however, this alternative method yields largely the same results as the variation in outdoor weather explains fair less of the variance than individual household fixed effects as shown in Section 3.2



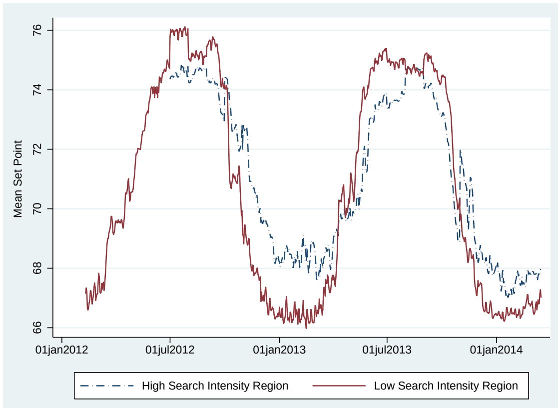
(a) (b)

Figure 4: Heterogeneity Due to Change Costs

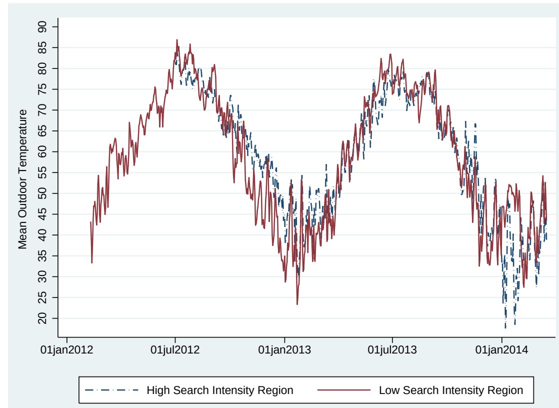
Note: Panels (a) and (b) plot the average set points and outdoor temperatures, respectively, based on the heterogeneity in the propensity to override temperature settings.

We also consider heterogeneity of household preferences due to shifts in cultural attitudes as measured by the monthly state level keyword Google search intensity on topics related to weather and environment. Search intensity varies over time allowing us to separate identify cultural attitudes from geographic fixed effects in our regression analyses. However, even by just looking at geographic differences, we see a pattern for how search intensity might matter. Panels (a) and (b) of Figure 5 plot the set point responses and outdoor temperatures, respectively, for states with the highest search intensity and states with the lowest search intensity. The patterns clearly suggest that while households in respective groups share similar average outdoor temperatures, households in high search intensity regions (i.e. more sensitive to weather patterns) show less habituation (compared to those living in low search intensity regions) as they set higher target temperatures in the winter and lower set points in the summer. Households living in high search intensity regions tend to pay more attention to weather and could thus be more sensitive to changes in outdoor conditions which leads to less habituation. Such patterns support the *Awareness Hypothesis*.

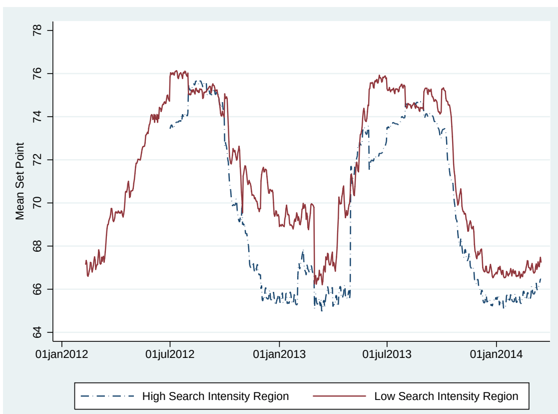
Panel (c) and (d) of Figure 5 explore the role of cultural attitude toward the environment and plot the set point responses and outdoor temperatures, respectively, based on the search intensity of environment related topics from the relevant states. Again, while households



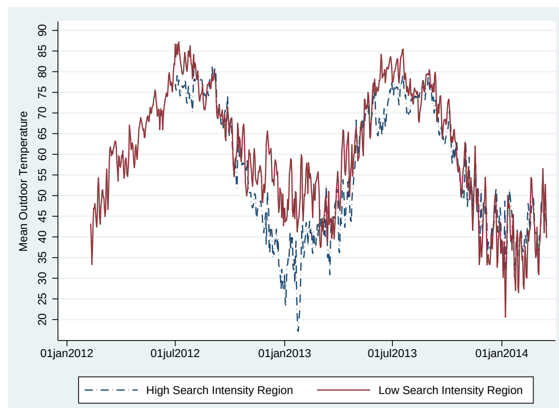
(a)



(b)



(c)



(d)

Figure 5: Heterogeneity Due to Cultural Awareness

Note: Panels (a) and (b) plot the set point responses and outdoor temperatures, respectively, for states with the highest search intensity for weather related terms and states with the lowest search intensity. Panel (c) and (d) plot the set point responses and outdoor temperatures, respectively, based on the search intensity of environment related terms.

in each respective group experiences similar average outdoor temperatures, their set point patterns differ, with more environmentally aware households (households from high search intensity states) setting a lower thermostat temperature, particularly in the winter months. We will further investigate both types of cultural attitudes in the empirical analysis.

6 Empirical Strategy

The descriptive statistics provides strong evidence that set point choices are persistent over time.[16] To look at responses to external shocks, we estimate consumers' short run thermostat usage patterns as a response to external weather shocks and how they depend on underlying heterogeneity due to variation across households and shifts in culture attitudes. We finally conduct an event study of household responses to extreme and unexpected weather shocks.

6.1 Fixed Effects and Linear Probability Models

Our main regression model estimates the frequency consumers adjust set point temperatures and the magnitude of such adjustments in response to external weather patterns. For household i, the changes of the average outdoor temperature from the previous day is given by

$$\Delta T_t = T_t - T_{t-1}$$

where T_t represents outdoor temperature.

Similarly, the dependent variable of interest is the day-to-day change in the average set point given by

$$\Delta S_t = S_t - S_{t-1}$$

where S_t is the set point temperature on day t.

We then estimate the following baseline model with household specific fixed effects:

$$\Delta S_{it} = \alpha_0 + \theta_1 \cdot ||\Delta T_{it}|| \cdot \mathbf{1}(\Delta T_{it} > 0) + \theta_2 \cdot ||\Delta T_{it}|| \cdot \mathbf{1}(\Delta T_{it} < 0) + \tau_t + \xi_i + \mu_{it} \tag{3}$$

[16] In Appendix A, we consider alternative empirical specifications based on dynamic panel models to further study the persistence of habits.

where $\mathbf{1}(\Delta T_{it} > 0)$ is an indicator function that equals to 1 if $T_t - T_{t-1} > 0$. Essentially, we decompose the outdoor temperature change into positive and negative components to address the potential asymmetric responses to temperature increases and decreases in different seasons. If consumers respond to weather shocks symmetrically, then we will expect $|\theta_1| = |\theta_2|$.[17]

We also augment Equation 3 with controls for other weather events and estimate the following full model

$$\begin{aligned} \Delta S_{it} = \alpha_0 + \theta_1 \cdot \Delta T_{it} \cdot \mathbf{1}(\Delta T_{it} > 0) + \theta_2 \cdot \Delta T_{it} \cdot \mathbf{1}(\Delta T_{it} < 0) \\ + \lambda_1 Z_{i,t} + \lambda_2 Z_{i,t-1} + \tau_t + \xi_i + \mu_{it} \end{aligned} \tag{4}$$

where Z_{it} is a vector of other external weather events faced by household i, including precipitation, snowfall and distributions and patterns of extreme day-to-day temperature changes such as dummies for temperature changes being within the highest and lowest 1st percentile, 10th percentile and 25th percentile for the region in a given year. We also control for the number of minutes the HVAC unit was active from the previous day in order to address variations in house insulation.

The other main dependent variable we study is a dichotomous variable, C_{it}, that captures whether the household made a change in the set point relative to the day before and is given

[17] On the other hand, such response may also be reference-dependent, e.g. the response to a two-degree increase from 65 degrees can differ from that to a two-degree increase from 32 degrees. Following Deschenes and Greenstone (2011), we set 65 degrees Fahrenheit as the reference point for the outdoor temperature to capture possible reference-dependent responses to outdoor temperature shocks. The temperature 65 degrees Fahrenheit or 18 degrees Celsius is the typical threshold used to calculate a degree day, a unit used to determine building energy consumption. We introduce interaction terms that capture increases or decreases of outdoor temperatures relative to 65 degrees and estimate the following model:

$$\begin{aligned} \Delta S_{it} = \alpha_0 &+ \theta_1 \cdot \Delta T_{it} \cdot \mathbf{1}(\Delta T_{it} > 0) + \theta_2 \cdot \Delta T_{it} \cdot \mathbf{1}(\Delta T_{it} < 0) \\ &+ \phi_1 \cdot \Delta T_{it} \cdot (65 - T_{it}) \cdot \mathbf{1}(\Delta T_{it} > 0) + \phi_2 \cdot (65 - T_{it}) \cdot \Delta T_{it} \cdot \mathbf{1}(\Delta T_{it} < 0) \\ &+ \tau_t + \xi_i + \mu_{it} \end{aligned}$$

In this equation, coefficients ϕ_1 and ϕ_2, would tell us whether changes in outdoor temperature depend on 65 degrees as a reference. Our estimates (available upon request) do not show any dependence on a 65 degree reference point.

by

$$C_{it} = \mathbf{1}(\Delta S_{it} > 0; \Delta S_{it} < 0).$$

We have shown the importance of household fixed effects in Section 3.2. Nonlinear models, such as probit and logit, do not perform with the presence of fixed effects. The Chamberlain conditional random effects logit model also does not apply well in our context because it is reasonable to assume that variations in weather shocks can be correlated with location. Thus, despite its limitations, our main specification employs a linear probability model of C_{it} with household fixed effects.

To study households' override decisions, we adopt a model similar to Equation 4 but with the dummy for set point override as the dependent variable. Finally, we consider temporal and spatial variations of energy usage by separating the above specification by summer (May to September) and winter (November to March) seasons and consider heterogeneity in culture attitudes as measured by keyword search intensity.[18]

6.2 Event Study

Since not all households respond to temperature shocks on a regular basis, we follow the main analysis with an event study (as in Jacobson et al. (1993)) to consider households responses when facing the most extreme weather events. An event study also allows us to examine the temporal response to exogenous weather events. The extreme weather conditions include the days with the largest snowstorms in a given winter as well as the highest and lowest one percentile of the observed outdoor temperature for an MSA in a given year.

[18]In Appendix B, we utilize the same empirical specifications and explore additional sources of heterogeneity based on seasonality, time of the day, day of the week, time of the year, departure from the mean temperature, and political affiliations.

In particular, we estimate the following equation with household fixed effects:

$$S_{it} = \beta_0 + \xi_i + \tau_t + \mathbf{X}_{it}{}'\eta_1 + \sum_{k=-14}^{14} \vartheta_k I_{i,t-k} + \epsilon_{it} \quad (5)$$

where S_{it} is a household's (average) set point decision at time t; ξ_i and τ_t denote the household and time fixed effects, respectively; $\mathbf{X}_{it}$ is a vector of covariates that control for current weather conditions: outdoor temperature, precipitation, snowfall and snow depth (where applicable); $I_{i,t-k}$ is a set of event time dummies that take a value of 1 if the household is at day $t - k$ from the event and 0 otherwise. The key set of parameters, ϑ_k, captures the temporal effect of unexpected weather events.

7 Results and Discussion

7.1 Responses to Outdoor Temperature Shocks

7.1.1 Set Point Responses

We first consider household set point responses by decomposing the outdoor temperatures into positive and negative changes. The dependent variables include 1) a dichotomous variable that measures whether there is a change (positive or negative) in set points; and 2) the actual set point change compared to the day before. Panel (a) of Table 3 presents the baseline results. Columns (1) and (2) present the estimates from the linear probability model (with household fixed effects) on the set point change dummy. The results suggest that positive and negative day-to-day changes in outdoor temperatures will both increase the probability of changing set points in both winter and summer. For instance, every 10 degree increase in outdoor temperature in the summer months will lead to a 0.68 percentage point higher likelihood of changes in set points compared to the day before. We also find evidence for asymmetry. Columns (2) and (4) estimate the magnitude of set point changes using a household fixed effects model. *Decreases* in outdoor temperature are the main driver of set point change in winter while *increases* in outdoor temperature are the main driver for summer months. Overall, set point changes are positively correlated with changes in outdoor temperatures in both summer and winter months, suggesting *Habituation* (i.e. exposure to warmer outdoor temperatures will make consumers choose warmer indoor temperatures).[19]

The small magnitudes of the coefficients suggest that most consumers passively accept the setting as it was on the day before. However, while effects are small on any given day, cumulatively they become more meaningful. A 0.68% chance of adjusting the set point on any given day implies a 20% chance of adjusting in any given month. Temperature is not particularly salient on most days. Therefore, we proceed to examine whether households respond more to particularly salient (or extreme) weather changes.

Panel (b) of Table 3 considers the effect of extreme variations of day-to-day temperature changes, using a similar specifications as in Panel (a) but regressed on a set of indicator variables denoting the extremeness of weather that day. Columns 1 and 3 consider the probability of set point changes. Consistent across both winter and summer months, the more extreme a temperature change that one faces, the more likely we are to observe adjustments in set points. For example, in the summer months, if today's temperature relative to yesterday's is among the hottest 3 days of the year (i.e. top one percentile temperature in the MSA in a given year), then on average a household is 0.72 percentage points more likely to adjust its set points compared to the baseline.[20] In Column 2, we find that for day-to-day temperature changes in the top 90th percentile, people raise their set point by 0.022 degree, again supporting *habituation*. We observe a similar pattern for extreme cold changes in Column 4. Outdoor temperature changes in the coldest extremes cause one to lower indoor temperatures. This is consistent with how people may respond to small incremental changes

[19]Note the coefficient on the variable "$||\Delta T||$" corresponds to the magnitude of set point change. Thus, in summer months, decreases in negative outdoor temperature changes will lead a 0.00138 degree increase in set point. Although the sign of the coefficient goes against our habituation hypothesis, it size is an order of magnitude smaller than the other variables in the regression model, and of negligible size compared to the main habituation finding.

[20]We add up the current day coefficients on 99th percentile, 90th percentile and 75th percentile dummies since a 99th percentile hottest day-to-day change is also included in the 75th percentile based on our coding.

in outdoor temperatures as seen in Panel (a). Finally, the fact that extreme temperature changes yield increasingly larger and more frequent changes supports the *Choice Salience Hypothesis*.

It is worth noting that since most households do not make day-to-day changes the effect size conditional that a set point change made is noticeably larger. Also whether a consumer's response to extreme temperature *changes* is the same as their respond to extreme temperature *levels* may differ. To address these concerns, in Section 7.1.3, we will estimate our model conditionalal on making an active set point choice (i.e. overriding their temperature settings) during the most extreme weather days (hottest or coldest days of the year) and investigate how their response evolves over time using an event study approach.

7.1.2 Overriding Decisions

Another related empirical exercise we conduct is regarding when and why consumers decide to use the override feature to initiate a temporary override of the existing thermostat temperature settings. Overrides are active but temporary; they will be replaced by the original program once the desired temperature has been reached. We use the same fixed effects model as in the set point analysis but employ a dichotomous dependent variable "*override*" that is equal to 1 if the household overrides the thermostat settings. We also include a variable to capture the number of days since the last override. We consider two specifications, each separated for summer and winter, involving different combinations of outdoor weather patterns, and document the results in Table 4.

In each specification, the coefficient on the number of days since the last override is negative. In other words, the more days that have passed since the consumer last made an active choice, the less likely it is for her to make another one. The idea of *Choice Satiation* is that choices are costly, so immediately after an adjustment is made, the desire to re-adjust should be immediately reduced. We find the opposite, suggesting that it is likely that in addition to persistent habits, the salience of making an adjustment makes one want to make an adjustment again.

Positive temperature changes in the summer and negative changes in the winter both increase the likelihood of making an active adjustment. These results are consistent with those presented in the previous section, where set points are mostly influenced by positive day-to-day temperature changes in the summer and negative changes in the winter. In other words, when it feels less comfortable outside, one responds by making an active choice to habituate (via overriding the existing set point settings). Curiously, when facing extreme temperature changes, consumers are less likely to override when they face more extreme temperatures. Specifically, the most extreme temperature change in the summer (hottest one percentile) will make a household approximately 3 percentage points less likely to override while the coldest day-to-day changes in the winter will make one over 2 percentage points less likely to override, further supporting *habituation*. Given that the average probability of overriding for a household in the sample is about 20% (median 18%), the average estimated impact of the extreme weather on overriding is in fact quite significant. This is contrary to what we saw from Table 3 where extreme temperatures induce more frequent permanent program changes, suggesting that people may overreact to extreme weather events (Loewenstein et al., 2003).

Overall, it appears that consumers habituate to both winter and summer temperatures. In both seasons, when setting long term set points, choices are positively correlated with small and extreme outdoor temperature changes.

7.1.3 Event Study of Responses to Extreme Weathers

Here we present results of the event study as specified in Section 6.2 focusing on the subset of households that appear in the entire event window for a particular MSA and who overrode thermostat settings during the weather events of interest.[21] Panels (a) and (b) of Figure 6 plot the estimated event time coefficients, a week before and four weeks after the

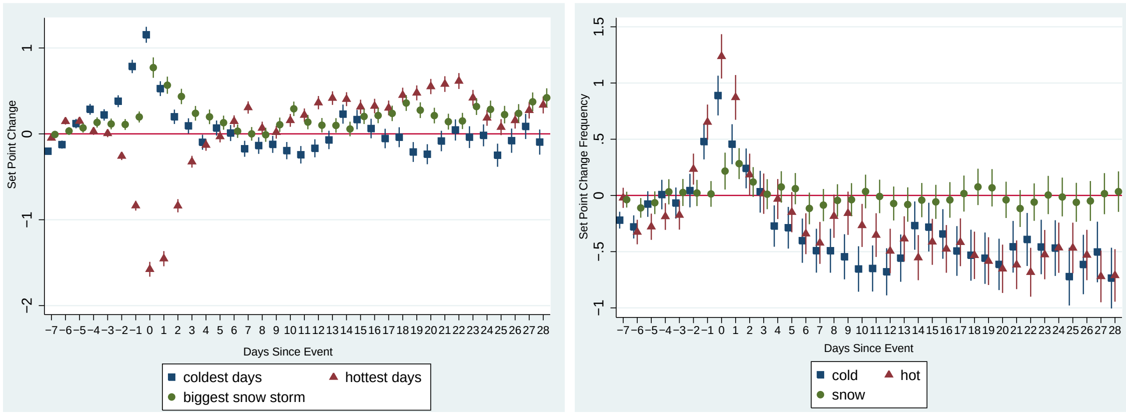
[21]This results in approximately 8,000 households.

event of interest, in terms of set point levels and set point change frequencies, respectively. These estimated coefficients represent the consumers' responses to extreme weather events, where the extreme weather events of interest include the coldest one percentile outdoor temperature, hottest one percentile outdoor temperature, and largest snow storm of the year. The event study results show that households do respond slightly in advance of the event (likely due to forecasts).[22] More importantly, we find strong evidence toward *homeostasis* and *cue salience* when facing extreme temperature related shocks - consumers significantly increase (in winter) and decrease (in summer) set points on the event day. The effect persists before fading away after three days following the event. When facing snow storms, we observe a similar pattern except households tend to maintain the higher set point for several more days after the event. Note that the magnitudes of the findings are larger than the average effects we find earlier, since here we are finding the average effect conditional on those who made an active choice.

What is also notable is that extreme events have a second order impact on set points that persist a month later. Just as people respond to hot temperatures outside with cooler temperatures within. Weeks later, people respond to cooler indoor temperatures with warmer set points three weeks later as they respond homeostatically to a preferred internal setpoint. The effect is more pronounced in response to hot days (F-test = 36.13, p-value < 0.001) peaking 23 days after the event, but can be observed in response to the coldest days as well, where the immediate response of warmer indoor set points is counteracted by cooler indoor set points several weeks later (F-test = 34.48, p-value < 0.001).

These findings are echoed by corresponding patterns in set point change frequencies as shown in Panel (b). However, here we see some evidence for the *choice satiation* hypothesis. While snow fall does not seem to have any lasting response, we see set point adjustments decline for a full month after an extreme hot or extreme cold event.

[22]We did collect forecast data from NOAA but results were difficult to interpret. It is difficult to know what forecasts people were paying attention to and when.



(a) (b)

Figure 6: Event Study of Responses to Extreme Weathers

Note: Panels (a) and (b) plot the estimated event time coefficients, a week before and four weeks after the event of interest, in terms of set point levels and set point change frequencies, respectively. The dependent variable is the target set point. The plotted coefficients are on days since the extreme weather event of interest, and 95% confidence intervals are presented. Standard errors are clustered at household level. Household and time fixed effects are included. $P < 0.01$ for F-test on the joint significance of the event coefficients.

7.2 Heterogeneity

To explore the mechanisms at play, we analyze heterogeneity by investigating how differences in household transaction costs affect the link between weather patterns and set point choices. We also explore additional sources of heterogeneity due to seasonality, time of the day, day of the week, time of the year, departure from the mean temperature, and political affiliations, and those results are reported in Appendix B.

7.2.1 Propensity of Households to Change Set Points

As discussed in Section 4.1, We divide the households based on their percentile ranking in the distribution of the average number of days since the last temporary override. We classify a change interval of 3 days or less (approximately the 25th percentile or below in the distribution) as "low change cost" and a change interval of 20 days or more (approximately the 75th percentile or above in the distribution) as "high change cost", under the assumption that a higher overriding frequency implies a lower cost of changing set points. We then estimate a linear probability model where the dependent variable is a permanent set point program change indicator as well as a model for size of set point change using the same specifications presented earlier. Table 5 presents the estimated outcomes on the main variables of interest for summer and winter months, respectively. The directions of the estimated coefficients are similar to baseline estimates in Table 3. However, we find strong roles of heterogeneity in terms of change costs - across most specifications, the low cost households respond more to daily temperature changes, in terms of the likelihood of set point changes and the magnitude of the set point changes, suggesting larger *Habituation* responses.[23]

7.2.2 Cultural Attitudes

We further investigate the role of heterogeneity in households' cultural attitudes. Here, we measure cultural attitudes using the monthly frequency that people in that state searched for certain keywords under the topics potentially related to thermostat usage, e.g. economy, weather, energy, thermostat, and environment (see Section 4.2 for more details on how these keywords were selected). Among the keywords, we are particularly interested in search intensity related to weather and environment.

Table 6 Panel (a) describes how consumers with different weather awareness (captured by the search intensity of weather related keywords) respond to weather cues. We compare households in months when their state has a high frequency (highest 25th percentile) of weather-related keyword searches against months when their state is less weather aware (lowest 25th percentile). The inclusion of household fixed effects ensure we are only capturing the time varying impacts. We also divide the comparison by seasons.

Consumers with high weather keyword search intensity demonstrate a stronger habituation response in winter months compared to those who living in low search intensity states, though such patterns are not apparent for summer months. The results support the

[23]In a separate specification, we also consider responses to extreme temperature changes based on heterogeneity and find that the low change cost group also demonstrates stronger evidence toward *Cue salience*, where active choices are positively autocorrelated due to the salience of the shocks.

Awareness Hypothesis, where the high search intensity group on weather related keywords is expected to pay more attention and be more responsive to weather patterns. Table 6 Panel (b) describes how households with different degrees of environmental awareness (captured by the search intensity of environment related keywords) respond to weather cues. Here, we do not find support toward *Awareness Hypothesis* as there is no clear pattern that "greener" consumers (with high environmental awareness) habituate more to the outdoor temperatures.

Overall, we find partial support for the imporance of cultural awareness. The results do underscore the importance of distinguishing between different types of heterogeneity when evaluating the impact of external stimuli on set point choice. In the appendix, we outline empirical results for the roles of additional sources of heterogeneity.

7.3 Discussion

Overall, our results support the persistence of habits in consumer's thermostat set point decisions. There is evidence that consumers tend to habituate to daily outdoor temperature variations in both summer and winter. However, when facing extreme weather events (in both summer and winter) that present large stimuli to their temperature comfort decisions, we find that on average households in the opposite direction, toward *homeostasis*. Responses also grow as the shocks becomes more salient. To get a sense of magnitudes of these effects, analysis with a small subset of the data (90 households from California) where we have access to electricity meter readings, tells us that each degree of set point change in summer months (for the entire day) can save as much as 3% or 39Wh of electricity per hour (by comparison the households in this sample used approximately 1300 Wh each hour). Over the course of a year, 39Wh per hour translates into approximately 340kWh. For an average electricity price in Californa of 18 cents/kWh, this works out to approximately $62 per year per household per degree set point change.[24]

[24]Such an estimate is certainly an upper bound as the impact would be largest in summer.

It is important for policymakers to understand how consumers respond to external shocks for decisions that they typically make implicitly and on a routine basis as well as the underlying heterogeneity at play. Recent growth in empirical studies on habit formation seeks to address key questions such as whether consumers form habits over time based on their past decisions, how persistent such habits are, and under what conditions they will alter the habit. For example, Bronnenberg et al. (2012) examine how preferences of migrants in the U.S. toward consumer packaged goods reflect their past experiences. Atkin (2013) finds that the food varieties that migrants in India consume resemble the typical diet of the region from where these migrants were born. And Fujiwara et al. (2016) confirm habit formation affects voting turnouts. Our study contributes to the discussion by considering a routinely made and yet largely ignored decision regarding home energy consumption.

Our findings also have important implications for policy and economic welfare. For example, While largely influenced by persistent habitual routines, consumers' energy consumption decisions do respond to external stimuli, even simply from increased cultural awareness as proxied by Google searches. The demonstrated importance of salience implies that policy campaigns in altering energy consumption decisions can be successful if the stimuli are salient enough. The successful implementation of such energy conservation policies also requires understanding the underlying household heterogeneity because our empirical results suggest that households with differing costs respond quite differently to identical events.

8 Conclusion

In this study, we utilize a proprietary dataset of households' smart thermostat usage to study habit formation in consumers' home energy consumption. We find persistent habits in thermostat setting behavior, where the current setting strongly correlates with past settings. Consumers habituate to small changes in outdoor weather but react in the opposite direction to extreme stimuli. In terms of when we make active versus passive choices, we find evidence against the idea of choice satiation. We are more likely to make active choices after having already made an active choice. Instead our results are more compatible with the importance of salience on choice.

Clearly, more could be done to further disentangle this rich dataset on consumers' thermostat usage. For instance, with the current ongoing discussion regarding big data and machine learning, one avenue would be to take advantage of the minute-by-minute nature of the dataset and explore the time-series patterns of consumers' set point decisions. Also, the pattern of permanent changes and temporary overrides could provide insight into behavioral theories of time inconsistency and projection bias. We leave that for future research. The intent here is to provide a first pass at understanding the patterns of how we make (or do not make) passive consumption decisions, how we develop habit, how we respond to external cues, and the relative importance of factors such as habituation, homeostasis, choice satiation, and salience. Beyond providing a better sense of how such choices are made, we also provide guidance on the impact of government nudges toward lasting solutions to shape household energy use.

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Appendix A: Dynamic Panel Models and Results

Dynamic Panel Specifications

As an alternative empirical strategy to examine the persistence of habits, we additionally estimate daily thermostat set points as a function of a series of past set point choices and past temperature cues. Specifically, we estimate the current thermostat set points as a function of lagged thermostat set points, current and lagged outdoor temperatures, day fixed effects, and household specific fixed effects. To fix ideas, we have the following baseline specification for household i on day t with a one-period lag on set points and outdoor temperatures:

$$S_{it} = \beta_1 + \delta_1 S_{i,t-1} + \gamma_1 T_{i,t} + \gamma_2 T_{i,t-1} + \tau_t + \xi_i + \varepsilon_{it} \tag{6}$$

where S_{it} is a household's (daily average) set point decision on day t; $T_{i,t}$ is the daily average outdoor temperature on day t; τ_t is the day fixed effect, captured by dummies for year, month and day of the week; ξ_i is the household fixed effect.

Intuitively, given the persistence of habits and indoor temperature being an often implicit choice, there are reasons to believe that set points yesterday would influence the set point decision today. However, econometrically, adding a lagged dependent variable to the list of independent variables brings in a series of complications when estimating panel data. Nickell (1981) shows that the demeaning process in fixed effect estimation can potentially lead to biased estimators in dynamic panel data (DPD) as the demeaned error may still be correlated with the regressors. Since the inconsistency of the estimator is of order $1/T$ in asymptotic theory, the bias can be especially acute in a "small T, large N" context, and a typical practical solution in the literature is to resort to dynamic panel techniques such as the Arellano-Bond (AB) GMM style estimator in order to obtain a consistent estimator.

On the other hand, because of the high frequency nature of the our dataset, we are effectively facing the "large T, large N" problem in our short run (daily) analysis ($T = 767$)

and employing an Arellano-Bond estimator would be computationally infeasible since it would create an enormous set of lagged variable-based instruments. Blundell and Bond (1998) show that in the context of dynamic panel, OLS estimates tend to overestimate and fixed effects tend to underestimate while consistent estimates (such as the AB-style estimates) should be between OLS and fixed effects estimates. Judson and Owen (1999) suggest that OLS is a good choice when T is large. Since the asymptotic bias of the estimator is approximately $-(1+\beta)/(T-1)$, with $T = 767$ in our sample and an assumed approximate $|\beta| < 1$, the magnitude of the bias will be less than 0.3%.[25] Therefore, given that the purpose of this study is to provide first evidence toward and discuss policy implications of the responsiveness of consumer energy usage behavior to various stimuli, we estimate fixed effect models to provide intuition for our short run analysis. The Wooldridge test for autocorrelation in panel data reveals a strong indication of serial correlation ($p < 0.0001$). With large T and N in the short run analysis, we can however cluster standard errors at zip code level to ensure standard errors to be robust to serial correlations and heteroskedasticity particularly since non-stationarity is rejected by the panel unit-root test ($p < 0.0001$).

Therefore, in addition to our baseline model, we estimate a specification with lags of the dependent variable as regressors, as well as multiple lags of independent variables to further explore short run patterns of changes in set points. We also augment the model with controls for other weather related events, such as precipitation, snowfall, and snow, which we denote as vector Z_{it}. For computational purposes, we limit our attention to three lags of independent variables. A general specification for household i on day t would take the following form:

$$S_{it} = \beta_0 + \sum_{k=1}^{3} \delta_k S_{i,t-k} + \sum_{k=0}^{3} \gamma_k T_{i,t-k} + \sum_{k=0}^{3} \lambda_k Z_{i,t-k} + \tau_t + \xi_i + \varepsilon_{it} \tag{7}$$

Our data also allow us to ask what is the long run persistence of habit. Therefore in

[25]In fact, when we compare estimates between OLS and fixed effects estimates for various specifications in our short run study, we find the gap between the estimates to be less than 0.2%

addition to our baseline model which is estimated at the daily level, we estimate a panel model where each observation represents one month. Because the long run model has the potential "small T" problem, we provide estimated results using an Arellano-Bond GMM style estimator.

Dynamic Panel Results

To study the persistence of habits in thermostat setting behavior, we adopt the general fixed effects estimation strategy with clustered standard errors and include a three-period lag for past set points, outdoor temperatures and weather conditions, including precipitation, snowfall and snow depth. For each specification, the dependent variable is the average daily set point on a given day. Similar to the analyses in the main text, we run separate regressions for summer and winter months.

Table 7 presents the results from the fixed effects model. The set point today is unsurprisingly positively correlated with yesterday's set point decision, and the correlation quickly erodes past yesterday. The patterns are consistent between summer and winter and across specifications. The results confirm the persistence of habits in set point choices. We also find evidence of habituation based on consumers' set point responses to changes in average outdoor temperatures. Specifically, changes in average outdoor temperatures seem to (marginally) affect the set point choices. The signs on the current and one-period lagged coefficients in both summer and winter months are positive, demonstrating the effect of habituation to small changes in outdoor temperature–when it is warmer outside, one would prefer it to be (slightly) warmer inside. The estimated coefficients on the 2-period and 3-period lagged outdoor temperatures suggest limited partial evidence for *homeostasis*. Table 8 presents the long run (monthly) estimates using Arellano-Bond GMM estimator. The results confirm the persistence of set point habits in the long run but also suggest that responses to outdoor temperatures in the long run are generally driven by those in the current month rather than from the previous months.

On average, a 10-degree increase in daily outdoor temperature effects a net increases in set point choice by approximately 0.15 degrees (if we add the coefficients from today, plus the lagged coefficients), which is admittedly small. On the other hand, such small magnitude of the impact is also intuitive since we consider the average impact of changes in outdoor temperatures on set point changes and due to persistent habits, many households may not respond to small changes in outdoor temperatures. The estimates are also consistent with the general findings in the energy nudge literature, that the effect sizes tend to be small; we are primarily interested in the patterns of impact in order to set the stage to evaluate how consumers respond to potentially larger nudges like television or social media campaigns.

Appendix B: Additional Sources of Heterogeneity

We utilize the empirical specifications described in Section 7.2.2 to explore the following additional sources of heterogeneity and their roles in set point adjustment decisions: 1) weekday vs. weekend; 2) time of the day, i.e. morning (6am to noon) vs. evening hours (6pm to midnight); 3) beginning vs. the ending months of a season; 4) departure from the mean temperatures rather than day-to-day temperature changes; and 5) political affiliations, i.e. Republican vs. Democratic counties. Table 9 reports the findings.

In Panel (a), similar to baseline results, we find that habituation dominates during both weekdays and weekends for both seasons, and households' set point behavior during weekdays does not significantly differ from that during weekends. However, if we further decompose set point decisions based on the time of the day, we notice that there is strong evidence of households preferring *homeostasis* during evening hours in both summer and winter, particularly for weekends. For instance, during a summer weekend, a household would decrease its set point by 0.008 degree for every positive degree increase in outdoor temperature. Such finding is to the contrary of our overall finding of consumers' tendency toward habituation, and it confirms the potential time of day level heterogeneity where evening changes could be more toward comfort as house occupants are more likely to be present during those hours.

In Panel (b), we first separate the set point responses based on whether temperatures are above or below 7-day average. While the estimates are still consistent with *habituation*, and the magnitudes of the responses are slightly larger when temperatures are above average in the summer and below average in the winter. This implies that in addition to behavioral explanations, households' desire to *cost* minimize may also play a role in set point decisions. Interestingly, households exhibit a much stronger habituation response in May, the beginning of the summer season, than in September. Such difference is not as obvious for winter months. In terms of political affiliations (measured by county-level vote share from the 2012 presidential election), we do not find significant differences in set point responses between households living in Democratic counties and those from Republican counties.

Table 3: Impact of Outdoor Temperature

	Summer		Winter	
	(1) Prob. of Change	(2) Set Point	(3) Prob. of Change	(4) Set Point
(a) Baseline Estimates				
$\|\|\Delta T\|\|$ if $\Delta T > 0$	0.00681***	0.0152***	0.00175***	0.000224
	(0.000110)	(0.000702)	(5.89e-05)	(0.000320)
$\|\|\Delta T\|\|$ if $\Delta T < 0$	0.00575***	0.00138***	0.00327***	-0.00886***
	(0.000100)	(0.000520)	(5.70e-05)	(0.000383)
Observations	4,223,270	4,223,270	4,575,183	4,575,183
No. of Households	26,095	26,095	25,050	25,050
Weather Covariates	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
(b) Extreme Temperature Changes				
99th Pctl ΔT	0.0555***	0.00953		
	(0.00412)	(0.0291)		
90th Pctl ΔT	0.0168***	0.0220***		
	(0.00128)	(0.00706)		
75th Pctl ΔT	-0.00169*	0.0203***		
	(0.000873)	(0.00490)		
1st Pctl ΔT			0.0183***	-0.0909***
			(0.00191)	(0.0111)
10th Pctl ΔT			0.00287***	-0.0249***
			(0.000978)	(0.00554)
25th Pctl ΔT			-0.00484***	-0.0326***
			(0.000744)	(0.00423)
Observations	4,223,270	4,223,270	4,575,183	4,575,183
No. of Households	26,095	26,095	25,050	25,050
Weather Covariates	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes

For Columns (1) and (3), the dependent variable is a dummy for whether there is a change in set point temperature, and the specifications are estimated using a linear probability model with household fixed effects. For Columns (2) and (4), the dependent variable is the set point change from the day before, and the specifications are estimated with household fixed effects. *75th Pctl* ΔT is a dummy that equals to 1 if the day-to-day temperature change is above 75th percentile for the location in a given year. Other extreme temperature change variables are defined in a similar way. Weather covariates include precipitation, snowfall and snow depth. Day dummies include dummies for year, month, and day of week. We also control for daily heating and cooling duration for relevant seasons. Robust standard errors shown in parentheses are clustered at zip code level. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Override Decisions and Extreme Temperatures

	(1) Override Summer	(2) Override Winter
Days since last override	-0.00384***	-0.00259***
	(9.38e-05)	(7.46e-05)
$\|\|\Delta T\|\|$ if $\Delta T > 0$	0.00164***	-0.00240***
	(0.000202)	(5.77e-05)
$\|\|\Delta T\|\|$ if $\Delta T < 0$	-0.00149***	0.00332***
	(9.60e-05)	(0.000111)
99th Pctl ΔT	-0.0243***	
	(0.00370)	
90th Pctl ΔT	-0.00455***	
	(0.00125)	
75th Pctl ΔT	0.000539	
	(0.000868)	
1st Pctl ΔT		-0.00991***
		(0.00177)
10th Pctl ΔT		-0.00521***
		(0.000947)
25th Pctl ΔT		-0.00685***
		(0.000716)
Observations	4,223,270	4,575,183
No. of Households	26,095	25,050
Weather Covariates	Yes	Yes
Day Dummies	Yes	Yes
Household FE	Yes	Yes

The dependent variable is the dummy variable for override decisions and is estimated with a linear probability model with fixed effects. *75th Pctl* ΔT is a dummy that equals to 1 if the day-to-day temperature change is above 75th percentile for the location in a given year. Other extreme temperature change variables are defined in a similar way. Weather covariates include precipitation, snowfall and snow depth. Day dummies include dummies for year, month, and day of week. Robust standard errors shown in parentheses are clustered at zip code level. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Heterogeneity in Temperature Adjusting Propensity

	Prob. of Change		Set Point	
	(1) Low Cost	(2) High Cost	(3) Low Cost	(4) High Cost
(a) Summer				
$\|\|\Delta T\|\|$ if $\Delta T > 0$	0.00794***	0.00468***	0.0246***	0.00539***
	(0.000251)	(0.000185)	(0.00158)	(0.00111)
$\|\|\Delta T\|\|$ if $\Delta T < 0$	0.00766***	0.00320***	-0.000803	0.00329***
	(0.000224)	(0.000168)	(0.00122)	(0.000874)
Observations	1,061,269	1,050,119	1,061,269	1,050,119
No. of Households	7,087	6,227	7,087	6,227
Weather Covariates	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
(b) Winter				
$\|\|\Delta T\|\|$ if $\Delta T > 0$	0.00264***	0.00108***	-0.000706	0.00155***
	(0.000133)	(0.000100)	(0.000694)	(0.000598)
$\|\|\Delta T\|\|$ if $\Delta T < 0$	0.00432***	0.00249***	-0.0149***	-0.00468***
	(0.000124)	(9.74e-05)	(0.000951)	(0.000613)
Observations	1,142,852	1,148,661	1,142,852	1,148,661
No. of Households	6,560	6,128	6,560	6,128
Weather Covariates	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes

For Columns (1) and (2), the dependent variable is a dummy for whether there is a change in set point temperature, and the specifications are estimated using a linear probability model with household fixed effects. For Columns (3) and (4), the dependent variable is the change in set point from yesterday, and the specifications are estimated with household fixed effects. Change cost is based on the override intervals, with a change interval of 3 days as high cost (highest 25% percentile) and 20 days as low cost (lowest 25% percentile). Other control variables are the same as as those in the baseline model in Table 3. Robust standard errors shown in parentheses are clustered at zip code level. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Heterogeneity in Cultural Attitudes

	Summer		Winter	
	(1) High Awareness	(2) Low Awareness	(3) High Awareness	(4) Low Awareness
(a) Weather				
$\|\|\Delta T\|\|$ if $\Delta T > 0$	0.00827***	0.0119***	0.00182***	0.000976
	(0.00116)	(0.00112)	(0.000617)	(0.000621)
$\|\|\Delta T\|\|$ if $\Delta T < 0$	0.00279***	-0.00505***	-0.0129***	-0.00650***
	(0.000989)	(0.000961)	(0.000751)	(0.000648)
Observations	1,018,713	975,269	1,139,843	1,136,425
No. of Households	12,353	12,062	11,876	11,124
Weather Covariates	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
(b) Environment				
$\|\|\Delta T\|\|$ if $\Delta T > 0$	0.0104***	0.0121***	0.00104	0.000546
	(0.00125)	(0.00111)	(0.000686)	(0.000589)
$\|\|\Delta T\|\|$ if $\Delta T < 0$	0.000246	-0.00297***	-0.000824	-0.00566***
	(0.00103)	(0.000959)	(0.000640)	(0.000618)
Observations	989,091	969,525	1,155,618	1,138,918
No. of Households	13,864	9,508	10,636	9,162
Weather Covariates	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes

The dependent variable is the change in set point from yesterday. Specifications are estimated with household fixed effects. Panels A) and B) group households based on their sensitivity to weather and environment related topics, respectively, as measured by the state level monthly keyword search intensity. High and low awareness are based on the highest and lowest 25th percentile in related key word search intensity. Control variables are the same as as those in the baseline model in Table 3. Robust standard errors shown in parentheses are clustered at zip code level. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Appendix: Short Run Persistence of Temperature Setting Habits

	(1) Set Point Summer	(2) Set Point Winter	(3) Set Point Summer	(4) Set Point Winter
L.target	0.811***	0.801***	0.810***	0.800***
	(0.00266)	(0.00258)	(0.00267)	(0.00258)
L2.target	-0.0240***	-0.0711***	-0.0231***	-0.0692***
	(0.00267)	(0.00279)	(0.00268)	(0.00279)
L3.target	0.0926***	0.102***	0.0908***	0.0998***
	(0.00134)	(0.00153)	(0.00135)	(0.00152)
outdoor	0.00439***	0.00399***	0.00383***	0.00262***
	(0.000364)	(0.000235)	(0.000369)	(0.000242)
L.outdoor	0.0107***	0.0121***	0.0108***	0.0131***
	(0.000497)	(0.000336)	(0.000498)	(0.000345)
L2.outdoor	-0.00178***	-0.00307***	-0.00132***	-0.00196***
	(0.000403)	(0.000291)	(0.000402)	(0.000292)
L3.outdoor	-0.00707***	-0.00636***	-0.00707***	-0.00619***
	(0.000342)	(0.000250)	(0.000337)	(0.000253)
Observations	4,154,510	4,519,783	4,154,510	4,519,783
No. of Households	26,028	25,025	26,028	25,025
Weather Covariates	No	No	Yes	Yes
Day dummies	No	No	Yes	Yes
Household FE	Yes	Yes	Yes	Yes

The dependent variable is the target set point. The specifications are estimated with household fixed effects. Weather covariates include precipitation, snowfall and snow depth. Day dummies include dummies for year, month, and day of week. Robust standard errors shown in parentheses are clustered at zip code level. *** p<0.01, ** p<0.05, * p<0.1

Table 8: Appendix: Long Run Persistence of Temperature Setting Habits

	(1) Set Point Summer	(2) Set Point Winter
L.target	0.599***	0.645***
	(0.0138)	(0.00726)
L2.target	-0.0685***	-0.122***
	(0.00545)	(0.00421)
L3.target	0.00246	0.0534***
	(0.00483)	(0.00357)
outdoor	0.0840***	0.0545***
	(0.00496)	(0.00302)
L.outdoor	0.0214***	-0.0320***
	(0.00498)	(0.00332)
L2.outdoor	0.0191***	-0.0415***
	(0.00444)	(0.00315)
L3.outdoor	-0.00600	-0.0405***
	(0.00569)	(0.00314)
Observations	84,754	151,008
No. of Households	14,140	23,733
Weather Covariates	Yes	Yes

The dependent variable is the monthly average target set point. The specifications are estimated with Arellano-Bond estimator. Weather covariates include current and lagged precipitation, snowfall and snow depth. *** p<0.01, ** p<0.05, * p<0.1

Table 9: Appendix: Additional Sources of Heterogeneity

(a) ADDITIONAL HETEROGENEITY: DAY OF THE WEEK & TIME OF THE DAY

	Weekday vs. Weekend				(Weekend) Morning vs. Evening				(Weekday) Morning vs. Evening			
	Summer		Winter		Summer		Winter		Summer		Winter	
	Weekday	Weekend	Weekday	Weekend	Morning	Evening	Morning	Evening	Morning	Evening	Morning	Evening
$\|\|\Delta T\|\|$ if $\Delta T > 0$	0.0152***	0.0127***	-0.00051	0.00167**	0.00440***	-0.00745***	-0.000897***	-0.00162***	0.00359***	-0.00483***	-0.000882***	-0.00262***
	(0.00074)	(0.00171)	(0.00034)	(0.00074)	(0.00033)	(0.00033)	(0.00014)	(0.00013)	(0.00012)	(0.00014)	(6.4E-05)	(6.3E-05)
$\|\|\Delta T\|\|$ if $\Delta T < 0$	0.00111**	0.00359***	-0.00877***	-0.00992***	-0.00031	-0.00101***	0.00180***	0.00311***	-0.00105***	-0.000457***	0.00164***	0.000502***
	(0.00056)	(0.00131)	(0.00039)	(0.001)	(0.00026)	(0.00025)	(0.00017)	(0.00016)	(0.00011)	(0.00011)	(5.7E-05)	(5.5E-05)
Observations	3,616,092	607,178	3,910,416	664,767	607,178	607,178	664,767	664,767	3,616,092	3,616,092	3,910,416	3,910,416
No. of Households	26,083	25,914	25,047	24,952	25,914	25,914	24,952	24,952	26,083	26,083	25,047	25,047
Weather Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable is the set point changes from yesterday. The specifications are estimated with household fixed effects. Morning hours are from 6am to noon, and evening hours are from 6pm to midnight. Weekend days include Saturday and Sunday. Weather covariates include precipitation, snowfall and snow depth. Day dummies include dummies for year, month, and day of week. Robust standard errors shown in parentheses are clustered at zip code level. *** p<0.01, ** p<0.05, * p<0.1

(b) ADDITIONAL HETEROGENEITY: DEPARTURE FROM MEAN TEMPERATURE, TIME OF YEAR & POLITICAL AFFILIATION

VARIABLES	Deviation from 7 Day Average Temp.				Beginning vs. End of Season				Republican vs. Democrat			
	Summer		Winter		May	September	November	March	Summer		Winter	
	$>$ 7d Mean	$<$ 7d Mean	$>$ 7d Mean	$<$ 7d Mean					Republican	Democrat	Republican	Democrat
$\|\|\Delta T\|\|$ if $\Delta T > 0$	0.0155***	0.0111***	0.00266***	-0.000684	0.0235***	0.00959***	0.00290***	0.00117	0.0167***	0.0145***	0.000052	0.000298
	(0.000833)	(0.00122)	(0.000423)	(0.000700)	(0.00141)	(0.00102)	(0.000846)	(0.000729)	(0.00119)	(0.000861)	(0.000541)	(0.000397)
$\|\|\Delta T\|\|$ if $\Delta T < 0$	0.0101***	-0.00138**	-0.00451***	-0.00626***	-0.00920***	0.000189	-0.0115***	-0.0148***	-0.00198**	0.00301***	-0.0121***	-0.00718***
	(0.00128)	(0.000615)	(0.000713)	(0.000409)	(0.00139)	(0.000800)	(0.000747)	(0.000792)	(0.000866)	(0.000645)	(0.000697)	(0.000454)
Observations	2,157,291	2,063,074	2,277,202	2,289,528	569,615	936,579	905,333	837,919	1,371,856	2,851,237	1,475,132	3,099,777
No. of Households	26,007	26,022	25,006	25,002	14,135	24,042	23,686	23,689	8,953	17,140	8,470	16,578
Weather Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable is the set point changes from yesterday. The specifications are estimated with household fixed effects. "$>$ 7d Mean" indicates that today is warmer than the seven-day average outdoor temperature in the region, and "$<$ 7d Mean" is similarly defined. Division of Republican vs. Democratic counties is based on the county level result of the 2012 presidential election. Weather covariates include precipitation, snowfall and snow depth. Day dummies include dummies for year, month, and day of week. Robust standard errors shown in parentheses are clustered at zip code level. *** p<0.01, ** p<0.05, * p<0.1