

which account for more than half of the residential energy use in the U.S.<sup>1</sup> On the other hand, smart thermostats that have programmable temperature settings to control the heating and cooling in a home have become increasingly popular among households, particularly in newer and remodeled homes. Smart thermostats also allow users to adjust their program settings (set points) and manually but temporarily override the temperature settings of their program when necessary. 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, an often implicitly made decision and 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 setting, rather than to passively continue with an implicit one; and 3) how does such relationship vary across the baseline heterogeneity in terms of consumers' different propensity of adjusting temperatures as well as their cultural attitudes toward weather and environment. Our analysis also provides direct policy implications on how conservation policies impact energy use.

The theoretical foundations of habit date back to Becker and Murphy's (1988) Theory of Rational Addiction. Becker extended the standard economics utility model to account for how repeated consumption of some goods can lead to habituation through the accumulation of addiction capital. Recent work in economic theories has focused on clarifying the theoretical formalism (see Rozen 2010) and in bringing attention to the importance of timing on habitual choices. 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 formulates an endogenous model of when decision points arise for addictive goods.

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<sup>1</sup>Source: U.S. Energy Information Administration (EIA), Residential Energy Consumption Survey.

Much of the empirical work on habit formation has focused primarily on small scale laboratory generated psychology studies (see Duhigg (2012) for a review). What has remained largely unstudied is the evidence of habit formation in a consumption decision made in the field, particularly one that is often made implicitly. Such vacuum is understandable due to the lack of high frequency data for a choice that people make every day. This is the gap in the literature that our paper seeks to address by analyzing a high frequency smart thermostat usage dataset.<sup>2</sup> Consumers' thermostat temperature setting behavior provides a good empirical testing ground for the study of habit formation because a programmable smart thermostat can help maintain a constant indoor temperature, and one would not expect the users to frequently adjust thermostat settings to accommodate changes in outdoor temperatures. On the other hand, exposure to extreme temperatures outside can make consumers change expectations or become more impatient toward the current ambient temperatures, which may in turn trigger active choices regarding the indoor temperatures. Thus, any observed variations in optimal temperature settings or temporary overrides would imply the relative cost of changing temperatures or utility loss and offer a unique opportunity for researchers to study (potentially competing) factors that trigger changes to habit. For example, in addition to habituation, consumers may also display homeostasis when adjusting temperatures, a tendency toward maintaining an internally preferred level of temperature.

Our empirical findings first confirm that habits are persistent in consumers' home energy consumption behavior proxied by the indoor temperature settings. We find that households' indoor temperature settings are highly correlated with their previous settings. On the other hand, we do find that that temperature choices can respond to external temperature shocks and confirm the role of heterogeneity in explaining part of the responses. We find evidence for both *habituation*—small increases in outdoor temperatures lead to increases in our preferred indoor set points—but also for compensation or *homeostasis*—our immediate response to an extremely warm day is to lower our indoor set points. We find that the *salience* of the

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<sup>2</sup>Allcott and Rogers (2014) have a related paper looking at long term impacts of the oPower smiley face on electricity bills.

weather shock matters. Extreme temperatures (e.g. in the 99th percentile) show greater (and faster) responses. In terms of when we make active versus passive choices, we find evidence against the idea of choice satiation, where one is less likely to make active choices immediately after having already made an active choice. The responses in turn vary by the types of underlying heterogeneity such as the variations in the cost of changing set points as well as cultural attitudes of the region toward topics such as weather and environment. For instance, we find that households living in regions with higher environmental awareness tend to exhibit a higher degree of habituation and respond less to extreme weather shocks compared to those living in areas with lower awareness toward the environment.

The paper is organized as follows. Section 3.2 provides a brief background on smart thermostats. Section 3.3 presents the conceptual framework. Section 3.4 discusses the data used in the study, followed by a series of descriptive analyses in Section 3.5. Section 3.6 outlines the empirical strategy in this study. Section 3.7 presents the main estimation results and discusses policy implications. Concluding remarks are offered in Section 3.8.

## **3.2 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 for example users to 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 speci-

fied temperature (under override) is reached.<sup>3</sup> In our data, despite the automatic nature of the smart thermostats once programmed, overrides still occur - a typical user on average overrides once every two weeks and a half.

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 has shown that providing users more information about their usage tends to reduce demand (Faruqui and Sergici 2010; Dulleck and Kaufmann 2000). Smart thermostats are becoming popular with utility companies as they give the companies more control for Demand Side Management (DSM) to reduce energy usage at times of peak demand and to help meet the federal home energy consumption guidelines. Such programs that give users temporal information about their energy consumption can help reduce long run demand by as much as 7% though they may exhibit little impact in the short run.

### 3.3 Conceptual Framework

We propose a number of competing behavioral hypotheses that can help guide our understanding regarding the persistence of habits as well as factors that may trigger active choices about the indoor temperature settings. We then conduct a heuristic empirical analysis to confirm the role of the baseline heterogeneity in explaining habits and propose further related testable hypotheses.

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<sup>3</sup>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 and we decide to ignore such observations.

### 3.3.1 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”  $S(t)$  which 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:

$$U_h(c) = \sum_{t=0}^{\infty} \delta^t u \left( c_t - \sum_{k=1}^{\infty} \lambda_k h_k^{(t)} \right) \quad (3.1)$$

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.*

If we consider the deviation of today’s set point from yesterday’s, then the *Habit Persistence Hypothesis* implies that such deviation should be at or close to zero in distribution since most households will rely on their habitual routines for indoor temperature settings.

We then ask questions regarding the factors that may 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 move their indoor set point in the opposite direction: i.e. lower (or higher) set points.*

Intuitively, we expect higher set points during summer months and lower set points during winter months as one adjusts to the outdoor temperatures, which supports the *Habituation Hypothesis*. Meanwhile, such habituation could also reflect variations in energy consumption costs over the seasons, e.g. heating (cooling) can be expensive in winter (summer) months and one would thus correspondingly lower (raise) the indoor temperature settings. Our data unfortunately do not allow us to directly test the relative strength between these two factors at household level, and our *Habituation Hypothesis* thus does not separate between the behavioral and economic responses.

Our analysis, however, departs from the typical models of habit in that most studies of habit focus on positive reinforcement (i.e. habituation). We argue that temperature preferences may also be negatively autocorrelated, particularly when facing strong weather shocks. Studies on thermal comfort and indoor energy consumption, such as Brager and deDear (1998), document through survey evidence that people experience *homeostasis* when it comes to ambient temperature. That is, our *Homeostasis Hypothesis* implies that the body has a preferred internal set point, and prolonged exposure to temperatures away from that set point, can increase the desire to return to this internal preference.

Furthermore, Becker-Murphy and Rozen, like most economic models, presume that an active choice is made 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) affect choice. Conceptually, our notion of habitual choice is akin to Landry (2013) for which the interval between when we make choices about consumption 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 active choices. Therefore, in terms of active choices of temperature settings, we can also have two competing theories, namely:

**Hypothesis 4** *Choice Satiation Hypothesis: If consumers make decisions according to choice satiation, then active choices should be negatively autocorrelated in likelihood.*

And

**Hypothesis 5** *Cue Salience Hypothesis: Consumers tend to make active choices when facing salient external shocks, i.e. active choices can be positively autocorrelated if salient cues are autocorrelated.*

In the simplest version of our 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. And therefore, changes in thermostat settings are only made when the benefits outweigh the costs of the choice.<sup>4</sup> The benefits to making a choice increase as the stock of habit or homeostatic reversion accumulates, or when the conditions change in a way that force consumers to re-optimize, such as household composition, information about global warming, or changes in prices. If making a choice today temporarily satiates the desire to make future choices, then we would expect an active choice today decreases the likelihood of active choices in the near future, which is implied in the *Choice Satiation Hypothesis*.

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<sup>4</sup>The fact that some consumers still adjust their settings so often suggests maybe that people who own smart thermostats might be more prone to attention and might actually enjoy playing with their new toy, using the phone app, and therefore adjustment might be a pleasure rather than a cost. We will look for evidence of this, but hope that over the two year time span of data, such novelty wears off.

On the other hand, the *Choice Satiation Hypothesis* still implicitly assumes that consumers are now choosing to make a choice, which in itself requires costly attention. Therefore, we will look at whether a model of cues, where choices are only made when cued by some external stimuli, might be 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).

In addition, users of a smart thermostat make program settings for the future, but in the future, they may either temporarily override these program settings, or completely change these settings. Thus, a related departure from rational addiction is that we want to allow for the possibility of time inconsistency. Part of such time inconsistency can be explainable by 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. Alternatively, people may underestimate the evolution of their habit stock, leading to re-evaluations in the future.

### 3.3.2 Heterogeneity

Intuitively, one would expect that consumers' thermostat setting habits and how they respond to external weather shocks can be heavily influenced by the baseline heterogeneity across households. Such heterogeneity can come from different kinds of climates and weather that households experience across different regions. Alternatively, heterogeneity can be household-specific. In particular, we are interested in two types of such household-specific heterogeneity, namely, the heterogeneity due to differences in the cost of changing temperatures and the heterogeneity due to temperature preferences.<sup>5</sup> The former can be implied by households' frequencies of thermostat setting changes while the latter may be proxied by households' cultural attitudes toward topics such as weather and environment.

If we broadly to parse the heterogeneity due to geographic locations from that due to household-specific fixed effects, then our first step toward exploring the impact of hetero-

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<sup>5</sup>Note that utility loss as a result of set point changes is potential source of heterogeneity and our data do not allow us to differentiate it from the cost of changing indoor temperatures.



geneity is to establish whether one type of heterogeneity dominates the other. As a heuristic exercise, we decide to 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  $R^2$ s of the corresponding specifications.  $R^2$  statistic is admittedly a crude measure for explanatory power, but we believe that it is still appropriate given the descriptive purpose of the heuristic analysis in this section. In addition, studies, such as Gronau (1998), have argued that  $R^2$  type goodness-of-fit measure can still be superior to other measures in a linear probability model setting.

We first consider the following specification:

$$C_{it} = \alpha_0 + \theta_1 \cdot \Delta T_{it} \cdot \mathbf{1}(\Delta T_{it} > 0) + \theta_2 \cdot \Delta T_{it} \cdot \mathbf{1}(\Delta T_{it} < 0) + \tau_t + \xi_i + \mu_{it} \quad (3.2)$$

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  $\Delta T_{it}$  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;  $\tau_t$  is the day fixed effect, captured by dummies for year, month and day of the week; and  $\xi_i$  is the household fixed effects.

We estimate Equation 3.2 using a linear probability model that captures the household fixed effects and obtain a  $R^2$  of 0.1278.<sup>6</sup> 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, we conclude that there is evidence that the household fixed effects provide much stronger explanatory power than the differences in weather conditions that household faces across different geographic locations. We will thus

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<sup>6</sup>Detailed estimated coefficients will be presented in the empirical results section.

focus on the role of such kind of heterogeneity in explaining set point reactions to weather shocks.<sup>7</sup>

Within the realm of household fixed effects, households can still differ in their costs of changing target indoor temperatures as well as their temperature preferences. Hence, we propose the following testable hypotheses regarding their respective roles, both of which are possibly driven by the role of attention because active choices require attention:

**Hypothesis 6** *Change Cost Hypothesis: Households with lower costs of changing temperature setting will respond more to external weather shocks.*

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 where there is higher awareness concerning the environment and weather, the household is more likely to be exposed to such awareness which in turn may cause it to make different set point and energy consumption decisions. On the other hand, cultural attitude toward environment is inherently different from that toward weather. In terms of the impact on set point behavior, while the former is about weighing the social cost against the private cost of energy consumption decisions, the latter concerns the role of attention. We thus hypothesize that more attention being paid to weather will make the

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<sup>7</sup>We also experiment with 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.

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