Energy Consumption and Habit Formation: Evidence from High Frequency Thermostat Usage Data

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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 in response to external shocks. In particular, we consider the impulse response of shocks such as weather events, local energy prices, political action, and news coverage of energy-related stories on how people set their thermostats. This allows us measure the responsiveness of consumer energy-use behavior to external stimuli. The analysis will help develop our understanding of habitual behavior that gives insight into what effects long term change and what triggers the choice to reconsider ones passive choices. We find that temperature choices do respond to external temperature shocks in both short run and long run, providing evidence for both habituation and homeostasis. There is also evidence suggesting that consumers do respond to both price and non-price external nudges in the long run as well. The results have direct policy implications 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–and how changing trends in climate, in energy prices, in news coverage, and political action, impact consumer behavior.

Keywords: thermostat usage; energy consumption; external shocks; high frequency data

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1 Introduction

Many of the consumption expenditure decisions we make every day are made implicitly, following habitual routines, often due to inattention, without active choice. While this category of habitual consumption includes the foods we eat, the brands we buy at the supermarket, the various grooming tasks of our morning routine, one particularly good example is the temperature settings for our home thermostats. The temperature settings on thermostats tend to remain the same from day to day; changing them often requires special attention. In this paper, we use high-frequency (minute by minute) data obtained from an ongoing relationship with a smart thermostat company from over 60,000 smart thermostats in households distributed across the United States to see the determinants of home heating and cooling expenditures and how they respond to external shock and stimuli. Smart thermostats have programmable temperature settings that control the heating and cooling in a home. We observe when people adjust their program settings and when they override the temperature settings of their program.

Our analysis seeks to ask three questions, 1) how do thermostat choices respond in the short run to shocks such as weather; 2) what does it take to effect persistent long run changes in behavior; 3) what triggers consumers to make an active choice, rather than an implicit one. Specifically, we analyze the short-run and long-run persistence of energy choices in response to external shocks. In particular, we consider the impact of shocks such as weather events, local energy prices, news coverage of energy-related stories on how people set their thermostats. We will also estimate the impulse-response function of these shocks over time. The analysis will help to develop a model of habitual behavior, as well as allow us measure the responsiveness of consumer energy-use behavior to external stimuli. Such analysis has direct policy implications on how conservation policies impact energy use, and how changing trends in climate, energy prices, news coverage and political action, impact consumer behavior.

The study of habituation is important to energy policy because most policy analyses rely on static assumptions about supply and demand, and therefore may overestimate the short-term impact of policy interventions to change consumption behavior, but underestimate the long-term impact of small behavior shifts, if such small shifts (like turning off the lights, or switching light bulbs) lead to long run changes in habit.

The theoretical foundations of habit date back to Becker and Murphy (1988)'s Theory of Rational Addiction, as an extension of the standard economics utility model to account for how repeated consumption of a some goods can lead to habituation through the accumulation of addiction capital. Recent work in economics 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 develops an endogenous model of when decision points arise for addictive goods.

Recent empirical work on habit formation has focused primarily on small scale lab psychology studies (see Duhigg (2012) for citations). What has remained largely unstudied is evidence of habit formation in a consumption decision in the field. What has been lacking is high frequency data for a choice that people make every day. This is the gap we hope to address (see Allcott and Rogers (2014) for a similar paper in this area that looks at long term impacts of the oPower smiley face on electricity bill intervention).

Using high frequency thermostat data, we consider three questions 1) how do people's temperature preferences adapt to external shocks like the outside weather patterns in the short run; 2) what stimuli prompts people to reconsider their temperature settings; 3) what kinds of stimuli lead to long term change.

We find that temperature choices do respond to external temperature shocks in both short run and long run. We find evidence for both *habituation*–long periods of abnormally hot weather lead to eventual increases in our set points–but also for compensation or *homeostasis*–our immediate response to a warm day is to lower the set point. These impacts are short lasting, nearly all impacts fade after three days. We find that *salience* matters.

Extreme temperatures (in the 75th or 99th percentile) show greater (and faster) responses. Long run results are generally similar in magnitude and there is evidence that consumers do respond to both price and non-price external nudges in the long run, though the response may vary greatly across different geographical regions.

These questions are only a start however. We find some evidence of heterogeneity in response between positive and negative changes, and between different regions of the country. We will consider the heterogeneity in nudge responses between Democrat and Republicans as noted in Costa and Kahn (2013). We will also explore the role of emotion in explaining heterogeneity by including the performance of local sports team as a proxy for emotion in the flavor of Agarwal et al. (2012).

The data will also allow us to test other behavioral economic models such as 1) projection bias (Loewenstein et al., 2003) which predicts that people over-react to current conditions, 2) procrastination (O'Donoghue and Rabin, 2001) and 3) reference dependence (Tversky and Kahneman, 1991), which predicts that people respond more to changes rather than absolute levels. We also will be able to compare how people program their future set points, versus how they set the current set point, as a way to look at time consistency of preferences.

We can exploit dynamic panel data techniques to estimate the real time impulse response to external events, and answer questions about whether such shocks have persistent effects on habits, or if the impact is transient and disappears over what period of time.

Finally, we are working to gather location specific news data, in order to follow work by Kahn and Kotchen (2010) who find that higher unemployment makes people believe in climate change less, and Brown and Minty (2008) who use instrumental variable analysis to find a causal effect of media coverage on charitable giving after the 2004 Tsunami.

The paper is organized as follows. Section 2 provides a brief background on smart thermostats. Section 3 presents the theoretical framework. Section 4 discusses the data used in the study, followed by an outline of empirical strategy in Section 5. Section 6 presents the main estimation results as well as policy implications. Concluding remarks are offered in Section 7.

2 Smart Thermostats

The data consists 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. In our data, we find overrides are quite frequent; the typical user overrides on average, once a week.

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 more information about their usage tends to reduce demand (Faruqui and Sergici (2010); Dulleck and Kaufmann (2000)). Smart thermostats are popular with utility companies as it gives utility companies more control for Demand Side Management (DSM)-reducing energy usage at times of peak demand-and to help meet federal guidelines. Such programs that gave users temporal information about their demand reduced long run demand by 7% though they had little impact in the short run.

3 A Theoretical Framework

The standard Becker and Murphy (1988) model of rational addiction 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 decrease the absolute utility from consuming today. In other words, given 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:

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

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.

Our analysis of thermostats here departs from these models in a few key ways. One is that in the case of temperature, reinforcement may be negatively autocorrelated. Brager and deDear (1998) document through survey evidence that people experience *homeostasis* when it comes to ambient temperature. 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 an active choice is made for every time period. However, in our data, we are interested in how external cues (like 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 you wait between making a choice, the greater the desire increases.

In the simplest version of our framework, people have finite attention. Making an active choice is costly (Peffer et al. (2011) finds that a big determinant of how smart thermostats are used depends on the ease of use of the design), and therefore, changes in thermostat setting are only made when the benefits outweigh the choice cost.[1] The benefits to making a choice increase as the stock of habit or homeostatic reversion accumulates, or when conditions change that force consumers to re-optimize, such as household composition, information about global warming, or changes in prices.

This model 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. External temperature will be the primary cue of interest, but the *salience* of the cue will be of particular importance (e.g.**?**).

Another departure from rational addiction is that we want to allow for the possibility of time inconsistency. 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 . What should we make of these changes?

Part of this must 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. Separating out these explanations for changes to the program (overrides or program changes), from structural changes (price changes for

[1]The fact that people adjust their settings so often suggests maybe that people who own smart thermostats 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, the novelty wears off.

example), require thinking about time inconsistent utility.

One final set of factors that might influence changes in set point is psychological. The Hawthorne effect suggests that we are more attentive to changes than to levels, and that one motive for changes in the set point is simply to experience the temperature changes. At the same time, cognitive dissonance reverses the economic notion that preferences leads to choice, and suggests that choice leads to preferences. Perhaps the act of setting the set point, changes peoples preferences about the set point they would most enjoy.

4 Data

The data used in this paper come from multiple sources, including proprietary smart thermostat usage data, energy prices from the Energy Information Administration (EIA), and weather data from the National Oceanic and Atmospheric Administration (NOAA). We also utilize Google Trends and the Bureau of Labor Statistics to match state level environment, energy or thermostat related internet searching data and MSA level monthly unemployment data, respectively.

4.1 Thermostat Usage Data

The proprietary smart thermostat usage 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. The raw dataset contains more than 50 billion minute-level observations for over 60,000 households across the country. We then aggregate the minute-by-minute observations to daily level, resulting in over 25 million daily observations. 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 shocks as well as aggregate measures of the economy in the neighborhood. The thermostat readings are ongoing, and for the purpose of this project, we consider a two-year sample period from February 2012 to March 2014. Due to computational burden, we restrict our attention to households who reside in one of the top 100 major Metropolitan Statistical Areas (MSA) around the country that has population over 500,000 people[2]. In addition, we drop households with less than 25 observations in the sample period, leading to a final sample of approximately 42,000 households and 16.5 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 helping reach the target temperature. The small variations of ambient and target temperatures also imply a relatively stable zone of comfort temperatures that do not vary a lot with respect to outdoor conditions. We divide the sample based on Census regions and find 40% of the sample live in the South while the rest of the sample is distributed fairly evenly across the Northeast, Midwest, and West. The average durations of running heating or cooling units are about 90 and 120 minutes, respectively, though as suggested by the standard deviations, there are large variations of how and when consumers operate these units.

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 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. We find that a household in the sample would on average override its thermostat setting every week. And as suggested in Table 1, an average household changes the thermostat set points far 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 they may choose to adjust the temperature set points themselves

[2]Due to limited availability of data on gasoline prices, we also perform a sub-sample analysis with the top 10 MSAs only, including Boston, Chicago, Cleveland, Denver, Houston, Los Angeles, Miami, New York, San Francisco, and Seattle.

if the room temperatures are not ideal. It is also interesting to note that the majority of the overriding takes place during the morning and evening hours when consumers are presumably at home even though the smart thermostats can be controlled remotely via mobile apps or wi-fi.

4.2 Energy Price and Weather Data

The main residential energy sources we consider are natural gas and electricity, which account for over 83% of household heating system in the U.S.. The Energy Information Administration (EIA) offers monthly average residential electricity and natural gas prices at state level[3]. The EIA also provides public data on the weekly retail gasoline prices sorted by major metropolitan areas[4]. The energy price data are then matched to household based on their MSAs or state of residence. The energy prices are admittedly quite aggregated, but they still provide reasonable proxies to the actual energy price shocks that consumers face in their everyday life. We will also collect heating oil price fluctuations as some households may be using heating oil for their heating units.

Weather data are from the National Oceanic Atmospheric Administration (NOAA). The data contain daily accounts of precipitation, snowfall and snow depths from the airport closest to the MSA of interest[5]. As expected, the weather data contain large variations. Additional weather measures, such as forecast temperatures, windchill, frozen days etc, will be collected in the next stage of the study.

4.3 Google Trends Data

Google Trends data track Google search traffic based on specific keywords entered. We utilize Google Trends to track inquiries related to the economy, environment and disasters,

[3]Electricity prices are measured in cents per kilowatt-hour (KWH), and natural gas prices are measured in dollars per thousand cubic feet.

[4]Gaosline data are used for a subgroup analysis that involves only residents in 10 MSAs

[5]Precipitation is measured in tenths of millimeters while snowfall and snow depths are measured in millimeters.

energy, weather, and thermostat [6] and group monthly inquiry volumes on different topics based on the states where the inquires are originated from. We then consider the natural logarithm of search inquiry volumes in our estimation.

5 Empirical Strategy

We are interested in exploring consumers' thermostat usage patterns in both short run (daily) and long run (monthly). In the short run, we consider a function of thermostat set points in terms of a series of past and present cues. Specifically, we estimate the thermostat set points as a function of lagged thermostat set points, current and lagged outdoor temperatures and various temperature patterns, a series of external shocks such as weather, time 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:

$$temp_{it} = \beta_1 + \delta_1 temp_{i,t-1} + \gamma_1 outdoor_{i,t} + \gamma_2 outdoor_{i,t-1} + \lambda_1 Z_{i,t} + \lambda_2 Z_{i,t-1} + \tau_t + \xi_i + \varepsilon_{it} \tag{2}$$

where $temp_{it}$ is consumer's (average) set point decision at time t, $outdoor_{i,t}$ is the outdoor temperature patterns, Z_{it} is a vector of external shocks, faced by household i, τ_t is the time fixed effect, ξ_i is the household fixed effect.

Intuitively and given the behavioral hypotheses we seek to test, there are reasons to believe that set points yesterday would influence the set point decision today, e.g. due to projection bias. 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

[6] Keywords related to 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".

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, the bias can be especially acute in a "small T, large N" context, such as the long run (monthly) analysis in our study ($T = 27$). Thus, given the dynamic nature of the monthly panel, we resort to dynamic panel techniques such as the Arellano-Bond GMM style estimator in order to obtain a consistent estimator in our long run analysis as suggested in Roodman (2009).

On the other hand, because of the high frequency nature of the our dataset, we face "large T, large N" problem in our short run study ($T = 767$) and employing Arellano-Bond estimator would be computationally infeasible since it would create an enormous set of lagged variable-based instruments. Roodman (2009) shows that in the context of dynamic panel, OLS estimates tend to overestimate and fixed effects tend to underestimate while consistent estimates (such as Arellano-Bond estimates) should be between OLS and fixed effects estiamtes. 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% [7]. 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 adopt one-way fixed effect model to estimate the data to provide intuition for 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 household 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 ($p < 0.0001$).

Building upon the baseline specification as in equation (2), we introduce multiple lags of independent variables to further explore short run patterns of changes in set points. We also include various outdoor temperature measures, including distributions as well as historical

[7] 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%

temperature patterns. In addition, we consider variables such as current and past difference between ambient and target temperatures to control for the effectiveness of thermostat and HVAC units. Thus, a general specification for household i on day t would take the following form:

$$temp_{it} = \beta_1 + \sum_{k=1}^{T} \delta_k temp_{i,t-k-1} + \sum_{k=0}^{T} \gamma_k outdoor_{i,t-k} + \sum_{k=0}^{T} \lambda_t Z_{i,t-k} + \tau_t + \xi_i + \varepsilon_{it} \tag{3}$$

Since theory does not offer a clear-cut prediction on the signs of key parameters in the set point specification above, we will also consider other dimensions of energy consumption as the dependent variable such as durations of heating or cooling and set point change frequencies. We adopt a model similar to equation (3) but with different dependent variables corresponding to different energy usage measures. Finally, we also consider temporal and spatial variations of energy usage by testing the above specification for different seasons and regions. In our long run analysis, we estimate a model at monthly level similar to that in equation (3) and introduce a rich set of external price and non-price shocks such as energy prices, local unemployment rates, and Google search intensity on topics related to energy, environment and thermostats. To address the potential dynamic panel bias due to "large N small T" problem, we resort to the Arellano-Bond GMM-style dynamic panel method.

To gain more insights toward thermostat setting behaviors, in addition to fixed effects models outlined above, we borrow time series techniques and employ panel data vector autoregression (VAR) techniques to investigate the interdependencies of various endogenous variables in our model since panel VAR assumes endogeneity of all variables involved and at the same time allows for unobserved individual endogeneity. Given the purpose of the paper, we apply existing panel VAR techniques and consider the following standard panel VAR model similar to that in Love and Zicchino (2006):

$$x_{it} = A_{0i}(t) + A_i(L)x_{t-1} + \xi_i + u_{it} \tag{4}$$

where X_t is a $D \times 1$ vector of variables such as set points and ambient temperatures and $X_t = (x'_{1t}, x'_{2t}...x'_{Nt})'$, $A_i(L)$ is a polynomial in lag operators, and $u_t \sim iid(0, \Sigma_u)$ with $u_t = (u'_{1t}, u'_{2t}...u'_{Nt})'$. We then derive a impulse response function to further quantify how consumers respond to various endogenous and external stimuli, e.g. testing the homeostasis about the relationship between ambient and target temperatures.

6 Results and Discussions

In this section, we present results from fixed effects estimates, dynamic panel estimates, and panel VAR estimates based on the empirical strategies outlined in Section 5.

6.1 Short Run Findings

6.1.1 Set Point Changes

One of the key questions we want to address in this study is on the determinants of consumer's short run set point change decisions when facing various temperature and weather shocks. For this analysis, we restrict the sample to those who make individual decisions of thermostat set points by overriding the scheduled thermostat settings. This results in a sample of approximately 38,500 households. We adopt the general fixed effects estimation strategy with clustered standard errors as outlined in Section 5 but include a 3-period lag for most of the shocks to explore the potential of short run memory. A total of twelve specifications are included and results are shown in Table 2, Table 3, and Table 4.

We explore how set point decisions are related to various external shocks in Table 2). Set points are unsurprisingly positively correlated with yesterday's set point decision but such dependence fades away in just two days; this result is consistent across all specifications. The magnitude of one-period lagged outdoor temperature is almost twice as large as that of the current period. Yet, earlier outdoor temperatures have a negative effect on the set point choices. Present and past perceptions of outdoor temperatures seem to have contradictory effects - increases in yesterday or current outdoor temperature will make the consumer increase set points (habituation) whereas increases in previous days will make consumers decrease set points (homeostasis). In addition, there is also support for long run memory as the average set points and outdoor temperature for the past week and past month are negatively correlated with set points.

Snowfalls generally lead to higher set points while rain leads to lower set points (except for the current period). Note that snowfalls are measured in millimeters and precipitation is in tenths of millimeters, which means the magnitudes of these shocks are actually more comparable than they seem to be. Snowfalls have a more consistent impact on set points across all lags, e.g. a large storm of 10 inches, whether it happened three days ago or today, would on average lead to approximately the same 0.25 degree increase in set points.

Table 3 documents the distributional impact of outdoor temperatures on target set points. Besides the similar patterns of the effects of past and present target and outdoor temperatures, consumers generally respond to extreme weather patterns as they become closer and their response is larger as the weather becomes more extreme, suggesting the importance of *salience*. For example, when the outdoor temperature reading is in the 75th percentile of the year (top 25% of hot days), consumers only seem to respond if the extreme temperature happens today or yesterday. When outdoor temperature reaches 99 percentile, consumers adjust present set points to even lower degree. A general similar trend (except for top 25 percent cold days) is observed for winter weather where consumers increase today's set points by as much as six times when experiencing a top one percent cold days compared to a top 10 percent cold day. In Specification 5, we explore the impact of consecutive days of extreme weather. The results suggest that when experiencing consecutive days of extremely hot weather, consumers respond by lowering temperatures and the magnitude increases as temperature becomes more extreme. On the other hand, there seems to be evidence for thermal comfort under consecutive days of cold weather though the pattern is not consistent.

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Finally, we also investigate how temporal and spatial differences influence set point decisions in Table 4. Summer coefficients generally appear to be comparable to those from winter months except for response to weather shocks. In terms of regional differences, signs and coefficients appear to be similar across regions with the exception that households in the southern and western states are much more sensitive to adverse winter weather.

6.1.2 Overriding Decisions

Another empirical exercise we conduct is about when and why consumers decide to override the existing thermostat temperature settings. We use the same fixed effects model as in Section 5 but employ a dichotomous dependent variable "*override*" that is equal to 1 if the household overrides the thermostat settings. We also include a variable "*d_override*" that captures the number of days since last override. We consider three specifications involving different combinations of outdoor weather patterns and document the results in Table 5. The results suggest that similar to set point decisions, the coefficients on past overriding decisions are positive but declining with respect to lags, and the time since the last override is negatively correlated with the override decision, both of which suggest evidence against *choice satiation*.

Current outdoor temperature negatively affect overriding decisions, though extreme outside temperature patterns, such as extremely hot or cold days or consecutive days of extreme temperatures, make the consumer more likely to override the thermostat settings. Furthermore, consumers tend to override quicker to recent episodes of extremely weathers. Consecutive days of hot weather make consumers more likely to override thermostat settings while we do not find similar evidence under consecutive days of cold weather. Overall, all the evidence seems to suggest against choice satiation.

6.2 Long Run Findings

In the long run analysis, we explore how consumers adjust monthly average set points as a response to shocks from outdoor temperatures, weather patterns, energy prices, unemployment, and social norm measured by keyword search intensity. We adopt the Arellano-Bond dynamic panel estimation strategy as outlined in Section 5. Long run results are reported in Table 6 including comparisons across different Census regions and Table 7 shows keywords search trend results.

Long run lagged set point results are similar to those in the short run - current month's set points are positively correlated with last month's average set point decision but such dependence becomes minimal past first lag. Present month and past months' perceptions of outdoor temperatures seem to have similar contradictory effects as we see in the short run outcomes - increases in current month's outdoor temperature will make the consumer increase set points (habituation) whereas increases in previous months will make consumers decrease set points (homeostasis).

In terms of energy price shocks, we find that consumers respond more to natural gas price shocks than electricity price shocks[8]. Current energy price shocks impose a larger effect than shocks in the past. On the other hand, there is no consistent trend of impact across different energy price shocks. In a subgroup analysis, we find it interesting that consumers seem to be more sensitive to electricity prices in the summer while they respond more to gasoline and natural gas prices in the winter. This would intuitively makes sense since AC units are electrically powered while many heating units use natural gas or heating oil, but also shows that these are real responses to price changes rather than some spurious correlation.

Different from the short run findings, precipitation leads to higher set points in the long run while snowfall leads to lower set points in the long run. In particular, current month's snowfall does not seem to affect set point decision but snowfalls from the past are negatively

[8]We also conduct a subgroup analysis of residents from top ten MSAs using similar specifications on responses to gasoline price shocks and do not find evidence that consumers adjust set points to reflect gasoline price fluctuations.

correlated with set points. Such pattern is also supported by a similar finding on snow depth.

Economy related keywords do not seem to affect long run set points in a consistent way, but recent local unemployment rates would lead to lower set points. Overall, internet searches related to energy/weather/thermostat do seem to correlate with set points. However, unlike other external shocks, the effect of keyword search intensity vary tremendously in magnitudes or signs across different geographic regions.

6.3 Panel VAR Findings

We also derive panel VAR estimates and impulse response functions at both daily and monthly levels [9]. Figures 1 to 5 presents graphs of lagged impulse response functions of set points in terms of various cues and the associated 5% error bands generated by Monte Carlo simulations. The cues we consider here include temperature variations, energy price shocks, weather shocks, and Google search trends.

At daily level, set points generally have a positive impulse response to outdoor temperature shocks. The impact is largest from the previous day and the impact dissipates as shocks become less recent with increasing margin of errors. This confirms the findings from the fixed effects estimates that consumers tend to respond most to recent temperature shocks and there is limited support for long run addiction. Interestingly, target temperature only negatively responds to ambient temperature shocks within one lag, and the impact dissipates almost immediately beyond the first lag with large error bands. We also observe a reciprocal response of ambient temperature to set point shocks. These facts would imply that the HVAC units are quite effective in achieving the target temperatures set by the smart thermostats.

At monthly level, Consumers seem to respond to energy price shocks in a consistent way, though the response to natural gas price has a smaller margin of errors. On the other hand, the results do not exhibit clear impulse responses to external energy price and weather

[9] We utilize the Stata's built-in panel VAR command `pvar` to implement the estimation.

shocks. As for weather shocks, snowfall presents a positive impulse to set points whereas the impact of precipitation is generally negative with a larger margin of error. Among the search intensity cues, searches on environment and disaster related topics present a clear negative impulse while consumers do not have clear impulse responses to other search cues.

7 Discussions and Conclusions

To get a sense of magnitudes of these effects, analysis with a small subset of the data (90 households) where we have access to electricity meter readings, tells us that each degree of set point change in summer months saves approximately 8Wh of electricity each hour (by comparison the households in this sample used approximately 1300 Wh each hour). Over the course of a year, 8Wh translates into approximately 70kWh. For a marginal electricity price of 30 cents/kWh, this works out to approximately $20 per year.

Clearly more needs to be done to disentangle this data, but hopefully we have provided here evidence for the determinants of how we make (or don't 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, and toward providing lasting solutions to shape household energy use.

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Figures

Figure 1 - Impulse Responses for 7 lag VAR of Daily Temperature Shocks

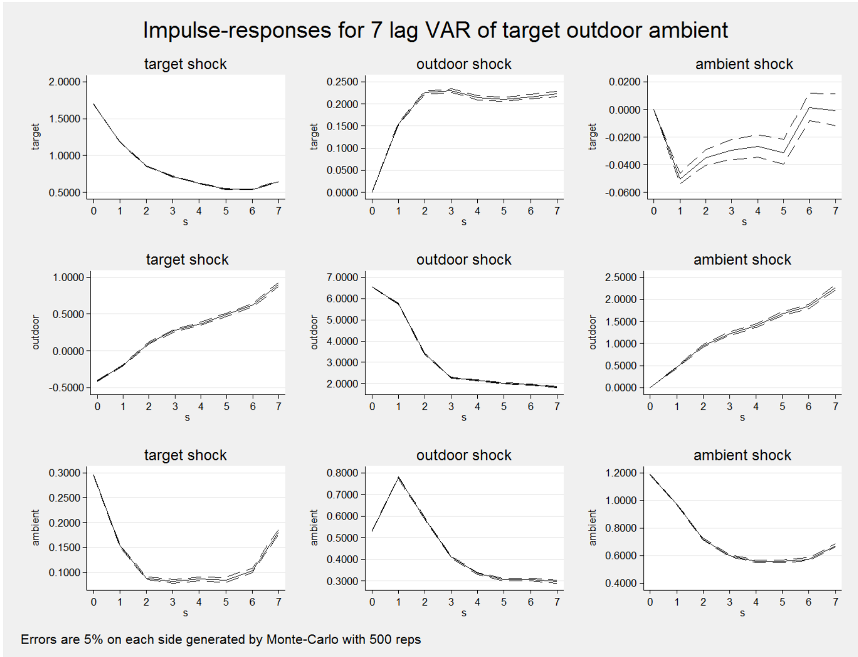


Figure 2 - Impulse Responses for 6 lag VAR of Monthly Price Shocks

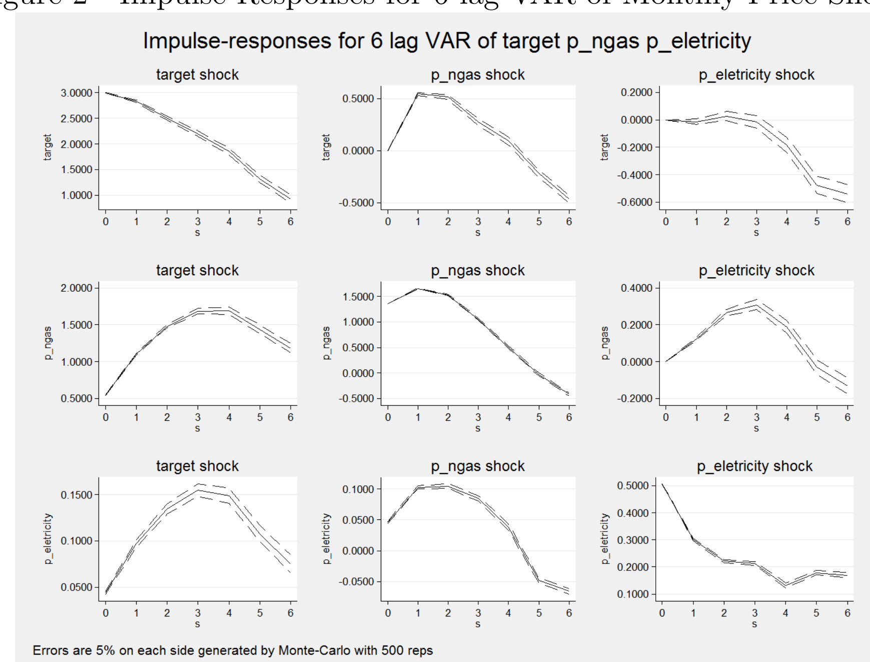


Figure 3 - Impulse Responses for 6 lag VAR of Monthly Weather Shocks

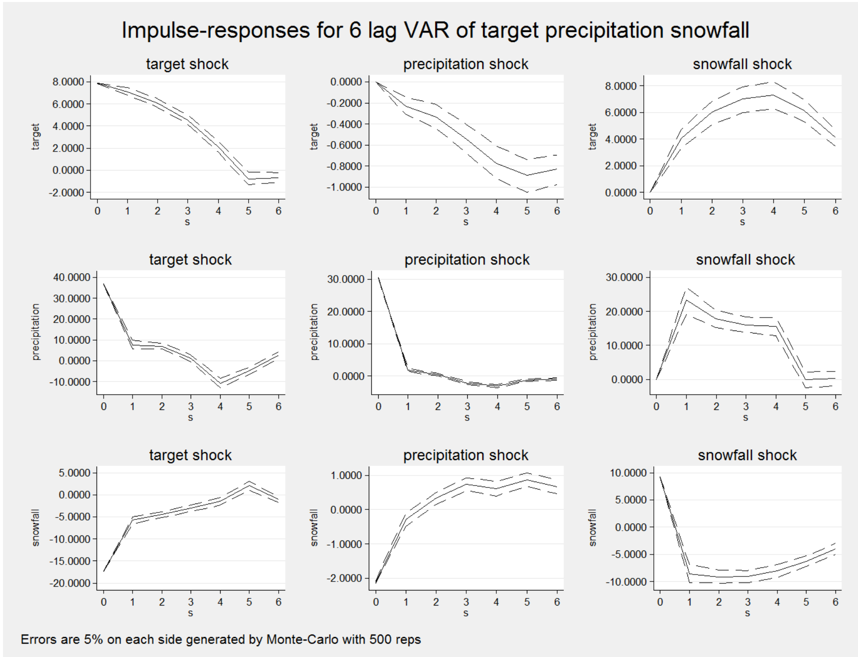


Figure 4 - Impulse Responses for 6 lag VAR of Keyword Searches

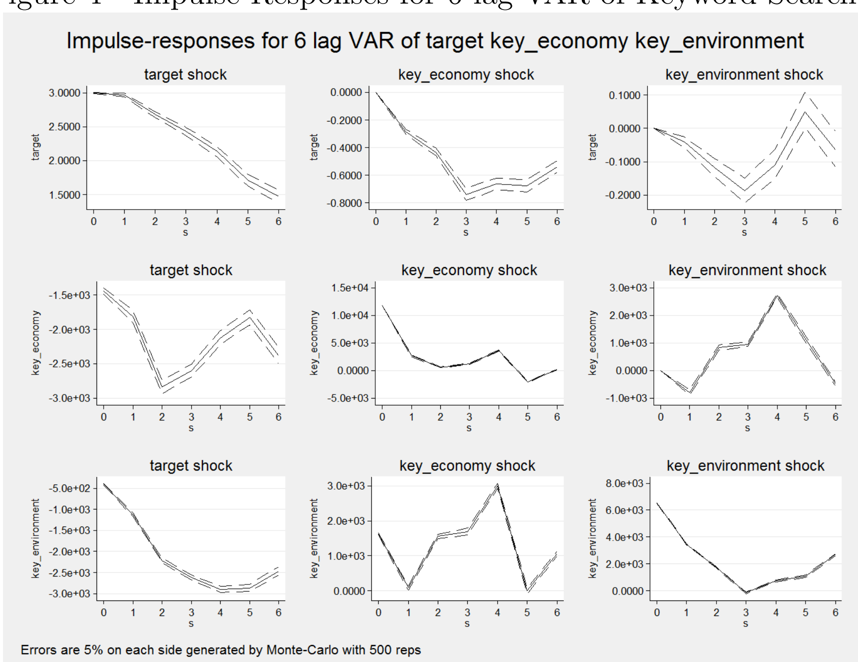
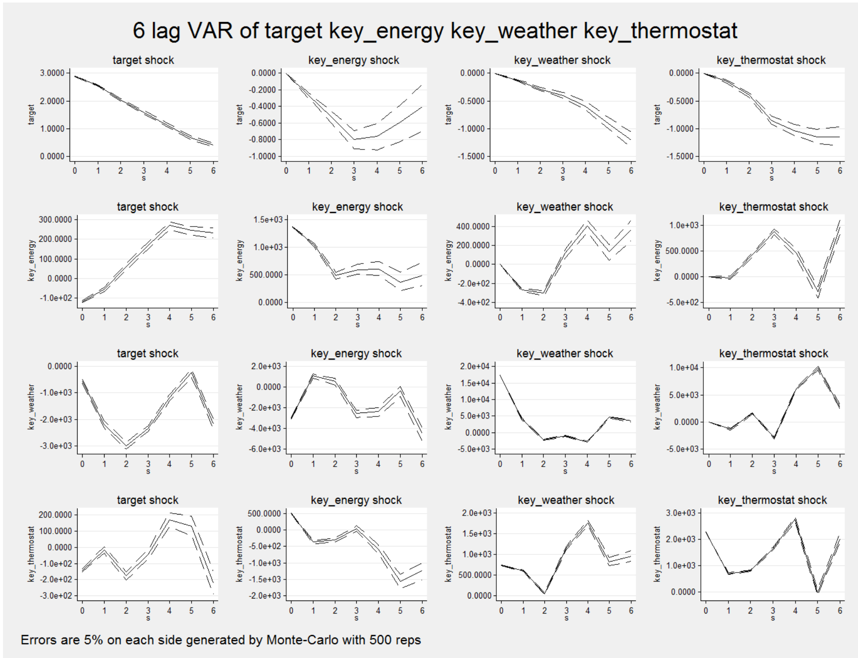


Figure 5 - Impulse Responses for 6 lag VAR of Keyword Searches (Continued)



Tables

Table 1: Summary statistics

Variable	Mean	Std. Dev.
outdoor	59.19	19.91
ambient	71.24	5.98
target	70.89	7.69
heating duration(minutes)	89.84	178.46
cooling duration(minutes)	120.83	220.76
morning target change freq	1.52	3.31
afternoon target change freq	1.29	3.25
evening target change freq	1.54	3.22
midnight target change freq	1.11	3.27
precipitation	24.72	82.87
snowfall	1.76	14.32
snow depth	8.08	42.89
monthly unemployment	7.27	1.54
monthly electricity price	12.86	2.73
monthly natural gas price	13.71	4.64
northeast	0.20	0.40
midwest	0.17	0.17
west	0.23	0.42
south	0.40	0.49
program target freq	1.91	1.28
total user target change freq	5.45	11.81
days since last override	6.68	21.20
Number of Observations	16,586,753	
Number of Households	41,897	

Table 2: Short Run Baseline Results

VARIABLES	(1) target	(2) target	(3) target	(4) target
L.target	0.737***	0.679***	0.679***	0.678***
	(0.00227)	(0.00235)	(0.00235)	(0.00235)
L2.target	0.0462***	0.00843***	0.00849***	0.00836***
	(0.00239)	(0.00236)	(0.00236)	(0.00236)
L3.target	0.124***	0.0197***	0.0197***	0.0197***
	(0.00140)	(0.00164)	(0.00164)	(0.00164)
target_mean7		0.189***	0.188***	0.189***
		(0.00266)	(0.00266)	(0.00266)
target_mean30		0.0426***	0.0427***	0.0420***
		(0.00101)	(0.00101)	(0.00101)
outdoor	0.00767***	0.00794***	0.00791***	0.00841***
	(0.000255)	(0.000250)	(0.000252)	(0.000255)
L.outdoor	0.0146***	0.0165***	0.0166***	0.0169***
	(0.000269)	(0.000292)	(0.000292)	(0.000295)
L2.outdoor	-0.00198***	-0.00114***	-0.00118***	-0.000813***
	(0.000233)	(0.000229)	(0.000229)	(0.000230)
L3.outdoor	-0.00782***	-0.00170***	-0.00177***	-0.00169***
	(0.000187)	(0.000189)	(0.000189)	(0.000190)
outdoor_mean7		-0.00479***	-0.00465***	-0.00493***
		(0.000316)	(0.000315)	(0.000318)
outdoor_mean30		-0.0102***	-0.0103***	-0.00957***
		(0.000291)	(0.000291)	(0.000296)
precipitation				3.37e-05***
				(9.58e-06)
L.precipitation				-0.000192***
				(9.67e-06)
L2.precipitation				-6.66e-05***
				(9.44e-06)
L3.precipitation				-1.31e-05
				(9.74e-06)
snowfall				0.00170***
				(5.86e-05)
L.snowfall				-2.14e-06
				(6.51e-05)
L2.snowfall				0.000934***
				(6.40e-05)
L3.snowfall				0.000730***
				(6.25e-05)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2: Short Run Baseline Results - Continued

VARIABLES	(1) target	(2) target	(3) target	(4) target
snowdepth				0.00148***
				(6.69e-05)
L.snowdepth				-0.000460***
				(8.34e-05)
L2.snowdepth				-0.000299***
				(8.41e-05)
L3.snowdepth				-0.000290***
				(5.65e-05)
Day of Week Fixed Effects	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	5,502,945	5,502,945	5,502,945	5,502,945
Households	37,921	37,921	37,921	37,921

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Short Run Impact of Outdoor Temperature Distributions

VARIABLES	(5) target	(6) target
L.target	0.679***	0.678***
	(0.00235)	(0.00235)
L2.target	0.00846***	0.00859***
	(0.00236)	(0.00236)
L3.target	0.0197***	0.0198***
	(0.00164)	(0.00164)
target_mean7	0.189***	0.189***
	(0.00266)	(0.00266)
target_mean30	0.0427***	0.0427***
	(0.00101)	(0.00101)
outdoor	0.00798***	0.00892***
	(0.000252)	(0.000309)
L.outdoor	0.0165***	0.0199***
	(0.000293)	(0.000411)
L2.outdoor	-0.00116***	-0.00214***
	(0.000229)	(0.000312)
L3.outdoor	-0.00180***	-0.00362***
	(0.000190)	(0.000261)
outdoor_mean7	-0.00472***	-0.00479***
	(0.000324)	(0.000316)
outdoor_mean30	-0.0102***	-0.0114***
	(0.000295)	(0.000316)
temp_75		-0.0291***
		(0.00337)
L.temp_75		-0.0188***
		(0.00372)
L2.temp_75		0.00353
		(0.00336)
L3.temp_75		0.0287***
		(0.00310)
temp_90		-0.0595***
		(0.00357)
L.temp_90		-0.0625***
		(0.00385)
L2.temp_90		0.000295
		(0.00353)
L3.temp_90		0.0385***
		(0.00332)
temp_99		-0.111***
		(0.00908)
L.temp_99		-0.103***
		(0.00958)
L2.temp_99		0.00344
		(0.00866)
L3.temp_99		0.0489***
		(0.00812)

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3: Short Run Impact of Outdoor Temperature Distribution - Continued

VARIABLES	(5) target	(6) target
temp_25		-0.0568***
		(0.00436)
L.temp_25		0.00153
		(0.00480)
L2.temp_25		-0.0262***
		(0.00411)
L3.temp_25		-0.00643
		(0.00392)
temp_10		0.0267***
		(0.00497)
L.temp_10		0.0917***
		(0.00510)
L2.temp_10		-0.0222***
		(0.00439)
L3.temp_10		-0.0365***
		(0.00421)
temp_1		0.137***
		(0.0110)
L.temp_1		0.132***
		(0.0103)
L2.temp_1		-0.0112
		(0.00933)
L3.temp_1		-0.0155*
		(0.00885)
hot5_75	-0.00610**	
	(0.00282)	
hot5_90	-0.0361***	
	(0.00523)	
hot5_99	-0.137***	
	(0.0427)	
cold5_25	-0.0306***	
	(0.00358)	
cold5_10	0.0231***	
	(0.00659)	
cold5_1	0.0369	
	(0.0475)	
Day of Week Fixed Effects	Yes	Yes
Month Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Observations	5,502,945	5,502,945
Households	37,921	37,921

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Short Run Subgroup Results

VARIABLES	Summer target	Winter target	Northeast target	South target	West target	Midwest target
L.target	0.556***	0.584***	0.662***	0.665***	0.695***	0.672***
	(0.00417)	(0.00443)	(0.00528)	(0.00308)	(0.00588)	(0.00527)
L2.target	0.0452***	0.00831*	0.0436***	-0.0101***	0.0154**	0.0254***
	(0.00339)	(0.00440)	(0.00447)	(0.00260)	(0.00681)	(0.00502)
L3.target	0.0352***	0.0149***	0.0287***	0.0122***	0.0288***	0.0194***
	(0.00257)	(0.00322)	(0.00304)	(0.00194)	(0.00466)	(0.00356)
target_mean7	0.189***	0.142***	0.188***	0.179***	0.180***	0.177***
	(0.00481)	(0.00549)	(0.00547)	(0.00342)	(0.00719)	(0.00556)
target_mean30	0.0267***	0.0444***	0.0251***	0.0756***	0.0245***	0.0367***
	(0.00237)	(0.00296)	(0.00187)	(0.00190)	(0.00186)	(0.00219)
outdoor	-0.00458***	0.000966***	-0.00266***	0.0203***	0.00243***	0.00242***
	(0.000562)	(0.000331)	(0.000368)	(0.000497)	(0.000551)	(0.000401)
L.outdoor	0.00577***	0.0138***	0.0103***	0.0250***	0.0146***	0.0104***
	(0.000632)	(0.000367)	(0.000460)	(0.000513)	(0.000689)	(0.000529)
L2.outdoor	0.00426***	8.77e-05	0.00198***	-0.00494***	0.00311***	0.00102**
	(0.000524)	(0.000288)	(0.000392)	(0.000399)	(0.000584)	(0.000404)
L3.outdoor	0.000305	-0.000742***	-0.000973***	-0.00158***	0.000128	-0.00114***
	(0.000470)	(0.000259)	(0.000334)	(0.000326)	(0.000543)	(0.000358)
outdoor_mean7	0.00165**	-0.00134***	0.00209***	-0.0101***	-0.00282***	-0.00104*
	(0.000732)	(0.000418)	(0.000564)	(0.000567)	(0.000814)	(0.000578)
outdoor_mean30	0.00192**	-0.00203***	-0.00280***	-0.00892***	-0.0126***	-0.00132**
	(0.000773)	(0.000610)	(0.000676)	(0.000595)	(0.000654)	(0.000654)
precipitation	2.26e-05*	0.000226***	0.000106***	8.22e-05***	4.67e-05	0.000215***
	(1.25e-05)	(2.79e-05)	(1.96e-05)	(1.17e-05)	(4.90e-05)	(3.36e-05)
L.precipitation	1.14e-05	-0.000407***	-0.000193***	-3.90e-05***	-0.000402***	-0.000216***
	(1.27e-05)	(2.67e-05)	(2.20e-05)	(1.16e-05)	(5.45e-05)	(3.33e-05)
L2.precipitation	5.60e-05***	-0.000349***	-5.69e-07	3.67e-05***	-0.000499***	-8.73e-05**
	(1.23e-05)	(2.81e-05)	(2.02e-05)	(1.14e-05)	(5.64e-05)	(3.40e-05)
L3.precipitation	2.67e-05**	-1.95e-05	5.75e-05***	5.97e-05***	-0.000365***	-1.53e-05
	(1.28e-05)	(2.81e-05)	(2.09e-05)	(1.20e-05)	(5.06e-05)	(3.37e-05)
snowfall		0.00120***	0.00137***	0.00220***	0.00207***	0.000504***
		(6.32e-05)	(8.43e-05)	(0.000166)	(0.000265)	(9.59e-05)
L.snowfall		4.37e-05	-0.000290***	0.000332	1.80e-05	-0.000533***
		(7.30e-05)	(9.11e-05)	(0.000220)	(0.000346)	(0.000113)
L2.snowfall		0.000738***	0.000116	0.00233***	0.000705**	0.000240**
		(7.14e-05)	(8.89e-05)	(0.000195)	(0.000292)	(0.000111)
L3.snowfall		0.000296***	-0.000143	0.00196***	0.000985***	0.000370***
		(6.76e-05)	(8.86e-05)	(0.000165)	(0.000282)	(0.000110)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Short Run Subgroup Results - Continued

VARIABLES	Summer target	Winter target	Northeast target	South target	West target	Midwest target
snowdepth		0.00114***	0.000675***	0.00308***	0.00243***	0.00119***
		(7.21e-05)	(9.25e-05)	(0.000219)	(0.000323)	(0.000115)
L.snowdepth		-0.000450***	-0.000519***	-0.000925***	0.000494	-0.000285**
		(8.80e-05)	(0.000123)	(0.000234)	(0.000363)	(0.000136)
L2.snowdepth		-0.000119	0.000178	-0.00129***	-9.41e-05	-0.000245*
		(8.80e-05)	(0.000124)	(0.000224)	(0.000316)	(0.000144)
L3.snowdepth		-0.000276***	-0.000171**	0.000762***	-0.000535**	-0.000409***
		(6.12e-05)	(8.20e-05)	(0.000176)	(0.000239)	(9.20e-05)
Day of Week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,435,988	1,595,689	1,018,949	2,306,330	1,377,124	800,542
Households	32,759	32,196	6,982	15,397	9,131	6,411

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Short Run Determinants of Thermostat Override Decisions

VARIABLES	(7) override	(8) override	(9) override
L.override	0.337***	0.336***	0.337***
	(0.000986)	(0.000986)	(0.000986)
L2.override	0.119***	0.120***	0.119***
	(0.000808)	(0.000807)	(0.000809)
L3.override	0.113***	0.113***	0.113***
	(0.000729)	(0.000729)	(0.000729)
d_override	-0.00339***	-0.00339***	-0.00339***
	(8.73e-05)	(8.73e-05)	(8.73e-05)
outdoor	-0.000652**	-0.000375*	-0.000650**
	(0.000284)	(0.000224)	(0.000279)
L.outdoor	0.000194	6.35e-05	0.000177
	(0.000160)	(8.50e-05)	(0.000158)
L2.outdoor	0.000278***	9.90e-05	0.000261***
	(9.32e-05)	(7.20e-05)	(9.62e-05)
L3.outdoor	8.93e-05***	5.56e-05	5.95e-05***
	(1.02e-05)	(3.94e-05)	(1.17e-05)
temp_75		0.0116***	
		(0.00146)	
L.temp_75		0.00516***	
		(0.000514)	
L2.temp_75		-0.00294***	
		(0.000704)	
L3.temp_75		-0.00725***	
		(0.000469)	
temp_90		0.00389***	
		(0.00110)	
L.temp_90		0.00619***	
		(0.000551)	
L2.temp_90		-0.000430	
		(0.000605)	
L3.temp_90		-0.00511***	
		(0.000470)	
temp_99		-0.0257***	
		(0.00180)	
L.temp_99		0.0151***	
		(0.00122)	
L2.temp_99		-0.00236*	
		(0.00125)	
L3.temp_99		0.00602***	
		(0.00110)	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Short Run Determinants of Thermostat Override Decisions - Continued

VARIABLES	(7) override	(8) override	(9) override
temp_25		0.0180***	
		(0.00209)	
L.temp_25		-0.00350***	
		(0.000581)	
L2.temp_25		-0.00537***	
		(0.000932)	
L3.temp_25		-0.00472***	
		(0.000638)	
temp_10		0.0139***	
		(0.00172)	
L.temp_10		-0.00479***	
		(0.000669)	
L2.temp_10		-0.00365***	
		(0.000805)	
L3.temp_10		-0.00493***	
		(0.000591)	
temp_1		0.0121***	
		(0.00224)	
L.temp_1		-0.00460***	
		(0.00125)	
L2.temp_1		-0.00702***	
		(0.00127)	
L3.temp_1		0.00343***	
		(0.00116)	
hot5_75			0.00109**
			(0.000520)
hot5_90			0.00585***
			(0.000771)
hot5_99			0.0115**
			(0.00504)
cold5_25			-0.00552***
			(0.000803)
cold5_10			-0.00108
			(0.000878)
cold5_1			0.00666
			(0.00784)
Day of Week Fixed Effects	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	15,563,611	15,563,611	15,563,611
Households	40,535	40,535	40,535

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Long Run Results

VARIABLES	All target	All target	Northeast target	South target	West target	Midwest target
L.target	0.712***	0.725***	0.632***	0.719***	0.673***	0.585***
	(0.00454)	(0.00480)	(0.00987)	(0.00794)	(0.00839)	(0.0116)
L2.target	-0.0631***	-0.0418***	-0.0210***	-0.0201***	-0.0656***	-0.0137*
	(0.00300)	(0.00305)	(0.00586)	(0.00487)	(0.00621)	(0.00704)
L3.target	0.0191***	0.0175***	-0.0145***	0.0330***	0.00583	-0.0198***
	(0.00267)	(0.00272)	(0.00548)	(0.00426)	(0.00569)	(0.00630)
outdoor	0.117***	0.104***	0.0947***	0.115***	0.158***	0.0992***
	(0.00216)	(0.00224)	(0.00855)	(0.00333)	(0.00549)	(0.00394)
L.outdoor	-0.0697***	-0.0851***	-0.0616***	-0.0775***	-0.121***	-0.0642***
	(0.00181)	(0.00204)	(0.00610)	(0.00300)	(0.00503)	(0.00408)
L2.outdoor	-0.00293**	-0.0116***	0.00376	-0.00950***	-0.0240***	0.000544
	(0.00128)	(0.00147)	(0.00398)	(0.00241)	(0.00436)	(0.00330)
L3.outdoor	-0.00885***	-0.0140***	-0.000773	0.00150	-0.00366	-0.00101
	(0.00137)	(0.00152)	(0.00354)	(0.00246)	(0.00458)	(0.00319)
p_eletricity		0.114***	0.0417**	0.481***	0.0600	-0.0352
		(0.0138)	(0.0195)	(0.0371)	(0.0396)	(0.0396)
L.p_eletricity		0.0351***	0.101***	-0.241***	0.00826	-0.187***
		(0.0133)	(0.0206)	(0.0352)	(0.0357)	(0.0383)
L2.p_eletricity		-0.0131	0.0502***	-0.0739**	-0.187***	0.186***
		(0.0126)	(0.0185)	(0.0337)	(0.0356)	(0.0343)
L3.p_eletricity		0.147***	0.120***	0.270***	0.0940**	0.0329
		(0.0145)	(0.0243)	(0.0374)	(0.0401)	(0.0390)
p_ngas		0.282***	0.0396*	0.261***	0.506***	-0.0304**
		(0.00663)	(0.0212)	(0.00941)	(0.0308)	(0.0144)
L.p_ngas		-0.102***	-0.103***	-0.0189*	-0.212***	0.112***
		(0.00707)	(0.0197)	(0.00972)	(0.0292)	(0.0154)
L2.p_ngas		-0.154***	-0.0124	-0.194***	-0.121***	-0.0967***
		(0.00588)	(0.0179)	(0.00896)	(0.0259)	(0.0119)
L3.p_ngas		0.117***	0.0396***	0.0954***	0.263***	0.0504***
		(0.00482)	(0.0153)	(0.00783)	(0.0260)	(0.00980)
unemp		-0.109***	0.101	-0.0898**	-0.162*	-0.0999**
		(0.0276)	(0.0912)	(0.0411)	(0.0864)	(0.0466)
L.unemp		-0.0638**	-0.229**	0.0755*	-0.109	0.0276
		(0.0270)	(0.0958)	(0.0447)	(0.0744)	(0.0461)
L2.unemp		0.130***	0.335***	0.154***	0.370***	-0.230***
		(0.0301)	(0.107)	(0.0497)	(0.0810)	(0.0574)
L3.unemp		0.140***	-0.0205	0.994***	0.192**	0.180***
		(0.0337)	(0.104)	(0.0543)	(0.0817)	(0.0674)
precipitation		0.000455*	-0.00230***	0.00145***	0.000802	0.00112
		(0.000273)	(0.000714)	(0.000333)	(0.00130)	(0.000710)
L.precipitation		0.000335	-0.00206***	0.00195***	-0.00243*	0.000629
		(0.000253)	(0.000718)	(0.000307)	(0.00130)	(0.000786)
L2.precipitation		0.000512**	-0.000664	0.00116***	0.00563***	-0.00133**
		(0.000224)	(0.000633)	(0.000276)	(0.00118)	(0.000655)
L3.precipitation		0.000159	-0.00215***	-2.22e-05	0.0137***	0.000270
		(0.000203)	(0.000582)	(0.000249)	(0.00121)	(0.000545)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Long Run Results - Continued

VARIABLES	target	target	target	target	target	target
snowfall		0.000833	0.00536**	-0.00493*	-0.0149***	0.00276
		(0.00122)	(0.00209)	(0.00284)	(0.00453)	(0.00207)
L.snowfall		-0.0203***	-0.00305	-0.0119**	-0.000989	-0.0128***
		(0.00168)	(0.00258)	(0.00513)	(0.00703)	(0.00225)
L2.snowfall		-0.0282***	0.000478	-0.000104	0.00735	-0.000775
		(0.00191)	(0.00248)	(0.00694)	(0.00574)	(0.00276)
L3.snowfall		-0.00486**	-0.00364	0.0770***	-0.0203***	-0.00523
		(0.00232)	(0.00345)	(0.0134)	(0.00622)	(0.00352)
snowdepth		0.000979***	-0.000193	0.00935***	0.0316***	0.00154***
		(0.000230)	(0.000412)	(0.00205)	(0.00246)	(0.000389)
L.snowdepth		-0.00332***	0.000409	-0.0143***	-0.0236***	-0.000693
		(0.000310)	(0.000446)	(0.00252)	(0.00262)	(0.000492)
L2.snowdepth		-0.00364***	3.23e-05	0.000728	-0.00555**	-0.00287***
		(0.000511)	(0.000822)	(0.00346)	(0.00282)	(0.000776)
L3.snowdepth		-0.00135*	-0.000290	-0.0111	-0.0131***	-0.00340***
		(0.000780)	(0.00140)	(0.00704)	(0.00290)	(0.000961)
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	338,523	338,523	62,509	143,905	73,367	58,742
Households	35,788	35,788	6,563	14,627	8,452	6,146

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Long Run Keywords Search Results

VARIABLES	All target	Northeast target	South target	West target	Midwest target
key_economy	0.0999	-0.685***	-0.686***	0.247	1.052***
	(0.0733)	(0.164)	(0.146)	(0.214)	(0.177)
L.key_economy	0.201***	-0.0850	-1.017***	3.083***	0.972***
	(0.0675)	(0.150)	(0.135)	(0.211)	(0.169)
L2.key_economy	-0.704***	-0.150	-0.0392	-1.623***	0.0283
	(0.0682)	(0.148)	(0.138)	(0.254)	(0.180)
L3.key_economy	0.0462	0.247	0.0963	1.393***	0.233
	(0.0776)	(0.184)	(0.145)	(0.252)	(0.192)
key_environment	1.078***	2.646***	-0.163	4.929***	1.409***
	(0.119)	(0.359)	(0.179)	(0.329)	(0.330)
L.key_environment	-0.0459	0.133	0.658***	3.608***	-1.444***
	(0.107)	(0.307)	(0.170)	(0.335)	(0.302)
L2.key_environment	1.935***	0.351	-0.940***	3.821***	1.300***
	(0.112)	(0.335)	(0.157)	(0.285)	(0.391)
L3.key_environment	1.300***	0.993***	1.922***	-0.287	1.260***
	(0.111)	(0.339)	(0.172)	(0.322)	(0.336)
key_energy	1.165***	-0.0364	0.694***	-0.789**	-1.041***
	(0.0787)	(0.222)	(0.139)	(0.327)	(0.224)
L.key_energy	0.300***	-1.207***	-1.188***	-1.102***	1.236***
	(0.0778)	(0.194)	(0.125)	(0.325)	(0.215)
L2.key_energy	0.712***	0.478**	-0.555***	-1.850***	-0.698***
	(0.0773)	(0.223)	(0.115)	(0.270)	(0.236)
L3.key_energy	0.584***	-0.187	0.270**	1.177***	-1.986***
	(0.0748)	(0.189)	(0.116)	(0.279)	(0.228)
key_weather	-0.188***	0.361	-0.680***	-0.539**	0.111
	(0.0549)	(0.277)	(0.0914)	(0.224)	(0.210)
L.key_weather	-0.270***	0.528**	0.00309	-3.226***	-0.118
	(0.0475)	(0.240)	(0.0660)	(0.221)	(0.164)
L2.key_weather	0.422***	-0.494**	0.0849	0.936***	0.264
	(0.0449)	(0.227)	(0.0675)	(0.190)	(0.173)
L3.key_weather	-0.714***	-0.263	-0.335***	-0.811***	0.106
	(0.0483)	(0.230)	(0.0632)	(0.207)	(0.182)
key_thermostat	0.599***	1.232***	0.120	-0.770***	1.863***
	(0.0874)	(0.325)	(0.155)	(0.274)	(0.282)
L.key_thermostat	1.643***	-0.502	0.00460	4.034***	0.788***
	(0.0822)	(0.346)	(0.156)	(0.271)	(0.242)
L2.key_thermostat	2.086***	-0.216	0.754***	5.422***	-0.569**
	(0.0781)	(0.292)	(0.137)	(0.279)	(0.237)
L3.key_thermostat	-0.633***	0.621*	-1.799***	0.233	0.601***
	(0.0882)	(0.338)	(0.166)	(0.246)	(0.227)
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	289,316	53,421	122,060	63,273	50,562
Households	34,887	6,381	14,207	8,264	6,035

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1