

Factors Affecting Override Behavior during Demand Flexibility from High-Resolution Smart Thermostat Data

Opeoluwa Wonuola Olawale, Advanced Energy Systems Graduate Program, Colorado School of Mines/National Renewable Energy Laboratory, USA

Janet Reyna, National Renewable Energy Laboratory (NREL), USA

Ben Gilbert, Colorado School of Mines, USA

ABSTRACT

In this study, we delineate key weather and demographic predictors of override behavior in residential buildings during connected thermostats demand response events. Anticipating and reducing overrides is critical to demand flexibility (DF) program success. We use high-dimensional fixed effects linear regression techniques on a large ecobee dataset for about 5,000 enrolled households in the United States. We identify critical weather (indoor and outdoor temperature), building (housing type), and occupant (previous DF overrides and previous DF event exposure) factors influencing the override patterns of customers during thermostat demand response. We also differentiate DF events by season to understand the different indoor and outdoor conditions that might influence seasonal override rates. We found significant differences in override rates between building types, with single-family semi-detached homes generally having the highest overrides. Having a history of overrides was additionally a critical factor in predicting occupant response to future DF events. Understanding these override differences is necessary for rural electric cooperatives and emerging DF programs without access to large DR historical data. Overall, we provide critical information on technical and local demographic characteristics that may be correlated to building type to influence strategies to reduce overrides and improve the adoption of DF technologies.

Introduction

Demand flexibility (DF) presents a huge financial and environmental opportunity as it could forestall nearly \$13 billion of the expected future \$80 billion national grid infrastructure investment in peak capacity generation while lowering electric bills by 10–40% (“The Economics of Demand Flexibility” 2015; U.S. Energy Information Administration 2021). Responsive peak demand at critical times of renewable energy availability can also lower dependence on fossil fuels (Goldenberg and Dyson 2018; Neukomm, Nubbe, and Fares 2019). Essentially, DF could be a valuable resource in avoiding expensive grid capacity expansion to cover peak demand, which is growing disproportionately to average daily demand (“Hourly Electricity Consumption Varies throughout the Day and across Seasons - Today in Energy - U.S. Energy Information Administration (EIA)” 2020). According to the Rocky Mountain Institute, DF is an umbrella term for communication and control technologies that facilitate demand response (DR) to dynamic market conditions through price signals and other mechanisms (“The Economics of Demand Flexibility” 2015). This definition includes both existing demand response programs as well as more futuristic options which do not yet exist in the market. Existing DF programs typically involve connected thermostats (CTs), HVAC compressor

control, or smart water heaters (SWHs) (Bonneville Power Administration (BPA) 2018; KEMA 2006).

However, low DF program enrollment, high attrition (i.e., opt-outs), and frequent thermostat override challenge DF goals to reduce peak demand (Bonneville Power Administration (BPA) 2018; Schellenberg, Lemarchand, and Wein 2017). As of 2020, only 8% of US residential electricity customers (11 million out of 136 million) are enrolled in DF. Furthermore, only about 40% of the theoretical average residential DF potential is realized annually in the United States (3,504 MW actual peak demand savings out of 8,535 MW potential peak demand savings as of 2020) (U.S. Energy Information Administration 2021). High override rates during DF events (upwards of 30%) contribute to the low realization of DF potential (Schellenberg, Lemarchand, and Wein 2017; Sarra et al. 2021; Bonneville Power Administration (BPA) 2018).

Undoubtedly, occupant comfort and the perception of comfort (i.e., if occupants *think* DF enhances or compromises their comfort) play a significant role in these overrides. There are several outstanding questions on how utilities and product designers might be responsive to these customer comfort needs (Wirtshafter, Peters, and Haeri 2018). In a recent work, we show how different single-family residential customer types represented as four persona types enrolled in DR might deviate from DF estimates of peak demand reduction capacity by up to 20% based on comfort-driven priorities (Olawale, Gilbert, and Reyna 2022). A study in the literature however suggests that keeping the override feature of DF is an essential option necessary for consumer acceptance of DF programs (Xu et al. 2018). This comfort-design balance question on how customers might respond with less override led us to explore factors influencing override rates.

In this study, we aim to better understand the relationship between factors related to occupants' comfort and customer engagement during DF enrollment. We focus on connected thermostats (CTs) since CTs are more common than SWHs in residential DF programs (Bonneville Power Administration (BPA) 2018). Also, CTs are directly related to both heating and cooling loads, which together account for about 40% of residential energy demand and about 60% of peak demand ("End-Use Load Profiles for the U.S. Building Stock" 2018).

There are existing studies that examine DF overrides relative to either outdoor or indoor temperature (Sarra et al. 2021; Huchuk, O'Brien, and Sanner 2018; Kane and Sharma 2020; Sharma and Kane 2020; Ge and Ho 2019). Summer outdoor temperatures and the duration of a demand response event have been demonstrated both as positive predictors of override using log-odds and proportional hazard models (KEMA 2006) and as a non-predictor of override using cluster analysis (Huchuk, O'Brien, and Sanner 2018). On the other hand, a 2021 winter Canadian study published that six Kelvin lower-than-average indoor temperatures and longer DF event duration results in high override rates up to 70% while four Kelvin higher than average indoor temperature results in up to 10% override rates using an agent-based stochastic model (Vellei, Martinez, and Le Dréau 2021). Outdoor temperatures are determined by weather patterns while indoor temperatures could point to the comfort preferences of household occupants. Yet, there are no integrated studies to date that quantify the comparative importance of both indoor and outdoor temperatures on DF overrides. To tackle this, we study how DF thermostat override decisions vary with seasonal and overall indoor and outdoor temperatures in this work.

Furthermore, it is unclear what key factors play significant roles in determining override decisions since recent studies continue to use different and numerous predictors (Kane and Sharma 2020; Sharma and Kane 2020; Kane and Sharma 2019). For instance, one study developed a neural network model with 28 technology and weather features using about 1,200

single-occupant homes enrolled in DF in the United States (Kane and Sharma 2020). Another study used decision tree analysis to identify CT use behavior, outdoor temperature, DF duration, and general experience with DF as top features for predicting override patterns without considering other factors including occupant comfort and constraints (Sarran et al. 2021). Given that none of these studies consider all the factors together, we, therefore, consider the relative importance of comfort preferences (average indoor temperatures), weather (outdoor temperatures), occupant constraints (such as building characteristics which can be useful as a proxy for occupant socioeconomic and demographic information), and occupants' previous experiences with DF events to large-scale residential override behavior while controlling for DF duration and household location in this study.

Previous studies have focused on only single-occupant building units (Sharma and Kane 2020) as we also cover a diverse range of households with multiple occupants by using the existing ecobee Donate Your Data (DYD) for 5,000 different DF-enrolled households in the United States. Also, unlike earlier studies with complex, hard-to-interpret data-driven neural network models, we use relatively simple regression analysis to systematically understand the factors influencing different customers across the US to override DR signals. Our results show critical weather/comfort (outdoor and indoor temperature), building (housing type), and occupant (previous DF overrides and previous DF event exposure) factors influencing the override patterns of customers during CT demand response. We also differentiate DF events by season to understand the different indoor and outdoor conditions that might influence seasonal override rates. We found significant differences in override rates between building types, with single-family semi-detached homes generally having the highest overrides. Also, having a history of overrides was additionally a critical factor in predicting occupant response to future DF events. Understanding these override differences is necessary for rural electric cooperatives and emerging DF programs without access to large DR historical data. Overall, we provide critical information on technical and local demographic characteristics that may be correlated to building type to influence strategies to reduce overrides and improve the adoption of DF technologies to support decarbonization efforts.

The rest of this work is organized into sections: Methodology, Key Results and Discussions (on the effects of weather, comfort preferences, household characteristics, and occupant experience on CT DF override rates), and Conclusions (including scope limits and recommendations for future work).

Methodology

In this section, we briefly overview the primary research questions, the hypothesis, data, and the regression specifications within the empirical framework developed in this study. Table 1 briefly describes the data and methodology we employed in this project to understand how occupant comfort drives setpoint override behavior within CT residential DF programs.

Primary Research Questions:

To understand the key factors influencing DF thermostat overrides for buildings enrolled in connected thermostat (CT) demand response (DR), we ask:

1. What is the marginal effect of outdoor and indoor temperature conditions on DR override during a DR event controlling for household fixed effects?

2. How does household heterogeneity (e.g., occupant living conditions and constraints such as building characteristics) affect DR overrides??
3. How do occupant experiences within the CT DF program affect their override decision?

Table 1: Summary description of data/methodology for this study

Data	Ecobee (a non-utility, third-party CT vendor) publishes de-identified household/occupant characteristics and 5-minute interval thermostat data. Ecobee data represents a subset of existing DR data containing DR signal response, de-identified building characteristics, external weather data, and thermostat data with temperature setpoints.
Analysis tools	Linear regression analysis combined with high dimensional fixed effects given the high number of households.
Output variable	The decision to override thermostat DR signals (0 or 1).

Hypothesis

Accounting for indoor conditions, building characteristics, and occupant experiences in addition to weather conditions can improve our description of DF override rates, and how different occupant groups may respond to DF signals differently.

Data

The 2015-2018 ecobee thermostat donate your data (DYD) contains 5-minute panel observations for about 96,000 dwelling units with CTs. Out of all these units, 5,917 units are enrolled in DF, i.e., they have a record in the DYD of their CT unit in response to DR events issued by a third party (could be a utility or an aggregator). This is approximately 7% DF enrollment among ecobee CT owners. Based on the available cross-section of characteristics in the metadata, we focus on the 5,759 households within the United States (the prevalent country).

With our focus on the US, of the 60,536 individual DR events (varying from 5 minutes to 14 hours in duration) that occurred from 2015 to 2018 across the different US households, 24,231 override responses from 3,769 dwelling units occurred. This translates to a 40% chance of override for each event and 65% of households engaging in at least one override. This high per event and per household rate of overrides in the whole sample further emphasizes the need to understand the motivators of overrides in DF programs. Table 2 outlines the descriptive statistics for the US dataset of DR events.

Empirical Framework

We present a basic linear regression specification in Equation (1) to estimate the probability of override per event.¹

$$C_{it} = \sum_k \gamma_k T_{k,it} + \delta F_{it} + \xi_{iym} + \mu_d + \epsilon_{it} \quad (1)$$

¹ Equation (1) is estimated as a Linear Probability Model (LPM). LPMs are frequently chosen in the applied literature over alternatives like probit or logit for a variety of reasons, including ease of interpretation of the coefficients and computational feasibility in large samples, particularly panel data with high-dimensional fixed effects – all of which are relevant for this study. See, for example, Currie and Gruber 1996; Heckman and Snyder 1997; and Klaassen and Magnus 2001.

- where C_{it} is a binary indicator for an override for household, i , per DR event at date t .
- $T_{k,it}$ - k th temperature bin using 10 °F intervals for either indoor or outdoor temperature experienced by household i at time t , where the bins are defined as binary variables equal to one if the temperature was in a given interval.
- γ_k - coefficients for the contemporaneous effect on DR override decision, C_{it} for either the outdoor or indoor temperature in the k^{th} temperature bin
- $\mathbf{F}_{it}$ - control variables including DR event duration to avoid omitted variable bias and state location to account for climate zone differences
- ξ_{iym} - household-year-season fixed effects, and μ_d - day-of-the-week fixed effects
- ϵ_{it} - stochastic error term

Table 2: Summary statistics for the dataset used in this project's analysis

Variable	Mean	Standard deviation (SD)
Indoor temperature (°F)	76.6	5.5
Outdoor temperature (°F)	84.1	18.8
Setpoint cooling temperature (°F)	79.5	13.9
Setpoint heating temperature (°F)	65.7	19.0
Floor area (sq.ft.)	2400	1240
Number of floors (0 to 10)	1.7	0.9
Age of home (0 to 120 years)	23.5	23.2
Number of occupants (0 to 20)	1.4	1.7
Previous month thermostat override count (every 5 minutes)	3352.4	3267.6
Previous month DR count (every 5 minutes)	94.6	138.9
DR event override probability	0.322	0.467
Number of observations of DR events per occupancy mode (awake, away, home, asleep, or customized schedule)	81,029	
Number of households	5,759	

To answer what average indoor or outdoor temperature conditions during DR most likely results in a DR override decision, (i.e., what is the marginal effect of dummy temperature changes (outdoor, indoor, or both) on the chances of override), we estimate the specifications in Equation (1) with (a) outdoor temperatures, (b) indoor temperatures, and (c) both outdoor and indoor temperatures for the entire sample and different seasons (summer [May - August], shoulder [March, April, September, and October], and winter [November - February]). The dummy temperature variable $T_{k,it}$ (indoor or outdoor) equals one if the per-event average temperature is in the k th bin. We use ten temperature bins similar to previous studies (Ge and Ho 2019; Deschênes and Greenstone 2011) but set 60–70°F temperature bin as the baseline temperature bin instead of 50–60°F. This is because we consider the minimal occupant comfort preferences reflected in the average and median setpoint heating temperatures of 65.7°F and 66.8°F, respectively, and the seasonal indoor conditions and frequencies (Table 3).

We also explore the role of building characteristics and occupant experiences on override decisions by modifying the basic regression specification shown in Equation (2) below. How strongly do an occupant's previous DR override count and an occupant's continued exposure to DR events correlate to overrides? Here, we include the average indoor and outdoor temperatures, $T_{in,it}$ and $T_{out,it}$, during each event instead of the ten temperature bins for ease of interpretation while focusing on the role of the other factors. The average magnitude of DR per event (i.e., the difference between the customer's setpoint (heating or cooling) and the resulting indoor temperature during DR) was highly collinear with the average indoor temperature and was

therefore excluded. Also, since DR rewards, incentives, opt-in, or opt-out program policies were not observed directly in the ecobee data, location was controlled for to account for possible differences in DR policies applied in different locations.

$$C_{it} = \beta \mathbf{H}_{it} + \tau \sum_j \mathbf{X}_{id-j} + \theta \sum_j \mathbf{D}_{id-j} + \gamma_{out} T_{out,it} + \gamma_{in} T_{in,it} + \delta \mathbf{F}_{it} + \mu_d + \epsilon_{it} \text{ for } j \in [0, 30] \quad (2)$$

- where $\mathbf{H}_{it}$ is a set of building and occupant characteristics including building type (detached, semi-detached, apartment, etc.), floor area (in sq.ft.), number of floors, age of home, number of occupants, whether the dwelling unit has electric heat or not, and has a heat pump or not.
- β coefficients represent the marginal effect of building characteristics on DR override decision C_{it} (relative to the baseline temperature bin and detached buildings)
- γ_{out} and γ_{in} are the coefficients for the marginal effects of average outdoor and indoor temperatures on DR override decision, respectively
- $\mathbf{X}_{id-j}$ is the number of times an occupant uses the ‘HOLD’ function on their thermostat on j th previous day from day d while $\sum_j \mathbf{X}_{id-j}$ is the total number of previous override events within the last month (j up to 30 days).
- τ coefficient represents the marginal effect of previous thermostat override decisions on DR override
- $\mathbf{D}_{id-j}$ is the number of times DR is recorded on the thermostat on j th previous day from day d while $\sum_j \mathbf{D}_{id-j}$ is the total count of previous DR events the occupants experienced in the past month (j up to 30 days).
- θ coefficient represents the marginal effect of prior DR exposure level on DR override decision

Table 3: Number of observations per temperature bin (outdoor and indoor) at different seasons from 2015 to 2018 in the DYD data

Bins	Outdoor Conditions			Indoor Conditions		
	Summer	Shoulder	Winter	Summer	Shoulder	Winter
<10 F			70			
10-20 F			555			
20-30 F		117	1,249			4
30-40 F		470	1,906			31
40-50 F		757	2,187		1	131
50-60 F	147	742	1,745		134	446
60-70 F	686	1,100	722	572	1,788	5,732
70-80 F	3,515	2,497	364	40,280	9,997	2,578
80-90 F	19,215	3,854	129	16,150	2,772	9
>90 F	33,776	5,206		349	55	

Notes: Empty cells indicate no data observations. The relatively low observation counts show seasonal extremes and sometimes with occupancy mode being away, home, or asleep. Summer (May-August), shoulder (March, April, September, and October), and winter (November-February) months.

Key Results and Discussions

The results indicate that occupants have a sensitivity to indoor and outdoor temperatures that impact levels of DR override. Further, we find that occupants in multifamily and attached housing types (condominiums and townhouses) are significantly less likely to override a DR

signal compared to those in single-family detached houses. Customers with frequent override history and increased exposure to DR override more frequently than those with occasional override history or newer to DR, suggesting that certain groups of people are more likely to override than others, and that overrides are not solely dependent on weather and comfort. This finding that increased exposure increases override likelihood is important for policy since this contradicts the anecdotal expectation that DR would get more effective with more experienced participants.

Weather and Comfort Preferences Effects on Override Rates

Outdoor conditions only:

We estimate the regression model specified in Equation (1) using only outdoor temperatures during the DR events assuming all other factors were fixed. Column (a)-(1) of Table 4 presents the baseline results of coefficients based on the whole sample for the houses with DR in the US. Statistically significant coefficients with p-values less than 0.05 have green stars if negative and red stars if positive in Table 4 to enhance readability and highlight variations per temperature bin. The results indicate that we have statistical significance for the coefficients of the extreme temperature bins indicating we have evidence of differences in the override rates at these extremes. The positive coefficients imply higher override likelihood at warmer outdoor temperatures while the negative temperature bin coefficients indicate lower override chances versus the reference temperature bin of 60 – 70°F. We observe no difference between the override rates in the 30 and 50°F bins given the non-significant coefficients (p-value > 0.05).

The full sample results, therefore, indicate that warmer outdoor temperatures beyond 50 degrees generally increase the chances of override by about 4 to 7% (highest at 80–90°F) while the reverse (lower override rates) is true at colder outdoor temperatures with a difference of about 8 to 14% relative to the reference temperature bin (lowest at outdoors <10°F). For example, an average outdoor temperature that falls between 80–90 °F shows a likelihood of override by 7.2% relative to the reference temperature bin of 60–70 °F. On the other hand, during DR overall, the lowest temperature bin (<10 F) results in a decreased likelihood of override by 14%.

Column (a)-(2) of Table 4 presents the outdoor coefficients for DR overrides during summer. The coefficients for the temperature bins are non-significant meaning there are no observable differences in the chances of override at these different outdoor temperatures relative to the base temperature bin considering only outdoor conditions, other factors fixed. This is similar during the shoulder season (Table 4, Column (a)-(3)), except that override chances are higher by 6.4% when outdoor temperatures fall within 80–90°F relative to the base temperature bin. During winter (Table 4, Column (a)-(4)), the trends for override with outdoor conditions are less clear except that override chances are higher by 9.2% when outdoor temperatures fall within 70–80°F versus the reference 60–70°F bin.

Indoor conditions only:

Using only average indoor temperature bins during DR events in Equation (1) similarly assuming that all other factors were fixed, we present the results in column (b) of Table 4 based on the whole sample (1), summer (2), shoulder (3), and winter (4), respectively. There are no observable differences seasonally nor at indoor temperatures higher than 80 degrees in general versus the reference indoor temperature. However, the full sample results indicate that the

Table 4: Marginal effects of outdoor and indoor temperatures on override decision during connected thermostat (CT) demand response

	(a) Outdoor conditions only				(b) Indoor conditions only				(c) Both outdoor and indoor conditions			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	All	Summer	Shoulder	Winter	All	Summer	Shoulder	Winter	All	Summer	Shoulder	Winter
Outdoor	<10 F	-0.136** (0.045)		-0.052 (0.058)					-0.111* (0.051)			-0.041 (0.060)
	10-20 F	-0.078* (0.037)		0.007 (0.049)					-0.058 (0.041)			0.021 (0.048)
	20-30 F	-0.129** (0.048)	-0.025 (0.047)	0.001 (0.032)					-0.102* (0.049)	-0.057 (0.052)	0.014 (0.031)	
	30-40 F	-0.078 (0.040)	-0.015 (0.043)	0.001 (0.027)					-0.060 (0.045)	-0.051 (0.046)	0.014 (0.030)	
	40-50 F	-0.015 (0.026)	-0.034 (0.037)	0.022 (0.020)					-0.003 (0.030)	-0.060 (0.036)	0.034 (0.020)	
	50-60 F	0.042* (0.019)	-0.136 (0.100)	0.038 (0.035)	0.027 (0.019)				0.049* (0.020)	-0.141 (0.104)	0.025 (0.032)	0.034 (0.019)
	70-80 F	0.045** (0.016)	0.035 (0.035)	0.025 (0.020)	0.092** (0.029)				0.045** (0.014)	0.052 (0.031)	0.027 (0.019)	0.082** (0.027)
	80-90 F	0.072*** (0.017)	0.044 (0.036)	0.064** (0.020)	0.015 (0.057)				0.075*** (0.015)	0.066 (0.032)	0.067** (0.019)	0.015 (0.053)
	>90 F	0.055* (0.022)	0.042 (0.044)	0.035 (0.022)					0.064** (0.020)	0.070 (0.040)	0.039 (0.022)	
	20-30 F				-0.184* (0.083)			-0.005 (0.147)	-0.119 (0.079)			-0.009 (0.138)
30-40 F				-0.229** (0.078)			-0.004 (0.094)	-0.183* (0.081)			-0.004 (0.089)	
40-50 F				-0.198* (0.058)		-0.061 (0.032)	0.065 (0.075)	-0.158* (0.042)		-0.057 (0.080)	0.067 (0.069)	
50-60 F				-0.138** (0.043)		0.049 (0.057)	0.021 (0.031)	-0.100* (0.043)		0.058 (0.054)	0.024 (0.028)	
70-80 F				0.056*** (0.015)	-0.010 (0.031)	-0.020 (0.021)	0.039 (0.019)	0.012 (0.018)	-0.042 (0.024)	-0.052 (0.025)	0.033 (0.018)	
80-90 F				0.016 (0.019)	-0.059 (0.036)	-0.008 (0.030)	-0.338 (0.214)	-0.032 (0.021)	-0.093** (0.029)	-0.043 (0.034)	-0.353 (0.226)	
>90 F				-0.031 (0.037)	-0.078 (0.059)	-0.073 (0.085)		-0.080* (0.037)	-0.116* (0.051)	-0.104 (0.090)		
Constant	0.276*** (0.016)	0.285*** (0.038)	0.275*** (0.021)	0.299*** (0.017)	0.284*** (0.013)	0.351*** (0.031)	0.322*** (0.018)	0.301*** (0.007)	0.271*** (0.025)	0.317*** (0.047)	0.319*** (0.030)	0.278*** (0.021)
R ²	0.460	0.496	0.533	0.491	0.459	0.497	0.532	0.491	0.461	0.497	0.534	0.492
Adjusted R ²	0.419	0.445	0.459	0.452	0.418	0.446	0.458	0.452	0.420	0.446	0.459	0.453
AIC	56638.5	36369.4	7584.6	5598.2	56756.5	36308.3	7624.8	5598.5	56494.6	36244.9	7582.6	5589.2
F	6.155	1.536	5.779	2.038	.	7.024	1.061	.	.	6.856	4.928	.
Observations	80,730	57,053	14,306	8,898	80,750	57,065	14,313	8,902	80,730	57,053	14,306	8,898
No. of HHs	5,493	5,152	1,805	508	5,493	5,152	1,808	508	5,493	5,152	1,805	508
Season FE	Y				Y				Y			

Notes: The dependent variable is the override decision from Equation (1) including the control variables, weekday FE, and HH-year FE. The outdoor and indoor temperature bins are based on average event temperatures. 60 – 70 °F is the baseline temperature bin. The control variables include the DF event duration and location. The coefficients provided are rounded off to three decimal places. The robust standard errors are in parentheses with two-way clustering at household and week level. FE stands for fixed effects and HH for households. * p < 0.05, ** p < 0.01, *** p < 0.001. Statistically significant coefficients with p-values less than 0.05 have green stars if negative and red stars if positive.

warmer indoor temperatures greater than the reference 60–70°F bin generally show higher chances of override (5.6% higher when between 70 and 80°F) while the colder temperatures show fewer chances of override if outdoor conditions were fixed. A statistically significant 18% lower rates in overrides occur when the average indoor temperature is between 20 and 30 °F, the chances improve with lower temperatures (see Table 4, Column (b)-(1)). These trends suggest that DF faces fewer overrides when indoor temperatures are low as customers may perceive DF would increase indoor temperature towards desired heating setpoints. These results also reinforce the notion that comfort preferences play a significant role in demand response that occupants tend to prefer certain temperature bands such as the selected reference bin in this study (60–70°F) given the distinct statistically significant negative coefficients below 60°F.

Both outdoor and indoor conditions:

We consider the different seasonal and whole sample trends similarly in response to both indoor and outdoor temperatures, as seen in the results in column (c) of Table 4. The previous inferences for the whole sample hold except that the coefficients change slightly when considering both outdoor and indoor temperatures (Table 4, Column (c)-(1-4)). During summer, however, there are significant negative differences between the override rates of 9% and 12% for the extreme temperature bins 80–90°F and 90°F respectively versus the reference temperature bin 60–70°F when considering changing outdoor conditions, rather than fixed. This result is counterintuitive as it implies that override rates are lower at warmer temperatures during summer. However, another significant study on energy use by thermostats (Ge and Ho 2019) reported similar temperature habituation supporting these results where people prefer warmer temperatures during warm seasons (high outdoor temperatures).

Household Characteristics and Occupant Experience Effects on Override Rates

We also consider different factors beyond temperature (building and occupant characteristics) that may contribute to override decisions using Equation (2). The results based on the whole sample are in column (1) of Table 5, while Columns (2), (3), and (4) present the results based on the summer, shoulder, and winter season, respectively.

Household characteristics:

We also plot the estimated coefficients for the building types relative to the detached buildings in Figure 1 to help visualize the differences in override likelihood with housing styles, aggregated by: (a) whole sample, (b) summer, (c) shoulder, and (d) winter. The results show that occupants in certain building types respond differently to DR signals, supporting the understanding of how different occupants might override DR. The responses also vary with season. For instance, condominium and townhouse occupants have statistical significance for the negative coefficients which indicates that the override rates are lower by about 3% in general and during summer compared to detached buildings. For condominiums, the observable difference is about 6% lower override rates relative to detached buildings during shoulder seasons. Some building types show no observable difference between their override rates and that for single-family detached dwelling units (p -values > 0.05). But there is also a classification of buildings tagged ‘Others’ in ecobee DYD which may include mobile homes. These building types show about 2% higher override rates versus detached buildings. These results support the possibility of targeting different multifamily housing units (townhouse and condominium customers) who tend to override less at various times of the year. These household type differences may also imply the

Table 5: Marginal effects of various factors on override decision during connected thermostat (CT) demand response

Variables	(1) Full sample	(2) Summer	(3) Shoulder	(4) Winter
Indoor and weather conditions	Average indoor temperature (°F)	-0.0043** (0.0014)	-0.0063*** (0.0012)	-0.0045 (0.0032)
	Average outdoor temperature (°F)	0.0017*** (0.0005)	0.0012 (0.0009)	0.0017 (0.0010)
Household characteristics	Building type relative to detached buildings			
	Apartment	-0.0054 (0.0182)	-0.0191 (0.0162)	0.0458 (0.0245)
	Condominium	-0.0318* (0.0127)	-0.0278* (0.0124)	-0.0618* (0.0275)
	Multi Plex	0.0154 (0.0330)	0.0203 (0.0400)	0.0437 (0.0372)
	Others	0.0228* (0.0107)	0.0240* (0.0101)	0.0380 (0.0207)
	Row House	-0.0074 (0.0173)	-0.0112 (0.0181)	0.0448 (0.0338)
	Semi-Detached	0.0240 (0.0200)	0.0422 (0.0243)	-0.1730 (0.0856)
	Townhouse	-0.0288* (0.0116)	-0.0331** (0.0113)	-0.0269 (0.0280)
	Floor area [ft ²]	1.19e-07 (3.63e-06)	2.58e-06 (3.39e-06)	-5.25e-06 (7.77e-06)
	Number of floors	-0.0107* (0.0042)	-0.0083 (0.0046)	-0.0089 (0.0105)
	Age of home [years]	0.0001 (0.0002)	0.0003 (0.0001)	-0.0004 (0.0005)
	Number of occupants	0.0008 (0.0021)	-0.0012 (0.0021)	0.0103* (0.0042)
	Has electric	-0.0496* (0.0220)	-0.0642* (0.0277)	-0.0139 (0.0318)
	Has a heat pump	-0.0081 (0.0127)	0.0035 (0.0107)	-0.0394 (0.0266)
Occupant experience/history	Previous month thermostat override count (every 5 minutes)	0.0000734*** (2.33e-06)	0.0000744*** (2.25e-06)	0.0000747*** (5.20e-06)
	Previous month DR count (every 5 minutes)	0.000102** (.0000338)	-0.0000183 (.0000969)	0.0001676** (.0000422)
Constant		0.265 (0.175)	0.522*** (0.0988)	0.294 (0.191)
R ²		0.322	0.330	0.355
Adjusted R ²		0.320	0.328	0.341
AIC		62753.1	47656.8	8820.7
F		101.4	120.4	100.7
Observations		68,743	52,753	10,333
No. of HHs		5,245	4,946	2,031
Season FE		Y		

Notes: The dependent variable is the override decision from Equation (2), the control variables and weekday FE, with no household fixed effects. The outdoor and indoor temperatures are average event temperatures. The control variables include the DF event duration and location. The coefficients provided are rounded off to three decimal places. The robust standard errors are in parentheses with two-way clustering at household and week level. FE stands for fixed effects and HH for households. * p < 0.05, ** p < 0.01, *** p < 0.001. Statistically significant coefficients with p-values less than 0.05 have green stars if negative and red stars if positive.

need to offer incentives to occupants in certain house types, such as condominiums, to reward lower overrides during summer and shoulder seasons. It is, however, important to further investigate how the building envelope may differ significantly between these house types as this may play a significant role in temperature sensitivity for occupants with different health or working conditions (e.g., work from home, elderly) or other occupant variabilities not observed in the data used in this study. We also note that different housing type definitions differ by location such that some townhouses may be called condominiums depending on homeowners' association definitions. Given that we controlled for location differences, we found that the lower override effects are consistent with communal/owner-occupied house types (condominium and townhouses).



Figure 1: Marginal effects of building types relative to single-family detached buildings on override decision (a) for the whole sample, (b) during summer, (c) shoulder, and (d) winter.

A square foot increase in the floor area of the dwelling unit appears to increase override generally but not statistically significantly (Table 5). This could be partially due to the strong multicollinearity with building type. Additionally, the more stories in the building (i.e., the number of floors), the less likely the probability of override (see the negative coefficients regardless of the season in Table 5). This result could suggest that having alternative spaces within the house can help the occupants maintain their desired comfort level even during DR events. Having more occupants within the household increases the chances of override during shoulder and winter periods but decreases the chances during summer. Family dynamics may play a role here and might require further investigation to understand what influences sole operators have on thermostat control. Having electric heating or a heat pump also reduces the tendency to override DR generally (i.e., whole sample), but heat pumps increase summer overrides, which intuitively makes sense since these are the seasons when this equipment might be used. Overall, except floor area, building characteristics play different roles in override decisions and need to be considered during DF program design. Household characteristics are also likely heavily correlated to sociodemographic variables that are currently not present in the ecobee DYD dataset.

Occupant experiences:

For every five minutes an occupant uses the ‘HOLD’ function on their thermostat, irrespective of the event type, we count this as one thermostat override, while every 5 minutes of exposure to DR signal on the thermostat gets one DR count. We consider the override history and prior exposure to DR for a month before each DR event in Equation (2) and present the results in Table 5. The occupants’ override history shows a statistically significant positive correlation with override decisions. Regardless of the season, the more an occupant uses the override feature on their thermostat, the more likely they will override a DR event in the future. Similar to this is the previous exposure to DR; although the coefficients are only statistically significant at the $p < 0.05$ level for the full sample and during the shoulder season, the occupants’ who have participated in DR previously tend to override new DR events. We expect that people who override in the past probably do not like DR in general. The fact that increased exposure INCREASES rather than DECREASES the likelihood of override is important for policy. We would have hoped that practice makes perfect or that DR would get more effective with more experienced participants – but this is not the case. A recent study also suggested the likelihood of such an increasing trend with override, and DR experience using decision tree analysis (Sarran et al. 2021) but did not consider the marginal effects, statistical significance, or other building characteristics. These results, therefore, provide evidence for the need to implement nudge policies (such as default options other than ‘HOLD,’ reinforcement rules, or incentives) or use of deterrents to discourage the use of the override feature, especially with new customers even though studies show that having the override option is necessary for consumer acceptance of DR programs (Xu et al. 2018).

Conclusions

Using high-resolution smart thermostat data records of demand response (DR) events for about 5,000 enrolled households in the United States, we find that considering both indoor and outdoor temperature conditions is essential to understanding override tendencies. This research provides insights into average indoor, outdoor, or both temperature conditions during DR that most likely result in a DR override decision and conditions at which fewer overrides are possible. The insights provide an opportunity for rural electric cooperatives and new DR programs to plan DR events towards indoor conditions given certain outdoor temperatures during which overrides are least likely as seasons change.

We also explore the differences in the role of building and occupant characteristics, the marginal effect of an occupant’s previous thermostat override experience, and how much an occupant’s exposure to DR event correlates to overrides. Relative to single-family detached buildings, different building types show varying degrees of override response but are statistically different for townhouses and condominiums. We demonstrate the possibility of targeting different customers who tend to override less at various times of the year while offering incentives to occupants in buildings to compensate for lower overrides and dissuade higher overrides.

We also show that occupants with increased previous override history and exposure to DR have higher chances of override. There is a need to dissuade override among new customers while establishing a sound motivation for demand flexibility among residential customers in the United States.

Scope Limits and Recommendations for Future Work

We have excluded some further analysis including the humidity and temperature interplay for occupant comfort preferences during CT DF considering the page constraints for this proceeding. We also did not include our two-stage least square regression analysis to delineate possible instrument variable relationships between indoor and outdoor temperatures and excluded possibly parabolic non-linear relationships between override rates and temperatures. We also excluded our detailed analysis of the two-dimensional matrix of dummy variables for what bins both indoor and outdoor temperatures fall. We found that the outdoor-only and indoor-only models were not significantly different from each other. A cluster-robust Vuong test of the non-nested full sample models for outdoor-only and indoor-only (against the null hypothesis that the models are different) showed a non-significant 0.00012 difference in the sum of the square of the residuals ($F = 1.43$, $p = 0.289$). We also tested for override rate sensitivity to the choice of reference temperature bin by using the previously studied 50–60°F reference bin and found similar but less clear trends between warmer ($>60^{\circ}\text{F}$) and colder outdoor/indoor temperatures ($<50^{\circ}\text{F}$).

In addition, this study did not address the differences between the two common residential DF technology groups – connected thermostats (CTs) and smart water heaters (SWHs) given data and funding limitations and therefore a question for future research. This difference is significant since these technologies impact different types of comfort: immediate thermal comfort (i.e., CTs) and the latter affecting a combination of convenience and thermal comfort due to the intermittent nature and varied applications of hot water use. For instance, a BPA pilot study (Bonneville Power Administration (BPA) 2018) examined comfort disruption as a possible outcome of DF enrollment. However, there is no clear evidence on how the perception of comfort disruption affects entry/participation/adoption decisions or exit/attrition from DF programs with connected water heaters. Such insights could improve SWH program design and technology features on the water heater itself, which might lend the appliance to more successful DF participation.

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