# Optimizing Thermostat Demand Response Program Performance—Blending Qualitative and Quantitative Research to Understand Customer Behavior

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## ABSTRACT

Thermostat technology has evolved rapidly over the past decade, as has the prevalence of thermostat-based demand response (DR) programs across the US. While the new capabilities of smart thermostats offer customers new ways to optimize their comfort and energy use, they also complicate estimation of savings from thermostat DR programs. In particular, capabilities of modern thermostats allow users to selectively override and opt out of thermostat DR events, especially in response to extreme weather. Accordingly, to ensure that thermostat DR programs deliver reliable savings, it is critical to understand how weather affects thermostat use and program participation behavior to inform program design and implementation. This study adds to the body of knowledge relating to weather, thermostat use, and DR program participant behavior.

The objective of this study was to explore how weather and program design factors influence DR program participant behavior, particularly customers' likelihood of overriding or opting out of events through interaction with their thermostats. We paired qualitative in-depth interviews with quantitative analysis and regression modeling to understand these relationships and provide recommendations for how to optimize DR program performance, mitigate opt outs, and maximize savings. From this research we found that both weather and event characteristics—specifically heat, humidity, event duration, and event timing—are key determinants of participant opt-out behavior.

### Introduction

DR programs come in many different forms; their goal is to decrease total load on a system during a given time by curtailing or decreasing residential and/or commercial customer loads, either manually or automatically. Thermostat-based DR programs, in which thermostats are used to decrease HVAC loads, make up a growing share of large-scale residential DR programs across the country. A recent Smart Electric Power Alliance (SEPA) survey found 49 utilities had thermostat DR programs and 21 utilities either offered thermostat DR pilots or were planning to implement them (SEPA 2018). However, only a small body of previous research exists on the relationship between weather (especially extreme weather), incentives, and DR program opt-out rates (Agnew, Goldberg, and Rubin 2004; Egan-Annechino, Lopes, and Marks 2005; Wang, Swisher, and Stuart 2005). The literature suggests a wide range of opt-out rates and while opt-out rates appear to be correlated with weather, few studies draw causal inferences. The wide range of opt-out rates and lack of consensus values in existing literature suggested that the team should account for a wide range of potential factors to adequately explain opt-out behavior.

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Unlike decades-old air conditioner switch-based programs,[1] modern thermostats give customers more control over their participation in DR, enabling customers to opt out or override settings for DR events. An issue for evaluation is trying to separate out energy savings from what would have occurred absent the program interventions. The ability to calculate this is hampered by the lack of data on how households currently use their cooling equipment during summer periods; specifically, what is the relationship between extreme weather use and thermostat control behavior. Parallel research conducted by the team shows that most users do not let the thermostat automatically control their cooling systems (Navigant and ILLUME 2018). Most households manually adjust their thermostat settings, which greatly complicates the measurement of DR savings. For thermostat-based DR to be a reliable resource, programs need to reward DR that represents a true program-induced behavior—and that means we need studies that illuminate how people use modern thermostats in response to weather and comfort preferences during DR events to optimize participation and program impacts.

In 2018, Navigant and ILLUME Advising worked with the Massachusetts Program Administrators and the Energy Efficiency Advisory Council (EEAC) to investigate how customers react to weather and use their thermostats during DR events to inform optimal program design and implementation. The team performed regression analysis using thermostat telemetry data from nearly 6,000 devices during the summers of 2016 and 2017. Combining this data with in-depth interviews with three DR service providers and 20 DR participants, we blended quantitative and qualitative approaches to understand participating customer's behavior during DR events. We combined data describing the event (e.g. duration) and customer quarter-hourly thermostat use data (e.g. set point) with quarter-hourly, ZIP-code level weather data including temperature, relative humidity, heat build-up (HBU),[2] and temperature-humidity index (THI) to estimate precise effects of weather and event parameters on opt-out behavior, and drew upon the insights from our in-depth interviews to validate and further explore causal channels for estimated effects.

This study provides insights on how weather affects opt-out behavior, customers' experience of event fatigue from back-to-back events or event duration, the extent to which customers react to weather and comfort concerns in the moment versus over longer periods, and tactics such as messaging, competitions, gamification, and program parameter adjustments the utility can use to mitigate opt-out behavior and optimize savings. Thermostat DR programs may play an increasing role in the energy landscape moving forward, and utilities and implementers will take away actionable insights from this paper to move their thermostat DR programs in the right direction.

## Methodology

The team conducted qualitative research that included in-depth interviews with DR service providers (DRSPs) and DR program participants. This research was combined with quantitative analysis that included visual and graphic data exploration and regression analysis to create a holistic view of weather and program design effects on participant opt-out behavior.

### DR Programs Overview

The Thermostat DR project is an opt-in demonstration project that includes two offerings: Connected Savings (CS) and Rush Hour Rewards (RHR). Program enrollment can occur through a bring

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[1] Early thermostat demand response (DR) programs tended to be implemented through a physical switch installed on HVAC equipment which enabled switching the load on or off.

[2] Heat build-up is a term that captures the build-up of heat over the course of several days, rather than just capturing momentary temperature; it sums the temperature over a number of days using a decay function to discount temperature farther back in order to capture temperature history.

your own thermostat (BYOT)[3] approach or as part of the home energy services (HES)[4] program through which a smart thermostat is installed as the result of an audit process. Table 1 summarizes the Thermostat DR project.

Table 1. Thermostat DR program summary

| Category | Connected Savings | Rush Hour Rewards |
|---|---|---|
| State | Massachusetts and Rhode Island | Massachusetts |
| Type of Program | Opt-in | Opt-in |
| Types of Thermostats | ecobee, Honeywell | Nest |
| Event Duration[5] | 2-4 hours | 3-4 hours |
| Advance Notification | Day of, more than 2 hours (customer notified)[6] | Day of, more than 2 hours (customer notified) |
| DR Event Opt-Out Option (Before Event, During Event) | No, Yes (ecobee) Yes, Yes (Honeywell) | Yes, Yes |
| Intended DR Setpoint Range[7] | 3°F | 3°F |
| Pre-cooling | ecobee: No Honeywell: Yes, -2°F | Yes, -2°F |
| Participant Incentive | BYOT: $25 for signup HES: Free thermostat and installation Both: $25 per year if complete 75% of events | $40 for signup then $25 per year. No event requirement or incentive |

Source: Navigant 2017.

Smart Energy Solutions (SES) is an opt-out dynamic pricing pilot[8] that offers customers technology packages, two of which include a Wi-Fi thermostat. Customers with a Wi-Fi thermostat are included in peak event days in which the program adjusts the thermostat temperature setpoints to help with load curtailment during peak periods. Customers are able to choose between two dynamic pricing options: Smart Rewards Pricing and Conservation Day Rebate. The Smart Rewards Pricing tiered rate structure combines time of use (TOU) and critical peak pricing (CPP), where customers pay higher rates during peak periods and peak events and pay lower prices during off-peak periods. The Conservation Day Rebate uses a peak time rebate (PTR), where customers are provided a rebate for reducing their energy consumption during peak events. Table 2 summarizes this program.

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[3] Bring your own thermostat (BYOT) programs allow customers the flexibility to purchase their own smart thermostat, which can include a variety of brands, and then they enroll in their utility's DR program.
[4] The HES program offers customers an opportunity to receive a Home Energy Assessment (HEA) conducted by a National Grid Energy Specialist. The Energy Specialist produces a custom home energy report outlining recommended energy efficiency improvements. The specialist will also install a number of energy-saving products at no cost, including a discounted Wi-Fi thermostat.
[5] The event duration for Connected Savings (CS) changed from 2-4 hours in 2016 to 3 hours in 2017. The event duration for Rush Hour Rewards (RHR) changed from 4 hours in 2016 to 3-4 hours in 2017.
[6] Customers were notified by either an email notification, an app notification, or a notification on the thermostat itself.
[7] The allowed temperature adjustment during a given event. The temperature setting will return to its prior temperature following an event. The intended DR setpoint range for CS changed from 2°F in 2016 to 3°F in 2017.
[8] Dynamic pricing programs offer alternative rate structures that aim to make the cost of electricity reflect the cost to produce it, which can vary based on the time of day due to changes in electric demand.

Table 2. SES program summary

| Category | Smart Energy Solutions |
|---|---|
| State | Massachusetts |
| Type of Program | Opt-out dynamic pricing with programmable communicating thermostat option. Customers choose between a TOU CPP rate and a PTR rate along with one of four technology packages. |
| Total Program Duration | 20 peak events in both 2015 and 2016 |
| Event Duration | Peak events lasted 4-8 hours |
| Advance Notification | Day before event |
| Tstat Setback | 2015: 3° or 4°; 2016: 2° or 3° |
| Customers with a Wi-Fi Thermostat | Approx. 280 |

*Source*: Navigant 2016.

**Qualitative Approach**

The team conducted three in-depth interviews with DRSPs to understand program design and implementation, and to discuss what factors, from their perspective, are most likely to influence DR event participation.[9] The team recruited DRSP interview participants from industry contacts, and all interviews were transcribed for analysis. DRSP respondents were prompted to comment on the role of weather (both discrete weather events and trends over time) and event characteristics on participant opt-out behavior. Interviewers also discussed how DRSP smart controls change settings to understand whether these controls enhance or inhibit DR objectives.

The team conducted 20 in-depth interviews with Thermostat DR project and SES pilot participants. The team interviewed 12 who participated in the Thermostat DR project and eight who participated in the SES pilot. The main goal of these interviews was to understand factors that contributed to customer decisions to opt in to the program initially and factors that contributed to the decision to opt out of an event or override preset controls, with a specific focus on the influence of weather and event characteristics. Interview participants received a $50 gift card incentive for their time. Table 3 summarizes the final completed interviews by program and opt-out status.

Table 3. Participation status summary for completed interviews

| DR Program | Had Never Opted Out | Had Ever Opted Out |
|---|---|---|
| SES | 2 | 6 |
| RHR | 2 | 4 |
| CS | 2 | 4 |
| Total | 6 | 14 |

*Source*: Navigant and ILLUME 2018.

The samples for each of the programs were created using self-reported opt-out and override behavior from post-event and end-of-season surveys. This information was used to target participants identified based on their opt-out behavior to ensure the team spoke with both people who never opted out or overrode settings and people who did. To better understand participant motivations to opt out or override thermostat setpoints, the majority of interviews targeted customers that had opted out or overrode thermostat setpoints during a peak event, while fewer interviews targeted customers that did

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[9] Note that throughout this section "DR event participation" or "DR participation" refers to participation either in SES or the Thermostat DR program interchangeably. While the team may refer to National Grid's SES pilot and its Smart Thermostat DR program separately, when the team refers to DR event participation, it refers more generally to both or either.

not. During recruitment, prospective interviewees were asked to verify their opt-out and override behavior, improving the team's confidence in the results. All resulting interviews were transcribed for analysis.

**Quantitative Approach**

While the SES pilot yielded meaningful interviews for the study's qualitative aspects, lack of variation in opt-out behavior made participation data from that program unsuitable for the quantitative analysis. Instead, our data analytics and regression modeling focused solely on participation data provided by the RHR and CS components of the Thermostat DR program, which contained significant variation in opt-out behavior by participants across the summer and across different thermostat types and program configurations.

Using participation data from the CS (Honeywell and ecobee) and RHR (Nest) components of the Thermostat DR project, the team conducted both detailed data exploration using advanced data visualization techniques, followed by regression analysis to generate granular insights into the effects of weather and program configuration components on participant opt-out behavior. The thermostat type most represented was Nest, followed by Honeywell and ecobee. Table 4 summarizes the counts of devices represented after removing records that were unenrolled or experiencing connectivity issues.

Table 4. Counts of enrolled, connected devices

| Thermostat Type | 2016 | 2017 |
|---|---|---|
| Nest | 1,331 | 2,804 |
| Honeywell | 300 | 1,007 |
| ecobee | 52 | 201 |
| Total | 1,683 | 4,012 |

*Source*: Navigant and ILLUME 2018.

The participation data included the summers of 2016 and 2017 and was composed of variables describing the event (i.e., event duration, event start time, length of time between events) and customer thermostat use (i.e., cooling setpoint, cooling status, indoor temperature at quarter-hourly intervals). The thermostat data was used to define customer participation status throughout the event. Participation data was available for event days and the 3 days preceding each event day. It was combined with quarter-hourly, ZIP-code level weather data, including temperature, relative humidity, HBU, and THI.[10] Weather data was available for the entire summer, not just event days.

The correlation of key variables, such as opt-out rates and certain independent variables (i.e., weather, event attributes, historical air conditioning use), was analyzed through scatterplots and other graphics, and yeilded key components of the exploratory data analysis. Building on the learnings gained through exploratory data analysis and DR participant and implementer interviews, the team used regression analysis to estimate causal relationships between weather and program variables and opt-out behavior. The team used a linear probability model to estimate the likelihood that a DR program participant chooses to override preset controls. The model statistically relates the choice made prior to or during each event to various attributes (e.g., event attributes, weather attributes). The team used

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[10] Temperature-humidity index (THI) is a weather variable that captures both heat and humidity as interactive effects, accounting for the fact that people do not experience either heat or humidity in isolation, and hence may be reacting to both. As an example, 90°F may feel much different to a DR participant on a day with 90% relative humidity versus 10%.

participation data from the 2016 and 2017 summer DR programs and used data from Thermostat DR demonstration project events spanning the summers of 2016 and 2017.

The preferred regression model includes variables characterizing the event, including event duration, event start time, length of time between events, and customer participation status throughout the event at quarter-hourly intervals. We aggregated the combined participation and weather data to the event level, where one record represents one device on the day of an event. Table 5 shows the number of events called each summer.

Table 5. Number of events called

| Thermostat Type | 2016 | 2017 |
|---|---|---|
| Nest | 13 | 11 |
| Honeywell, ecobee | 29 | 11 |

*Source*: Navigant and ILLUME 2018.

The summers of 2016 and 2017 exhibited relatively mild weather, with few extreme temperature days, and without prolonged periods of combined high heat and humidity. As a result, our team cautions against over generalization of our findings to higher temperatures and more extreme weather, where extrapolation from this linear regression may yield inaccurate results. An opportunity for future research would be to extend this research to include summers with more extreme weather to test weather/participation relationships under these circumstances directly.

Structural changes were made to the program over time; for example, changes to event frequency, cooling setpoint adjustments, event duration and start time. Most changes occurred between 2016 and 2017 and program parameters varied between Nest versus Honeywell and ecobee thermostat participation. The team's regression specification includes month-of-year fixed effects and interacts vendor with month-of-year to control for these structural program changes.

The team's model of opt-out behavior uses a linear probability model (LPM)[11] because the dependent variable is binary, taking a value of one when a participant opted out of the event and zero otherwise. LPM regression predicts a linear change in the probability of an outcome due to changes in the independent variables. The team compared performance across a variety of model specifications with slight differences in functional form, using cross-validation analysis to select the model with best fit.[12]

$$
\begin{aligned}
Y_{it} = MOY_t + \beta_{1t} \sum_t DOW_t &+ \beta_2 EventDuration_{it} + \beta_3 EventStartHour_{it} + \beta_4 TotalDailyCDH65_{it} \\
&+ \beta_5 MaxRH_{it} + \beta_6 LagTotalDailyCDH65_{it} + \beta_7 LagMaxRH_{it} \\
&+ \beta_8 ConsecutiveEvent_{it} + \beta_{9t} \sum_t (MOY_t \times Nest_i) \\
&+ \beta_{10t} \sum_t (ConsecutiveEvent_{it} \times Nest_i) + \varepsilon_{it}
\end{aligned}
$$

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[11] In addition to the linear probability model (LPM), the team built a series of logistic regression models. The logistic regression models gave similar results, but the LPM provided the best fitting model and most easily interpreted coefficients.

[12] The team conducted 50 iterations of each model, each time reserving 20% of the data as a test set. In comparing the models, the team calculated the distribution of the cross-validation errors using root mean squared error (RMSE) as the comparison metric. Though all model specifications had similarly low RMSE, we chose the model with lowest RMSE as our preferred model.

| $Y_{it}$ | = a binary variable taking on a value of 1 if customer $i$ opted out or overrode preset controls during event $t$ |
|---|---|
| $MOY_t$ | = a month-of-year fixed effect |
| $DOW_t$ | = a set of binary variables indicating on which day of week event $t$ took place[13] |
| $EventDuration_{it}$ | = the duration of event $t$ for customer $i$ |
| $EventStartHour_{it}$ | = the hour of day of the beginning of event $t$ for customer $i$ |
| $TotalDailyCDH65_{it}$ | = the total daily CDH (base 65) in customer $i$'s ZIP code on the day of event $t$ |
| $MaxRH_{it}$ | = the maximum relative humidity in customer $i$'s ZIP code during event $t$ |
| $LagTotalDailyCDH65_{it}$ | = the total daily CDH (base 65) in customer $i$'s ZIP code on the day before of event $t$ |
| $LagMaxRH_{it}$ | = the maximum relative humidity in customer $i$'s ZIP code on the day before event $t$ |
| $ConsecutiveEvent_{it}$ | = a binary variable taking on a value of 1 if customer $i$ was called for an event on the day prior to event $t$ |
| $Nest_i$ | = a binary variable taking on a value of 1 if customer $i$ is a Nest thermostat user |
| $\varepsilon_{it}$ | = an error term for customer $i$ during event $t$ |

The estimated coefficients, $\beta_x$, represent the effects of specific weather variables or event attributes on the propensity of a participant to opt out of a DR event.

## Results

The following section explores key findings from this study of the relationship between weather, program design factors, and participant behaviors. Findings are organized by 1) DR event participant types, 2) the effects of weather and event characteristics on opt-out behavior, and 3) how differences in program type design (i.e., Thermostat DR versus SES) interact with customer motivations for participation to affect propensity to opt out. We referenced quantitative and qualitative findings and synthesized the two to provide insights on each of the three key subjects.

### DR Event Participant Types

Qualitative research through in-depth interviews with DRSPs and program participants identified four main categories of DR program participants.

**Comfort Seekers:** These are program participants that will not go out of their way to make changes to their day to accommodate an event; they will opt out as soon as they come home or feel uncomfortable. They are accustomed to manually managing their thermostat when they get "a little too hot" and will not wait for their scheduled settings to adjust the temperature automatically.

**Hold Outs:** A subset of Comfort Seekers (as identified by the DRSPs), a Hold Out tends to set an indefinite hold on their thermostat, which automatically opts them out of an event, even if it was not directly in response to the event. Because this behavior is not in response to events yet precludes participation, this

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[13] The set of binary variables did not include Saturday or Sunday, as no events took place on weekends. The regression model eliminated the Wednesday indicator such that all other day of week effects are relative to Wednesday (i.e., the day of week with the lowest opt-out rate).

group of customers is not well-suited for participation in a DR program and is not likely to adjust their behavior to benefit events.

**Best-Effort Participants:** These program participants will try to push through an event by leaving their home, opening windows, or grilling instead of cooking inside; however, they may opt out if they exhaust their coping options and their comfort threshold is exceeded.

**Reliable Participants:** This type of participant will remain in an event regardless of personal comfort impacts or convenience considerations. They are often customers with flexible schedules, who may be retired, and who are easily able to adjust their plans to accommodate events. They may notice that their home is slightly warmer but will not make any adjustments once they realize that an event is occurring.

To understand the opt-out habits of individual customers, the team created a histogram showing the proportion of events for which each device type opted out.[14] Figure 1 shows opt-out behavior by device type throughout two summers. For example, the figure shows that in both 2016 and 2017, only 3% of thermostats opted out of all events. Our qualitative research identified these customers as Hold Outs.
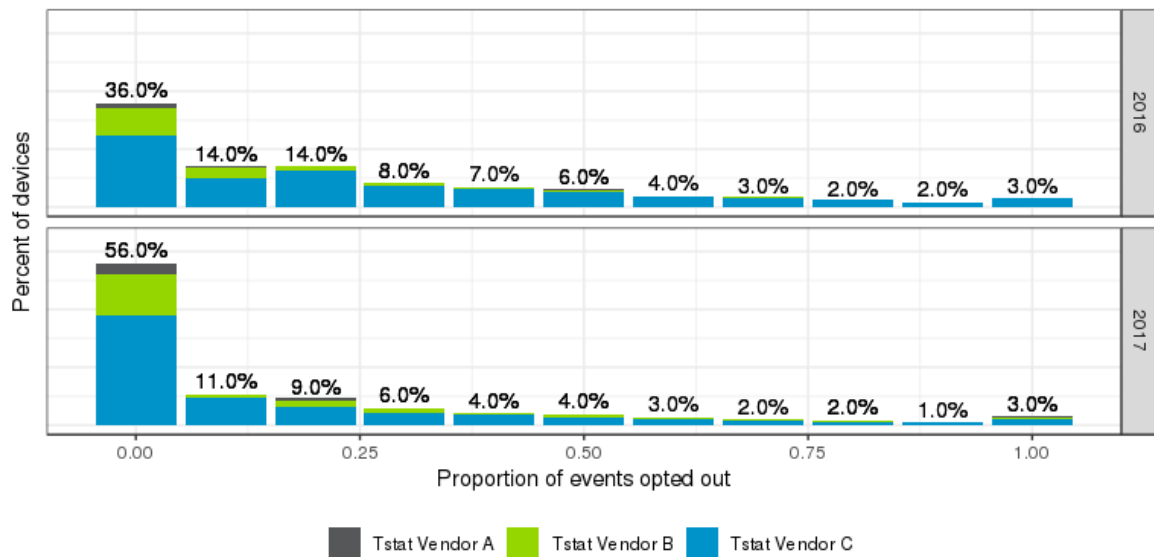


Figure 1. Proportion opt outs out of total events by device type *Source*: Navigant and ILLUME 2018.

A large proportion (approximately 50%) of customers in each summer never opt out of any DR event. These could be people who were generally not at home during the event period or perhaps people who have a higher tolerance for heat and humidity. Our qualitative findings classify these customers as Reliable Participants.

Of those that opt out of some events but not all, the majority (82% in 2016, 81% in 2017) opt out less than half of the time. These are Best-Effort Participants, who are interested in saving energy but will opt out if they become too uncomfortable. A smaller proportion opt out of half of the events or more and would be considered the Comfort Seekers. Both groups may decide whether to participate in each event

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[14] Nest, ecobee, and Honeywell are anonymized in this figure as A, B, and C, as opt-out behavior may have more to do with program design differences between channels each thermostat participated in than inherent differences by device or vendor.

based on their schedule, how their house heats up, and their personal comfort preferences, but the Comfort Seekers are more likely to opt out sooner and more often.

**Role of Weather and Event Parameters in Opt-Out Behavior**

**Heat and Humidity:** Participant opt-out decisions are made based on comfort in the moment. The team's qualitative research findings suggest a DR program participant's decision to opt out of an event is typically based more on comfort and their circumstances during an event than weather leading up to an event. Participants reported that they could usually anticipate when a peak event would be called based on the weather forecast, but that they typically would not decide to opt out until their comfort threshold was exceeded during the event.

In-depth interviews revealed that participants connect their discomfort during events to high humidity. Participants noted that humidity affected their comfort the most, especially when coupled with high temperatures, and recognized it is common for hot days to also be humid. Participants also noted that days with high humidity and temperatures in the 90s were likely going to trigger peak events. While participants had methods to mitigate high temperatures, such as turning on ceiling fans or opening windows, they noted that they did not have solutions for coping with humidity apart from adjusting their thermostat. This finding is consistent with responses from the DRSP interviewees who noted that days that are both hot and humid are most likely to affect customer participation in events.

Figure 2 plots the correlation between the opt-out rate and key daily high weather measures, including HBU, heat index, temperature, and THI. Both summers experienced similar daily high temperature ranges with few very hot days (temperature greater than 90°F), though Figure 2 shows a strong correlation between temperature and opt outs. Each point represents one event and its size represents the number of participants in that event, excluding customers with connectivity issues or whose system was off or in heating mode. The plot also shows trend lines along with shaded 95% confidence intervals. For thermostat makes A and B, there is a positive correlation between higher heat and humidity-related weather indicators and higher opt out rates. The team expects this to be the case as hotter, more humid weather leads to increased discomfort. In most cases, there is not enough data to determine the trend for thermostat make C.
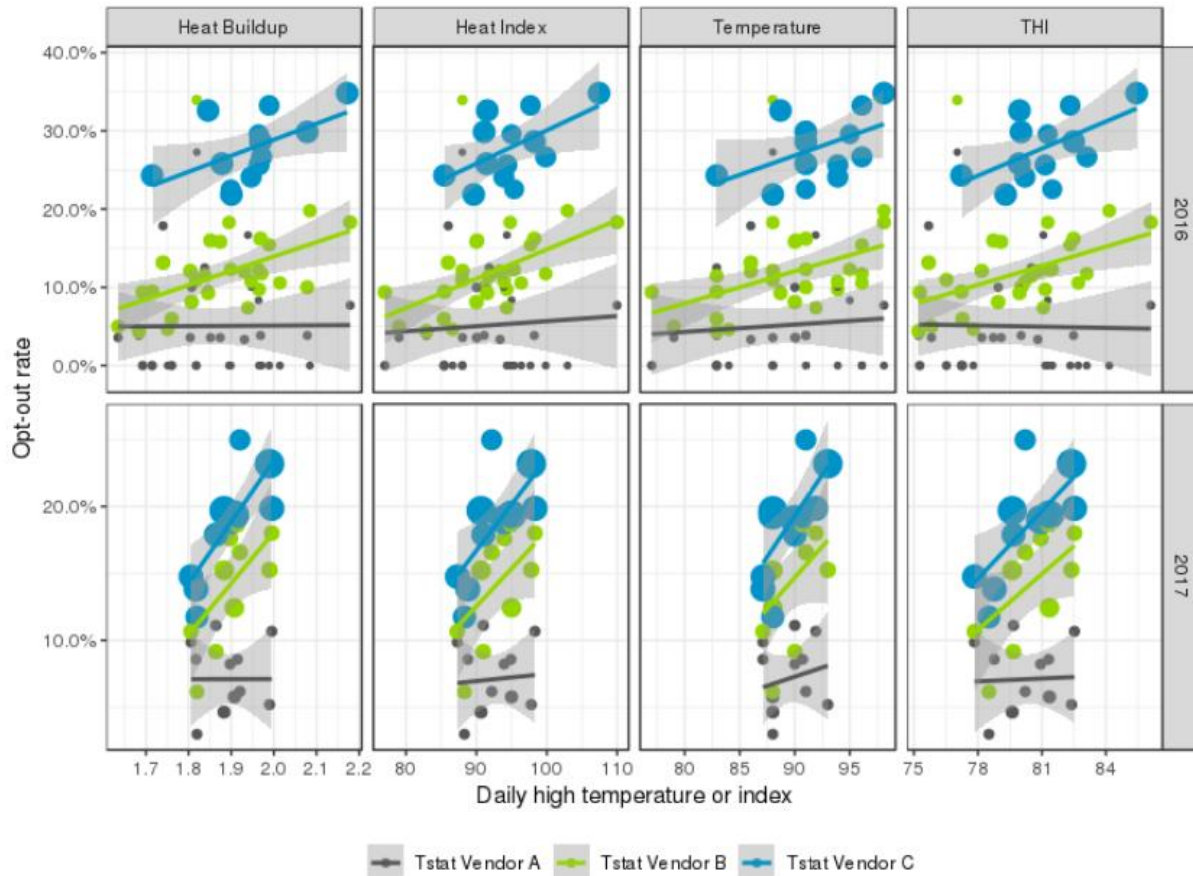
Figure 2. Correlation between daily weather variable highs and opt-out rates[15] *Source*: Navigant and ILLUME 2018.

Regression analysis using the LPM model revealed statistically significant relationships between weather variables and participants' likelihood of opting out of DR events. Heat in isolation was shown to have a statistically significantly positive effect on opt outs. On the day of an event, every degree-hour the temperature in a customer's ZIP code is above 65°F increases that customer's likelihood of opting out by 0.03%. For example,[16] an event day that is 3.7°F hotter during all hours of the day increases the likelihood of opting out by 2.6%, relative to the 3.7°F cooler day[17].

Regression results support the conclusion that customers are responding more to heat in the moment than to heat leading up to an event. Every degree-hour the temperature in a customer's ZIP code is above 65°F on the day before an event decreases that customer's likelihood of opting out by 0.01%. For example,[18] a day before an event day that is 3.7°F hotter during all hours of the day decreases the likelihood of opting out by 0.9%, relative to the 3.7°F cooler preceding day. This could signal that

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[15] As in previous figures, thermostat vendors are anonymized to A, B, and C.

[16] An additional 3.67°F over the course of a day results in 3.67 * 24 = 88 more cooling degree-hours. The likelihood of opting out of an event on the hotter day increases by 88 * 0.0003 = 2.6%. Note that 88 cooling degree-hours is one standard deviation in total CDH65 (the explanatory variable capturing the effect of heat) on the day of an event.

[17] Due to the relatively mild weather experienced during the summers of 2016 and 2017, it is not clear that this relationship would be the same under more extreme weather conditions.

[18] An additional 3.74°F over the course of a day results in 3.74 * 24 = 90 more cooling degree-hours. The likelihood of opting out of an event the next day decreases by 90 * 0.0001 = 0.9%. Note that 90 cooling degree-hours is one standard deviation in total CDH65 on the day before an event.

customers become more accustomed to high temperatures over time, or that they find themselves relatively less uncomfortable on a day where the preceding day was hotter and are less likely to opt out as a result.

Regression results suggest a statistically significant relationship between humidity and the likelihood of overriding thermostat settings to opt out of DR events. An increase in the maximum relative humidity during an event by 1% (absolute) increases the likelihood of opting out by 0.04%. For example,[19] the likelihood of opting out of an event with 17% (absolute) higher maximum relative humidity during the event increases by 0.7%, relative to the 17% less humid day. Unlike heat, the humidity on previous days was not found to have a statistically significant impact on opt outs.

**Event Duration and Timing:** In-depth interviews revealed SES participants adjust their daily routines to accommodate events. A major pain point communicated by participants was event duration, especially when events persisted later into the evening. Many commented that such events made it difficult for them to balance reducing their energy use with their needs. SES participants often said they would prepare for peak events by cooking food ahead of time or not doing dishes. However, they were frustrated when events lasted until 8 p.m. and had a difficult time cooling their home to a comfortable temperature before going to bed. Most SES participants mentioned they would pre-cool their home, cook food ahead of time or cook outside on a grill, and avoid running dishwashers, clothes washers, or dryers until after the event. These pre- and during-event actions are likely specific to SES participants due to the peak pricing of the program, which encourages participants to minimize overall energy consumption during events. By contrast, CS and RHR participants do not have that same financial motivation to reduce consumption. Few RHR or CS participants reported taking specific actions before or during an event.

Quantitative analysis of Thermostat DR customer behavior provided more insights into how they behave during different length events. Our analysis shows those who opt out of events tend to do so uniformly throughout the duration of event. Figure 3 summarizes the average cumulative opt-out rate throughout the events for 2-, 3-, and 4-hour events. The constant linear slope suggests that there are no specific triggers or thresholds that lead to simultaneous opt outs or sudden increases or decreases in opt outs. Rather, the point at which customers opt out differs by household and may be reflective of heterogeneous comfort preferences.

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[19] A 17% (absolute) increase in relative humidity increases the likelihood of opting out of an event by 17 * 0.0004 = 0.7%. Note that 17% (absolute) is one standard deviation in event maximum relative humidity. We believe program parameters specific to how the program was fielded for different manufacturers may explain more of the differences observed than inherent differences in the technologies.
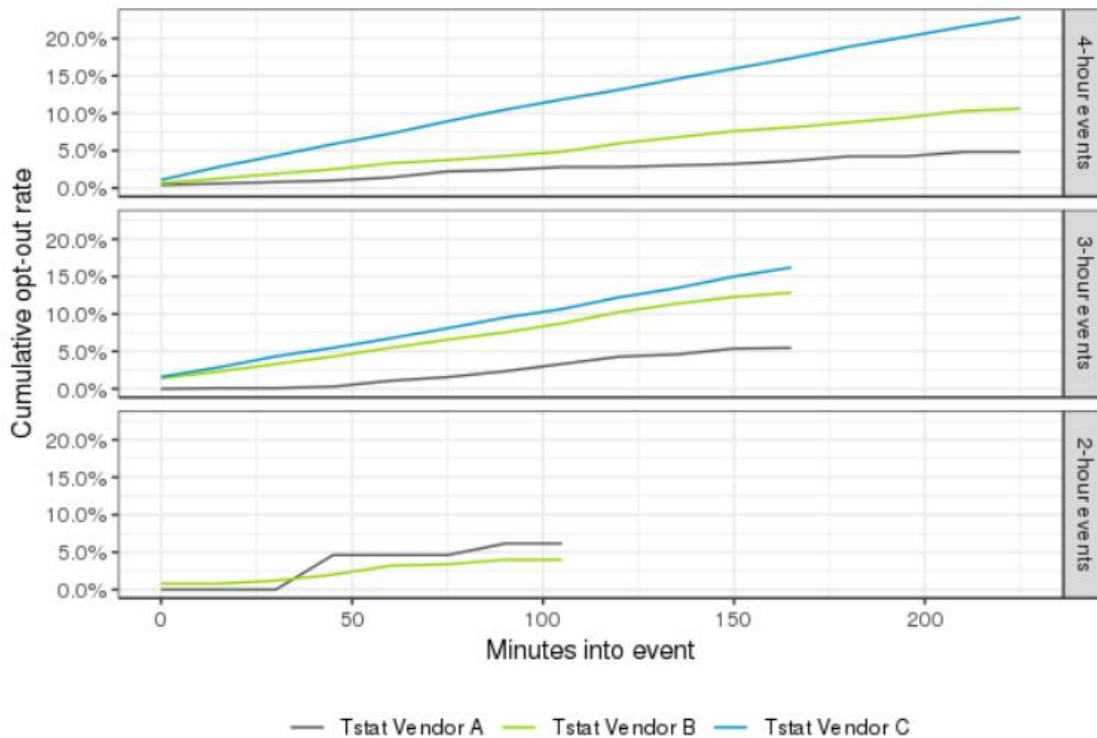
Figure 3. Average cumulative opt-out profile throughout events[20] *Source*: Navigant and ILLUME 2018.

The smooth cumulative opt-out profile could also reflect the distribution of times when people arrive home. The DRSPs hypothesize that there is a relationship between people coming home and opting out of an event, but they have not collected information to support this trend. Without access to occupancy data, it is not possible to know what proportion of people immediately opt out upon arriving home versus those who take more time to decide.

Findings from the team's LPM regression model concur with the exploratory data analysis findings. Every hour of additional event duration increases a participant's likelihood of opting out by 3.3%. Utilities must consider the clear tradeoff between savings generated through longer events with increasing customer drop-outs throughout the event reducing savings. Another consideration, suggested by our interview findings, is that customers may experience more frustration and lower levels of program satisfaction with these longer events, in addition to the event losing more customers to opt outs throughout the duration.

Regression analysis shows that the timing of events has a statistically significant impact on propensity for opt outs. DR participants have less tolerance for events held near the end of the week relative to the middle. Propensity to opt out increases by 3.6% on Thursdays and by 3.8% on Fridays relative to Wednesdays. These findings may reflect that people are likely to take Thursdays or Fridays off and hence be at home and be responding to events. They may also suggest that people have a lower tolerance for events as the work-week progresses. An event's timing also has a statistically significant impact on opt outs. Starting an event an hour later in the day increases a participant's likelihood of opting out by 2.4%.

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[20] We anonymized manufacturers in this comparison because we feel that program parameters, rather than inherent technology differences, may best explain differences shown in the diagram.

**Event Frequency and Fatigue:** Back-to-back events can lead to program fatigue and frustration. Most interview participants expressed that fatigue from back-to-back events could cause them to opt out because they grew tired of being uncomfortable in their home and/or adjusting their lives to accommodate events. This is consistent with responses from the DRSP interviewees, which also indicated that fatigue from back-to-back events negatively affected participation. Utilities should consider this finding when scheduling back-to-back events. The program implementer or the utility faces a tradeoff between increased customer frustration and opt outs relative to the incremental demand savings achieved through the consecutive events.

The team included variables to capture the effect of back-to-back events in the preferred regression model specification; unlike event duration or other parameters, consecutive-day-events had no statistically significant impact on DR participants' likelihood of opting out, even when interacted with thermostat type.[21] This discrepancy between the quantitative and qualitative findings could signal that, when asked in an interview, customers may feel that they are more likely to opt out of back-to-back events because the situation sounds unpleasant, but their actual behavior may not match their perceived behavior. In addition, due to program design, customers did not experience back-to-back events spanning more than 2 days during 2017. It is possible that the threshold for many customers is larger than 2 days, in which case future research using programs and designs holding multiple-day back-to-back events could be valuable.

**Program Type and Motivations for Participation:** Qualitative research combined with quantitative analysis provided insights into customer motivations for participation in DR programs, particularly with respect to how key program features—which vary between the Thermostat DR and SES programs—influence participation and opt outs.

Within the Thermostat DR program, differences exist between opt-out rates in its two channels. This represents a key finding related to program design and opt-out behavior. Opt-out rates for thermostats enrolled in the CS program are significantly lower relative to the RHR program. One key difference is that CS participants face disincentives to opt-out. The CS incentive structure requires participation in at least 75% of the DR events to receive a $25 annual reward. By contrast, RHR customers receive an incentive for joining the program and for each year they participate, but it is not contingent on not opting out of events. Thus, CS gives participants a stronger incentive not to override events. Another key difference to consider is equipment usability and how easy the thermostat interface makes opting out. Future research might explore how differences in thermostat user interfaces contribute to likelihood of overrides. Due to the small size of the reward, many CS customers still prioritized comfort over what they considered a small financial incentive. To make the most of the financial incentive's impact, the incentive should be sized appropriately to motivate participation. Utilities that want to maximize customer participation in events and minimize opt-out behavior may give preference to program designs that provide significant disincentives to opt-out behavior.

Primary motivations for participation are identical between the two program types. The DRSPs interviewed noted that the two key drivers motivating customers to enroll in a DR program are: 1) to get a free or reduced-price smart thermostat, and 2) to save money or receive an enrollment incentive. These drivers were consistent with the responses provided by the participants. Most SES participants indicated that receiving a smart thermostat was their primary motivation for enrollment. They cited saving money and being able to track their energy usage as secondary motivations. RHR and CS participants responded similarly. Most indicated they used the utility rebate to obtain the smart thermostat technology and then enrolled in the DR program as an additional way to save money or to help the utility. The team interviewed several participants in different programs who indicated confusion about program details (e.g., incentive

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[21] Thermostat type and consecutive events could be correlated, as some thermostat makes were more likely to be involved in consecutive DR events during 2016 and/or 2017.

structure, how much their thermostat was adjusted, what it meant to opt out). Continued engagement with the customer or improved education about the program could increase event participation by increasing customer awareness, making them feel more invested in the program, and decreasing the likelihood of opting out.

Customizable remote temperature control is perceived as another key benefit. Participants across both programs commented that the ability to remotely monitor and control the temperature of their home was their thermostat's primary benefit. Program participants discussed setting up temperature schedules on their smart thermostats to reflect when different household members were home. Many participants reported scheduling their thermostat setpoint to either increase or decrease during the night to increase comfort or use less energy. These observations speak to the importance customers place on being able to customize temperature settings in their home through their thermostat.

Customers enroll to save money and want to see evidence of their savings. Many program participants expressed skepticism about whether the DR programs led to savings. SES participants expressed interest in seeing what they would have paid had they not enrolled. Participants in RHR and CS were less concerned with whether their participation resulted in bill savings; rather, they expressed disbelief that any significant savings were being generated by the program as a whole. This belief made it easier for participants to justify opting out of events when they were uncomfortable. Despite these doubts, customers expressed commitment to their respective programs, often expressing a sense of duty to help the utility or to contribute to the greater good. Participants with a sense of duty or loyalty to their utility are motivated to participate in DR events. However, these customers do not always understand why the program is necessary or how to cope with its negative impacts on comfort and convenience. Providing customers with resources and strategies to mitigate and adapt to the effects of DR events would help them balance their desire to be comfortable while also supporting their interest in helping their utility. For instance, the utility or program provider could help customers develop DR event participation-conducive behaviors such as opening windows, using fans, leaving the house, and pre-cooling as alternatives to opting out.

Optimization strategies offer a solution to meet the needs of both the customer and the utility. The DRSPs discussed the importance of striking a balance between customer satisfaction and the utility's load shifting needs. DRSPs often offer optimization of temperature settings at the individual household level, referred to as adaptive algorithms, as a means of helping utilities attain this balance. DRSP optimization strategies often use basic household information provided by the customer during the enrollment process and smart thermostat data collected over time to understand the home's thermodynamics and build home-specific models to inform these adaptive algorithms. In some cases, weather data is coupled with the thermal model of the home so that the DRSP can simulate the effects of adjusting the AC for different lengths of time throughout the day, while keeping the home's temperature track within the customer's comfort band.

A final finding of this qualitative research on motivations for program participation is that trust in the utility and DRSP plays a key role in enrollment. The DRSPs provided key insights into success factors for customer enrollment and how customer enrollment is tied to utility goals and objectives. The DRSPs interviewed by the team primarily discussed the opt-in program design within which customers have the option to opt out of events and how, within this structure, event characteristics and incentives are customized to meet the utility's goals and needs. These DRSPs indicated that they typically work with utilities to promote the program by notifying customers that their utility offers a DR program at the time they install a smart thermostat in the home. In addition, many CS and RHR participants that the team interviewed mentioned that after they installed their smart thermostat they received a notification that their utility offered the DR program, which then motivated them to enroll. In both cases, trust of the utility and the DRSP appear to be a key consideration leading to increased enrollment.

## Summary and Conclusions

Blending qualitative and quantitative methods, our team created a holistic picture of participant behavior and motivations for DR program participation and opt outs, particularly in relation to weather factors, event characteristics, and program design. By connecting interview-based qualitative findings with quantitative analysis of thermostat telemetry data, our team provided qualitative evidence explaining patterns we observed through data visualization exercises and causal effects of weather on opt-out behavior estimated through regression analysis.[22]

DR program participants can be categorized into four broad participant types with distinct behaviors and motivations—Comfort Seekers, Hold Outs, Best-Effort Participants, and Reliable Participants. At the outset of programs, utilities can optimize program performance and make messaging cost-effective by considering the different behaviors and motivations of these participant types when developing program messaging. This could help optimize program performance, messaging, marketing, and recruiting cost-effectiveness.

Qualitative and quantitative analysis identified both weather and event characteristics—specifically heat, humidity, event duration, and event timing—as key determinants of participant opt-out behavior. Utilities should consider weather and event characteristics when planning to optimize program savings and customer satisfaction while minimizing opt outs.

Opt-out rates vary based on program design parameters, even within a program. The DR Thermostat project's two distinct participation channels, CS and RHR, vary by incentive structure and equipment type. Utilities should ensure that the incentive structure is appropriately designed to motivate participation and to discourage opt outs. Utilities may also consider focusing on technologies and behavioral strategies, like gamification, that deter customers from opting out, while understanding the tradeoff that this may lead to greater customer frustration or dissatisfaction.

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[22] As noted, 2016 and 2017 were relatively mild weather summers and so it is possible that the heat-tolerance thresholds for certain individuals were not met in this study. We believe future research involving more extreme weather could provide more insight into people's behavior at higher temperatures.