# Seasonal Savings Impacts in
# Pacific Gas & Electric Service Territory
Winter 2017/18

## Executive Summary

On January 12, 2018, Nest launched its Seasonal Savings schedule tune-up algorithm targeted at 47,000 thermostats in the Pacific Gas & Electric (PG&E) service territory. This report summarizes the impacts of Seasonal Savings on customer set points and energy use. The study included a randomly selected control group to provide unbiased impact estimates. The key findings are summarized in the table below.

| Summary of Impacts | Standard |
|---|---|
| **Participation** | 47,000 targeted |
| Qualified on-line, running heating schedule | 36,135 |
| % of targeted | 77% |
| Opted In | 26,726 |
| % of qualified | 74% |
| **Net Change in Set Point Temperatures per opt-in** | |
| Change in Scheduled Set Points | 0.90°F ±0.03°F |
| Change in Actual Set Points | 0.64°F ±0.03°F |
| **Heating Runtime Analysis** | |
| % Heating Savings (degree-day regression) | 6.7% ±0.9% |
| therms/ opt-in participant | 5.5 ±0.8 |
| therms aggregate | 141,246 |
| kWh aggregate (furnace fans and 6% heat pumps) | 206,928 |

note: ± values are 95% confidence intervals

## Intro

Seasonal Savings is a software algorithm that offers customers an opportunity to make their heating schedules more efficient through a series of very small adjustments to the scheduled temperatures over a three week period. The algorithm results in more energy efficient heating schedules going forward. Customers are offered the program on their thermostat and through the Nest phone app and must opt-in to participate.

## Participation

A total of 91,116 thermostats were identified as being in the potential target population -- which was defined as Nest customers with central heating in the PG&E service territory and located within California climate zones 4, 11, 12, or 13. PG&E requested a target population of 47,000 thermostats and so the population was randomly split between a treatment group and a control group with the remaining 44,116 thermostats.

The Seasonal Savings algorithm was deployed on January 12, 2018. Table 1 shows the participation rates.

**Table 1. Participation Summary**

| Group | # Thermostats | % of Total | % of Qualified |
|---|---|---|---|
| Targeted | 47,000 | 100% | |
| - Did not qualify | 10,865 | 23% | |
| = Qualified | 36,135 | 77% | 100% |
| Opted In | 26,726 | 57% | 74% |

Overall, 77% of the targeted thermostats qualified to participate in Seasonal Savings -- meaning they were online and running a heating schedule. A total of 26,726 thermostats opted in -- equal to 74% of qualified thermostats and 57% of the original target population.

## Savings Analysis

Seasonal Savings makes changes to customer heating schedules which then leads to more efficient heating set points which then leads to a reduction in heating system runtime hours.

The evaluation analyzed the changes in the customer's heating schedules and set points to demonstrate program impacts. Energy savings were quantified by analyzing heating system runtime. The randomized control group provided a true experimental design for the evaluation -- comparing the impacts for the entire targeted participant group (including those that did not opt-in) to the control group. This evaluation approach is called an Intent-to-Treat or Randomized Encouragement Design (RED).

An RED eliminates self-selection bias but directly estimates the impact of being in the target participant group -- not the impact of actually participating. To estimate the savings per participant that opted-in, the RED results must be adjusted for the opt-in rate. For example, if the RED analysis found 2% savings from being in the target group and there was a 50% participation rate then the estimated savings per opt-in customer would be 4% (2% / 50% = 4%).

### Analysis of Set Points

The average scheduled thermostat set points for the Seasonal Savings target population and the control group are shown in Figure 1 with a vertical line marking the date of deployment.

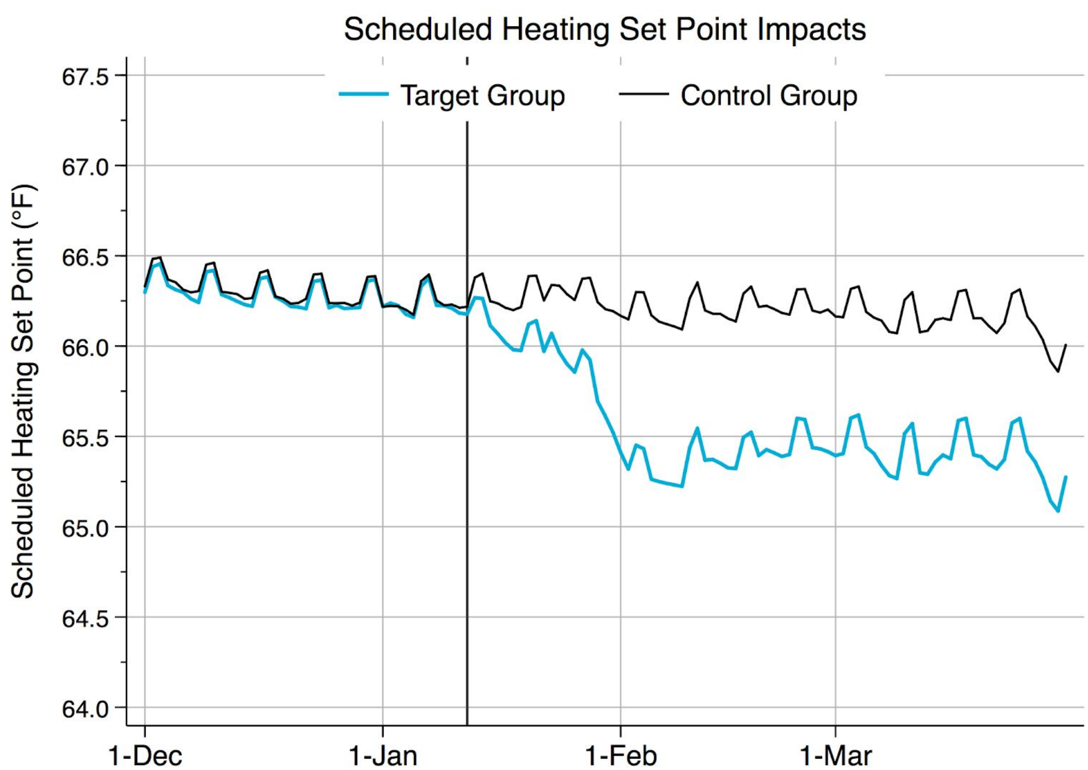


**Figure 1. Scheduled Heating Set Points over the season**

The treatment and control groups were virtually identical prior to deployment and then clearly diverge as the algorithm adjusts customer schedules over the next three weeks.

Figure 2 directly plots the difference between the two lines in Figure 1 -- providing a better illustration of the schedule impacts. It also plots the differences using the actual executed set points. Actual set points can differ from the schedule due to manual adjustments (via dial or app or web) or to the auto-away feature based on occupancy detection.

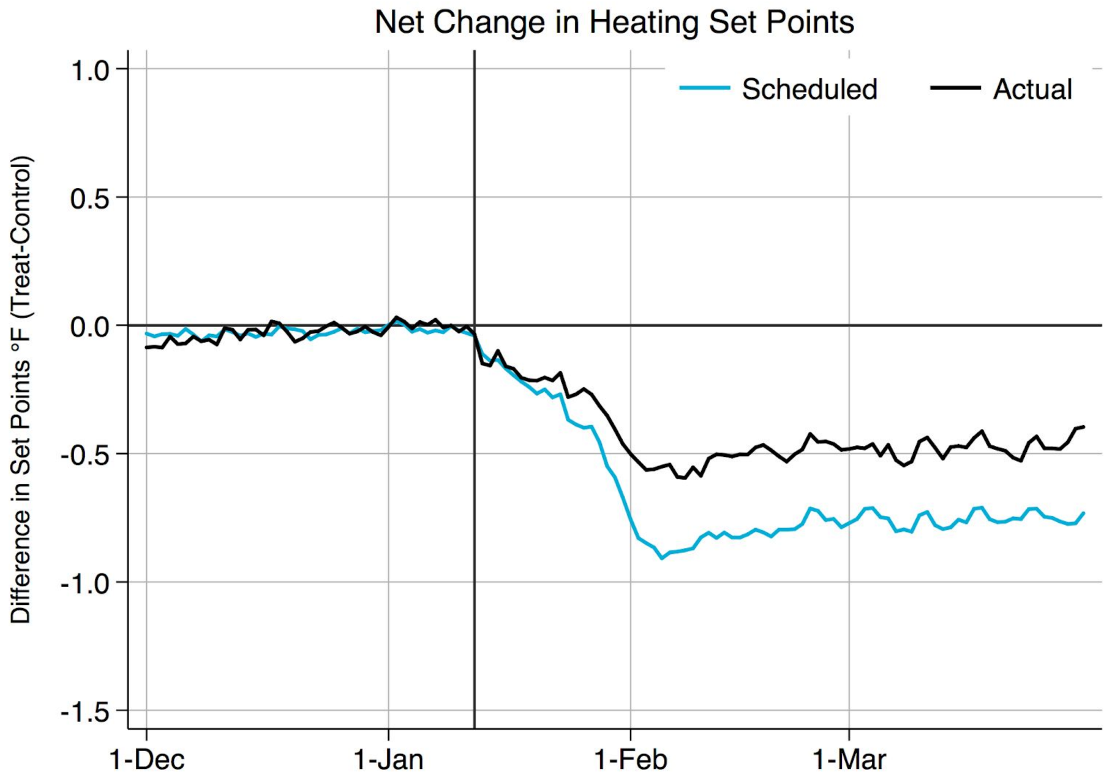


**Figure 2. Difference between Target and Control Group set points: Scheduled and Actual**

The figure shows a clear impact of Seasonal Savings on set points. The net change in set points during the season was quantified using a regression analysis that included both thermostat and date fixed effects (see Appendix A for details). The analysis found a net reduction in scheduled set points of 0.63°F per targeted thermostat, equal to 0.90°F per opt-in (70% opt-in rate for customers in the analysis). The average reduction in actual set points was 0.64°F (±0.03°) per opt-in participant.

## Heating Runtime Analysis

The heating runtime recorded by the thermostats can be used to assess savings. Figure 3 shows the average daily heating run time for the target and control groups over the season.

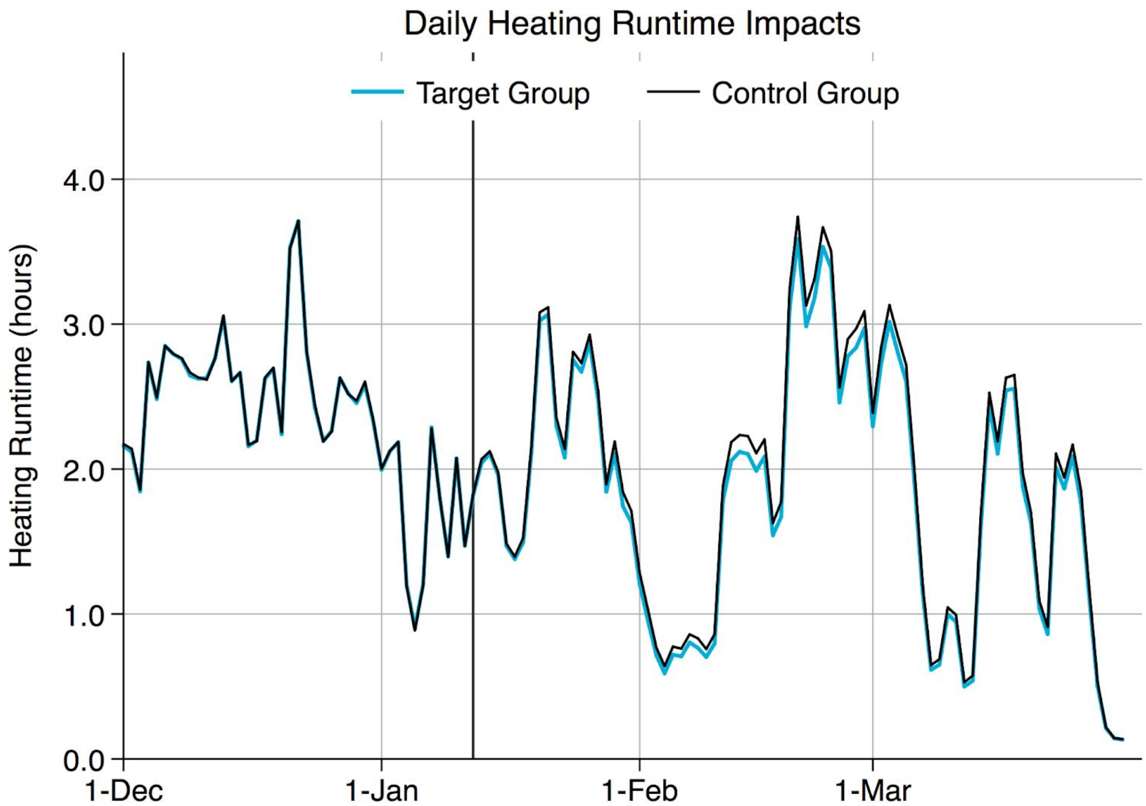


**Figure 3. Average Daily Heating Runtime: Target and Control Groups**

The graph shows that the two groups are indistinguishable prior to deployment but a clear reduction can be seen for the target treatment group especially in mid to late February.

The impact of Seasonal Savings on heating runtime was quantified using regression analysis similar to methods employed to analyze utility meter data. The analysis dataset included 15 million daily runtime observations from 45,290 targeted participants and 42,549 controls. HVAC runtime was modeled as a function of degree days with interaction terms for the post period and treatment group and including thermostat specific fixed effects. Appendix A provides more details on the modeling specifications.

The regression analysis estimated that Seasonal Savings reduced heating runtime by 4.0% per target participant which equals 6.7% (±0.9%) per opt-in participant.

## Energy Savings

The estimated percent heating savings were converted to units of therms and kilowatt-hours based on the actual heating run time of the participants during the post-deployment period and using estimated heating system natural gas and electric input rates.

We estimated the average gas furnace input rate at 47 kBtu/hr based on DEER averages by climate region. A reduction in heating hours will also result in a reduction in furnace electric usage -- primarily from the air handler fan but also other ancillary uses (e.g., direct vent fan). We estimated average furnace power draw at 528 W. In addition, 4.3% of the opt-in participants have heat pumps and so savings for those customers will be in electric usage. We estimated average power draw for the heat pumps at 3.3 kW. The energy savings were then calculated based on these input rates applied to the 6.7% percent savings from the runtime analysis, and the average post-deployment heating runtime for the gas furnaces and the heat pumps.

Table 3 shows the resulting savings per opt-in participant and in aggregate.

**Table 3. Energy Savings Summary**

| | Impacts per Opt-In Participant | | |
|---|---|---|---|
| | Gas Heat | Heat Pump | Aggregate |
| # Opt-in Participants | 25,544 | 1,150 | 26,694 |
| Hours Baseline | 175 | 189 | |
| Hours Saved | 11.8 | 12.7 | |
| Gas Savings (therms) | 5.5 ±0.8 | | 141,246 |
| Electricity Savings (kWh) | 6.2 ±0.8 | 42±6 | 206,928 |

This savings per gas heated opt-in participant averaged 5.5 therms of natural gas and 6 kWh of electricity. Savings per opt-in heat pump participant averaged 42 kWh. The aggregate savings from the deployment are estimated at 141,246 therms of natural gas and 206,928 kWh.

These savings results do not include any savings achieved after April 2018 (i.e., the end of the winter and persistence into the following heating season are both assumed to be zero) -- a full accounting of savings would likely result in a larger total.

*Note: This study is specific to the Seasonal Savings program deployed by Nest for eligible, participating PG&E customers during the 2017-18 heating season. The results found herein do not necessarily represent expected results from the Seasonal Savings program under different conditions.

# Appendix A: Statistical Methods

## Analysis of Net Changes in Set Points

The net impact of Seasonal Savings on customer set points is estimated by analyzed the daily average set points for all thermostats in the target participant group and the control group across the pre and post deployment data for the season. The analysis accounts for both thermostat-specific and date-specific effects using a two way fixed effects model and excludes days with no heating (cooling) runtime. The net impact of Seasonal Savings can then be estimated using a single explanatory variable – an indicator for post deployment period in the treatment group. This same model is used to analyze the scheduled set points and the actual executed set points. The statistical model is:

(Eq. 1) $Tset_{it} = \beta_1 * PostTreat_{it} + Tstat_i + Date_t + \varepsilon_{it}$

where:

> $Tset_{it}$ is the average set point for thermostat i on day t
>
> $PostTreat_{it}$ is a dummy variable equal to 1 if thermostat i is in the target treatment group and day j is in the post-deployment period, otherwise it is 0
>
> $Tstat_i$ is the thermostat specific fixed effect for thermostat i
>
> $Date_t$ is the date-specific fixed effect for date t
>
> $\beta_1$ is the net impact of Seasonal Savings on set points estimated by the regression model
>
> $\varepsilon_{it}$ is the random error term for thermostat i on date t. The variance is calculated accounting for clustering within thermostat

## Analysis of Runtime Savings from Daily Data

The HVAC runtime recorded by the thermostats can  be used to directly assess the impacts produced by Seasonal Savings. A variety of model specifications can be used and will tend produce similar estimates, especially in large scale RCT/RED designs. In this study, Nest employed a standard billing data analysis style fixed effects model that analyzes pre and post deployment runtime data for the treatment and control groups and includes degree day terms to account for weather.  An alternative model that simply employs a difference-in-differences type specification with both thermostat and date fixed effects is also used in some studies. But that model tends to work best when the climate doesn't vary much across the population and so was not employed in this study.

The degree day model specification is:

(Eq. 2) $Runtime_{it} = \beta_1 * DD_{it} + \beta_2 * Treat_i * DD_{it} + \beta_3 * Post_t + \beta_4 * Post_t * DD_{it} + \beta_5 * Post_t * Treat_i + \beta_6 * Post_t * Treat_i * DD_{it} + Tstat_i + \varepsilon_{it}$

where:

$Runtime_{it}$ is the hours of HVAC runtime for thermostat i on day t

$DD_{it}$ is the heating (cooling) degree days (base 60° heating, 65° cooling) for thermostat i on day t

$Post_t$ is an indicator variable equal to 1 if date t is after the deployment date, otherwise 0

$Treat_i$ is an indicator variable equal to 1 if the thermostat is in the target treatment group and 0 if it is in the control group

$Tstat_i$ is the thermostat specific fixed effect for thermostat i

$\beta_1$ is the estimated change in HVAC runtime per degree day

$\beta_2$ is the estimated additional change in HVAC runtime per HDD for thermostats in the target treatment group

$\beta_3$ is the estimated change in HVAC runtime in the post period

$\beta_4$ is the estimated additional change in HVAC runtime per degree day in the post period

$\beta_5$ is the estimated additional change in HVAC runtime in the post deployment period for thermostats in the target treatment group – which is an estimate of runtime savings that are constant per day for the treatment in the post period

$\beta_6$ is the estimated change in HVAC runtime per degree day in the post deployment period for thermostats in the target treatment group – which is an estimate of runtime savings per degree day for the treatment

$\varepsilon_{it}$ is the random error term for thermostat i on date t. The variance is calculated accounting for clustering within thermostat

The savings during the post deployment period are then calculated based on the coefficients $\beta_5$ and $\beta_6$ and the number of days and degree days in the post period. Percent savings are calculated based on post deployment runtime. The estimated standard errors of the savings are calculated using the variance-covariance matrix from the regression that accounts for clustering within thermostat.