STATE OF CALIFORNIA Edmund G. Brown Jr., *Governor*

PUBLIC UTILITIES COMMISSION
505 VAN NESS AVENUE
SAN FRANCISCO, CA 94102-3298

November 20, 2017

Advice Letters 5204-G
5204-G-A

Ronald van der Leeden
Director, Regulatory Affairs
Southern California Gas
555 W. Fifth Street, GT14D6
Los Angeles, CA 90013-1011

SUBJECT: Approval for Southern California Gas Company to Implement the Seasonal Savings Program

Dear Mr. van der Leeden:

Advice Letters 5204-G and 5204-G-A are effective as of November 18, 2017.

Sincerely,

Edward Randolph

Edward Randolph
Director, Energy Division

Ronald van der Leeden
Director
Regulatory Affairs

555 W. Fifth Street, GT14D6
Los Angeles, CA 90013-1011
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October 19, 2017

Advice No. 5204
(U 904 G)

Public Utilities Commission of the State of California

Subject: Approval for Southern California Gas Company to implement the Seasonal Savings Program

Southern California Gas Company (SoCalGas) hereby requests expedited approval from the California Public Utilities Commission (Commission) to implement a Seasonal Savings Program.

Purpose

This Advice Letter seeks approval for the implementation of a Seasonal Savings Program in SoCalGas' service territory. The program consists of a software service to deliver incremental savings using remote set point adjustments offered to SoCalGas residential customers with operational Nest smart thermostats. Program activity will be an element of, and funded by, the existing residential program, SCG3701 SW-CALS-Energy Advisor.

Background

SoCalGas proposes to implement a Seasonal Savings Program in its service territory to achieve incremental energy savings using software controls of existing Nest smart thermostats. This innovative offering is proposed to be rolled out territory-wide following a pilot that concluded April 2017. Nest smart thermostats are programmable devices which can be set up to adjust temperature set points based on recurring customer patterns such as when occupancy drops or during sleep hours. Energy savings can be achieved upon installation and programming of these units. The amount of energy savings delivered depends on how much the temperatures are changed compared to before installation and programming of the smart thermostat or simply making manual set point adjustments.

Seasonal Savings Program

SoCalGas is partnering with Nest for the implementation of the innovative, software-driven Seasonal Savings Program to increase the amount and persistency of energy savings from the normal use of smart thermostats. The program will be conducted annually over the course of the winter season (November - March). During this period, SoCalGas residential customers who own Nest smart thermostats will be invited to participate in the program via a message on the thermostat interface. If a customer opts-in to the pilot, customer-specific algorithms will be delivered to make micro-set point adjustments on the Heating, Ventilation, and Air Conditioning (HVAC) equipment over a three-week period. These adjustments are intended to be small enough to maintain customer comfort while still large enough to deliver incremental savings over those achieved with the current use of the energy management device.

Nest describes their third party-designed Seasonal Savings program as an approach that promotes deployable and persistent energy efficiency. It has been implemented in other states during winter and summer seasons, and in 2017, was piloted in SoCalGas' service territory.[1] Nest documented the results of the SoCalGas Winter Seasonal Savings pilot and their analysis showed the following results:[2]

- 51% of the total target group participated in the Seasonal Savings pilot;
- Participants' set points declined by an average of 0.63°F per opt-in participant over the course of the three-week algorithm deployment; and,
- Seasonal Savings reduced heating usage by an average of 8.4% based on actual heating run time of participants and using estimated heating system natural gas and electric input rates.

The Seasonal Savings Program addresses the Long-Term Energy Efficiency Strategic Plan goals as well as strategies required for the enactment of legislative initiatives. Results from the program will contribute to the quickly-expanding collective knowledge on the use of smart thermostats and optimization for energy savings.

As part of the Energy Advisor program, the Seasonal Savings Program will continue to empower customers by helping them understand and manage their energy use by making small tweaks to their thermostat's temperature schedule to save energy and stay comfortable. The program will utilize a customer's behavior to automatically tweak temperatures in the customer's schedule to make temperature preferences more efficient. The interactive tools used in the Seasonal Savings Program are designed to engage customers and to encourage participation in innovative initiatives to reduce their

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[1] SoCalGas filed AL 5028, later supplemented by AL 5028-A and effective October 15, 2016, requesting approval of its Winter Seasonal Savings Pilot. The Pilot ran from January 19, 2017 through April 30, 2017.
[2] Seasonal Savings Impacts: Southern California Gas Winter 2016/2017 Report, 2017.

energy consumption through behavioral solutions, program recommendations and, as appropriate, integrated demand-side management opportunities.

Attachments

This Advice Letter includes the following attachments:

- **Attachment A**: Nest Seasonal Savings Impacts: Southern California Gas Winter 2016/2017 Report
- **Attachment B:** Nest White Paper - Energy Savings from the Nest Learning Thermostat: Energy Bill Analysis Results

Protests

Anyone may protest this Advice Letter to the Commission. The protest must state the grounds upon which it is based, including such items as financial and service impact, and should be submitted expeditiously. The protest must be made in writing and must be received within 20 days of the date of this Advice Letter, which is November 8, 2017. There is no restriction on who may file a protest. The address for mailing or delivering a protest to the Commission is:

CPUC Energy Division
Attn: Tariff Unit
505 Van Ness Avenue
San Francisco, CA 94102

Copies of the protest should also be sent via e-mail to the Energy Division Tariff Unit (EDTariffUnit@cpuc.ca.gov). A copy of the protest should also be sent via both mail and facsimile to the address shown below on the same date it is mailed or delivered to the Commission.

Attn: Ray B. Ortiz
Tariff Manager - GT14D6
555 West Fifth Street
Los Angeles, CA 90013-1011
Facsimile No.: (213) 244-4957
E-mail: ROrtiz@SempraUtilities.com

Attn: Corinne M. Sierzant
Regulatory Affairs Case Manager - GT14D6
555 West Fifth Street
Los Angeles, CA 90013-1011
Facsimile No.: (213) 244-4957
E-mail: CSierzant@SempraUtilities.com

Effective Date

SoCalGas believes that this Advice Letter is subject to Energy Division disposition and should be classified as Tier 2 (effective after staff approval) pursuant to General Order (GO) 96-B. This filing is consistent with D.09-09-047. Therefore, SoCalGas respectfully requests that this filing be approved on November 18, 2017, which is 30 days after the date filed.

Notice

A copy of this Advice Letter is being sent to SoCalGas' GO 96-B service list and the Commission's service lists for R.13-11-005. Address change requests to the GO 96-B should be directed by electronic mail to tariffs@socalgas.com or call 213-244-2837. For changes to all other service lists, please contact the Commission's Process Office at 415-703-2021 or by electronic mail at Process_Office@cpuc.ca.gov.

Ronald van der Leeden
Director – Regulatory Affairs

Attachments

CALIFORNIA PUBLIC UTILITIES COMMISSION

ADVICE LETTER FILING SUMMARY
ENERGY UTILITY

MUST BE COMPLETED BY UTILITY (Attach additional pages as needed)

Company name/CPUC Utility No. **SOUTHERN CALIFORNIA GAS COMPANY (U 904G)**

Utility type:
☐ ELC ☒ GAS
☐ PLC ☐ HEAT ☐ WATER

Contact Person: Ray B. Ortiz
Phone #: (213) 244-3837
E-mail: ROrtiz@semprautilities.com

EXPLANATION OF UTILITY TYPE

ELC = Electric GAS = Gas
PLC = Pipeline HEAT = Heat WATER = Water

(Date Filed/ Received Stamp by CPUC)

Advice Letter (AL) #: 5204

Subject of AL: Approval for Southern California Gas Company to Implement the Seasonal Savings Program

Keywords (choose from CPUC listing): Energy Efficiency

AL filing type: ☐ Monthly ☐ Quarterly ☐ Annual ☒ One-Time ☐ Other

If AL filed in compliance with a Commission order, indicate relevant Decision/Resolution #:
D.09-09-047

Does AL replace a withdrawn or rejected AL? If so, identify the prior AL: No

Summarize differences between the AL and the prior withdrawn or rejected AL[1]: N/A

Does AL request confidential treatment? If so, provide explanation: No

Resolution Required? ☐ Yes ☒ No

Tier Designation: ☐ 1 ☒ 2 ☐ 3

Requested effective date: 11/18/17

No. of tariff sheets: 0

Estimated system annual revenue effect: (%): N/A

Estimated system average rate effect (%): N/A

When rates are affected by AL, include attachment in AL showing average rate effects on customer classes (residential, small commercial, large C/I, agricultural, lighting).

Tariff schedules affected: N/A

Service affected and changes proposed[1]: N/A

Pending advice letters that revise the same tariff sheets: N/A

Protests and all other correspondence regarding this AL are due no later than 20 days after the date of this filing, unless otherwise authorized by the Commission, and shall be sent to:

CPUC, Energy Division
Attention: Tariff Unit
505 Van Ness Ave.,
San Francisco, CA 94102
EDTariffUnit@cpuc.ca.gov

Southern California Gas Company
Attention: Ray B. Ortiz
555 West 5th Street, GT14D6
Los Angeles, CA 90013-1011
ROrtiz@semprautilities.com
Tariffs@socalgas.com

[1] Discuss in AL if more space is needed.

ATTACHMENT A

Advice No. 5204

Nest Seasonal Savings Impacts:
Southern California Gas Winter 2016/2017 Report

Seasonal Savings Impacts: Southern California Gas Winter 2016/17
January through April 2017

Prepared for Southern California Gas

Intro

On January 19, 2017, Nest launched its winter Seasonal Savings algorithm targeted at 99,520 thermostats in the Southern California Gas (SoCalGas) service territory. This report summarizes the estimated heating impacts of Seasonal Savings on these home

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. This report summarizes the estimated heating impacts of Seasonal Savings in SoCalGas territory.

Participation

A total of 120,365 thermostats were identified in the target population of SoCalGas Nest customers. In order to provide for a high quality evaluation, the target population was randomly split into treatment and control groups within each of 7 climate zones. The sampling was performed by house, not by thermostat, so that either all thermostats in the same home were in the same group.

In order to maximize the size of the participant group while maintaining acceptable precision for the evaluation, the control group was limited to a maximum of 3,000 homes per climate zone. In climate zones with fewer than 6,000 homes (zones 14, 15 and 16) the population was split 50/50 between treatment and control groups. The sampling plan is shown in table 1.

Table 1. Sampling Plan by Climate Zone

	Homes		Thermostats	
Climate Zone	Treatment	Control	Treatment	Control
6	13,896	3000	18,604	3,994
8	14,794	3000	17,711	3,617
9	35,928	3000	46,302	3,824
10	8,753	3000	10,890	3,704
14	791	790	933	945
15	2,751	2751	4,117	4,065
16	585	584	709	696
Total*	77,498	16,125	99,520	20,845

*note: columns do not sum to totals due to 254 thermostats with unclear or changing location data

The randomization of homes was performed by SoCalGas M&V consultant DNV GL. Nest provided a list of homes with climate zone and DNV GL randomized the list according to the plan and sent the resulting assignments back to Nest for deployment.

The Seasonal Savings algorithm was deployed in January 19, 2017. Overall 65% of the 99,520 target thermostats qualified to participate (i.e., were online and running a heating schedule) and 79% of the qualified thermostats had the customer opt to participate. In total, 50,904 thermostats participated in the Seasonal Savings event -- 51% of the total target group. Table 2 shows the participation data by climate zone.

Table 2. Participation by Climate Zone

	# Thermostats		Participation Rates			
Climate Zone	Targeted	Opted-In	Opted-In % of qualified	Opted-In % of total	Opted Out % of total	Not Qualified % of total
6	18,604	9,137	77.7%	49.1%	14.1%	36.8%
8	17,711	9,111	78.9%	51.4%	13.8%	34.8%
9	46,302	24,548	80.0%	53.0%	13.2%	33.8%
10	10,890	5,785	78.8%	53.1%	14.3%	32.6%
14	933	507	77.5%	54.3%	15.8%	29.9%
15	4,117	1,409	65.3%	34.2%	18.2%	47.6%
16	709	310	65.1%	43.7%	23.4%	32.9%
Total	99,520	50,904	78.6%	51.1%	13.9%	34.9%

The opt-in rates ranged from 65% to 80% of those qualified across climate zones with two distinct groupings -- climate zones 15 and 16 were both near 65% opt-in while the other four zones all had opt-in rates between 77% and 80%. Climate zone 15 had the lowest qualification rate with 48% not qualifying to participate due to the mild winter climate. Nearly half of the opt-in group is in climate zone 9 and close to 20% each are in zones 6 and 8. Zones 14, 15, and 16 combine for under 6% of the opt-in participant group.

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. This evaluation assesses each of these impacts.

The primary analysis of energy savings was based on statistically analyzing daily heating system runtime data from the thermostats using methods similar to those employed in a pre/post treatment/control billing data analysis. In addition, the evaluation analyzed how Seasonal Savings affected scheduled and actual heating set points and how those changes are expected to affect heating energy use.

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 entire control group. This evaluation approach is called a Randomized Encouragement Design (RED).

An RED eliminates self-selection bias by directly estimating the impact of being in the target participant group -- not the impact of actually participating. This analysis is a true randomized control trial (RCT). To estimate the savings per opt-in participant, the results per targeted customer are adjusted for the opt-in rate. For example, if the 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%).

Given the variations in weather and heating patterns across climate zones and the use of varying control group sizes across zones, the analysis was conducted separately for each climate zone and then the results combined based on the participant group size in each zone. Climate zone 9 included nearly half of the participants and so is used as the example analysis in the sections below.

Set Points Analysis

The set points based analysis involved assessing the change in each customer's heating setpoints from the day the algorithm launched (January 19, 2017) through the end of April 2017. The daily average scheduled thermostat set points for the target population and control group for climate zone 9 are shown in Figure 1.

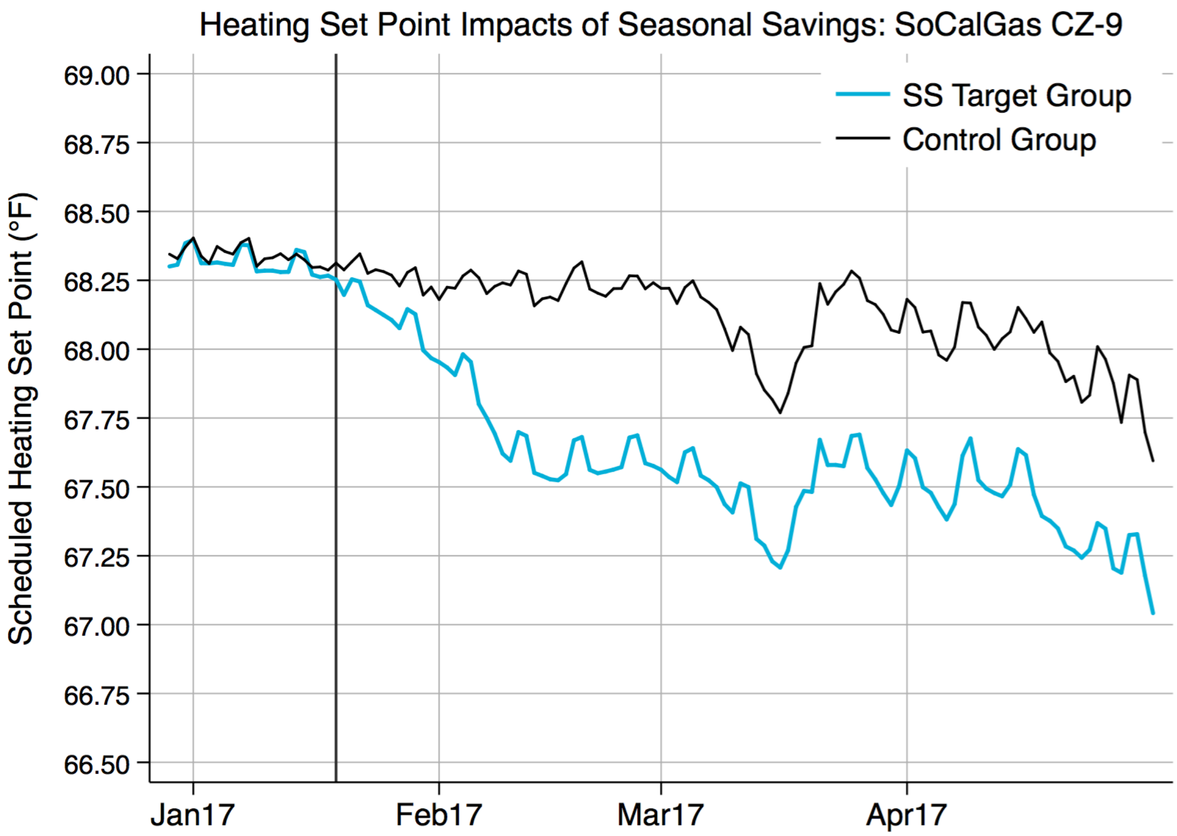

Figure 1. Scheduled Heating Set Points over the season

The vertical line indicates the date the algorithm was deployed. The up and down pattern is largely due to differences between weekends and weekdays. The two groups start out with nearly identical set points and then diverge rapidly during the three week period of small schedule adjustments made by Seasonal Savings. Set points shift over time due to mild weather.

Figure 2 directly plots the difference between the two lines in Figure 1 -- providing a better illustration of the schedule impacts. Seasonal Savings has a clear impact during deployment and the changes appear to persist through the remainder of the season at about 0.6°F.

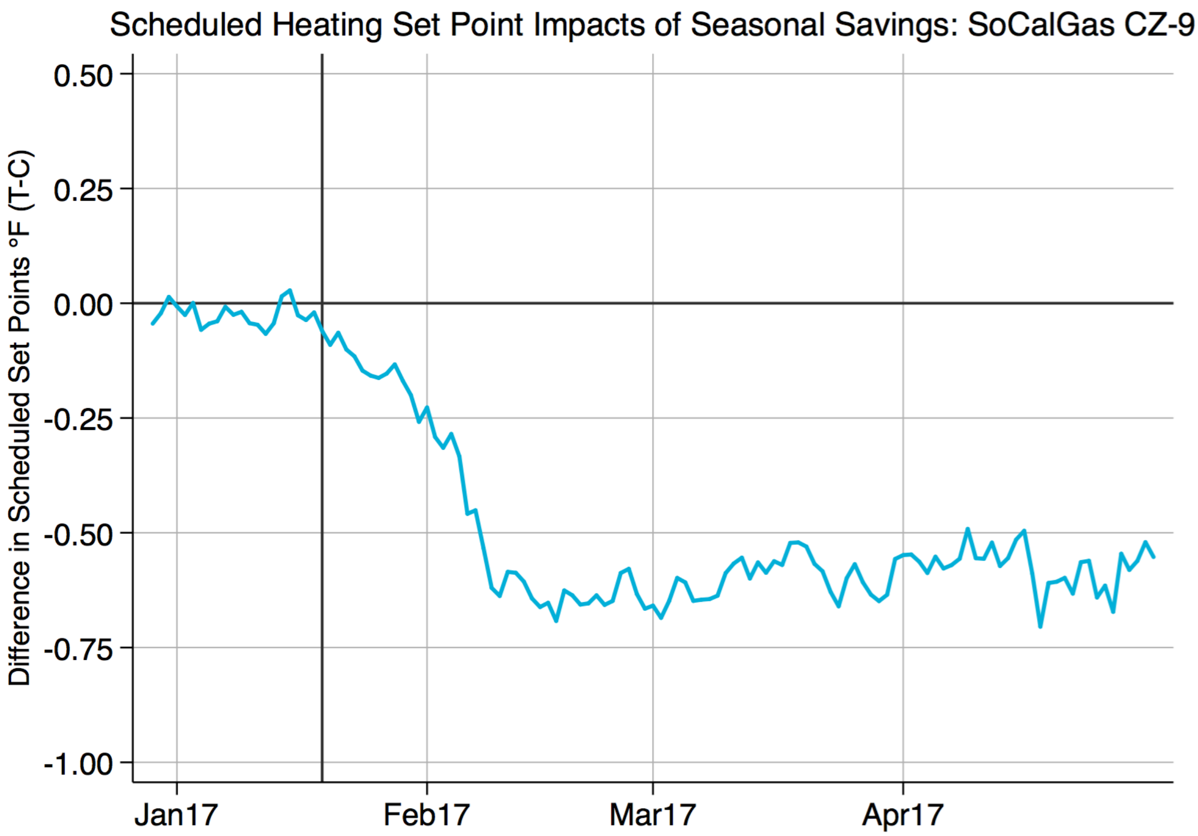

Figure 2. Difference in Scheduled Set Points: Target Treatment Group minus Control Group

Seasonal Savings directly affects customer set point schedules, but the set points that are actually executed often differ from the schedule due to either manual adjustments (via dial or app or web) or to the auto-away feature based on occupancy detection of the Nest Learning Thermostat.

Figures 3 and 4 repeat the graphs in figures 1 and 2 but using the actual executed set points. The data are noisier but the impacts from the algorithm are still clear and there no longer seems to be any degradation of impacts over the season.

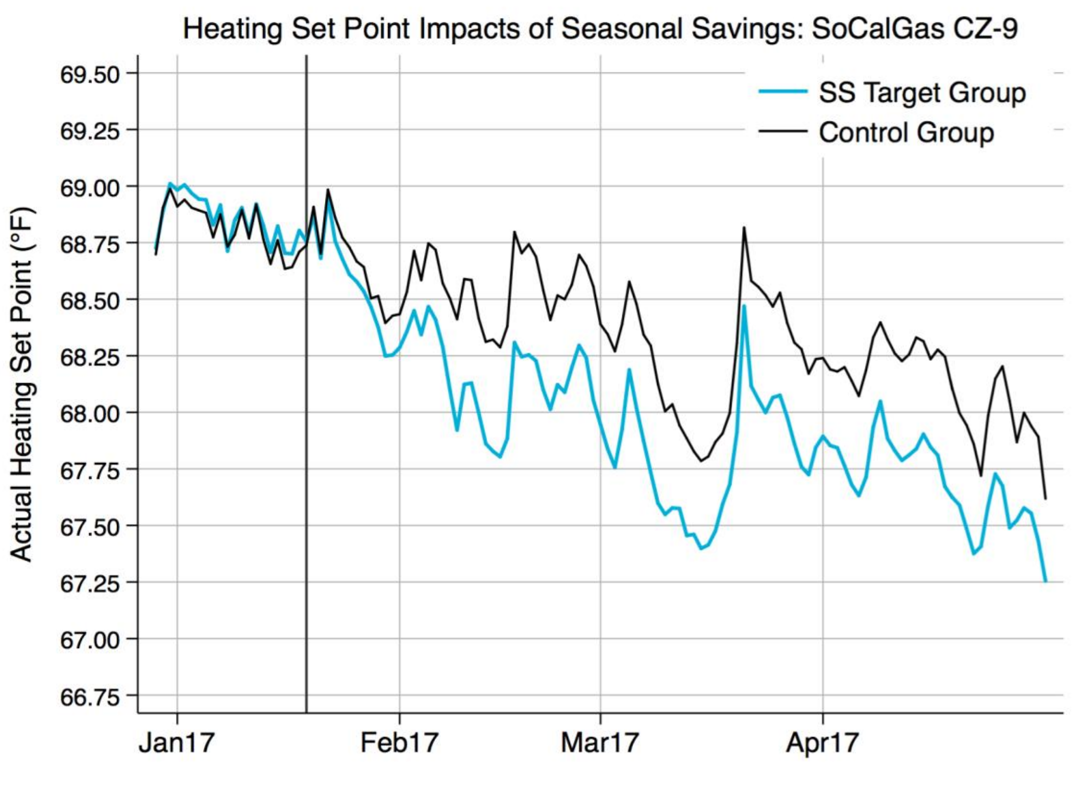

Figure 3. Actual Heating Set Points over the season

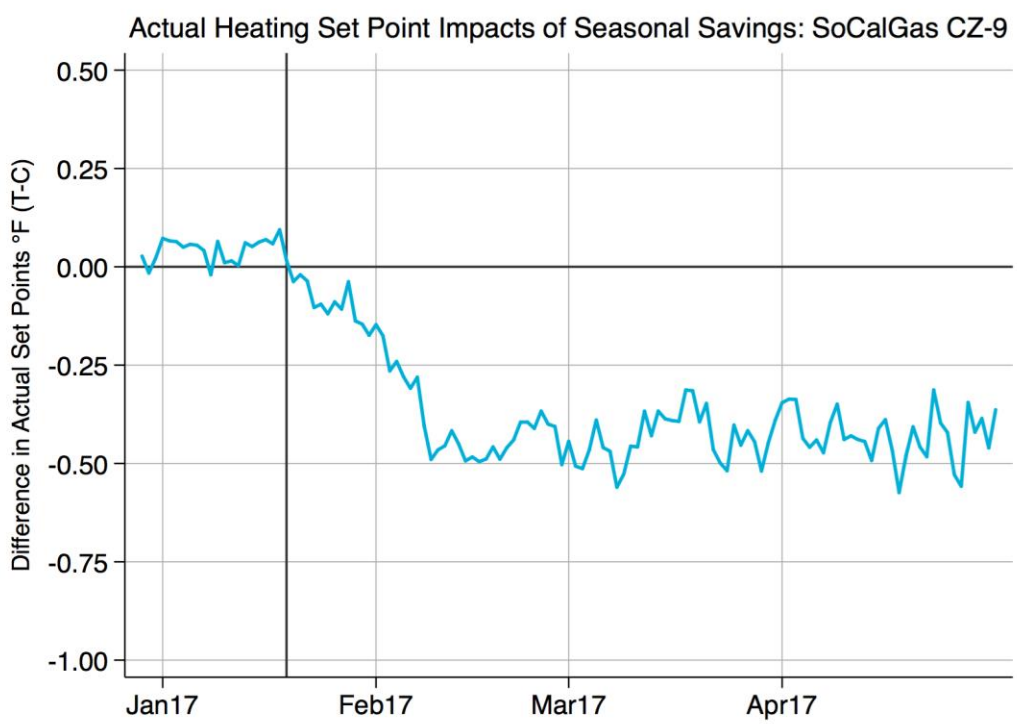

Figure 4. Difference in Actual Set Points: Target Treatment Group minus Control Group

The net change in set points from Seasonal Savings can be quantified using a regression analysis of set points for the entire target and control groups. A simple difference model that included both thermostat and date fixed effects was specified to estimate the net change in set points per targeted participant. The impact per opt-in participant was then calculated by dividing this result by the opt-in rate. The analysis for climate zone 9 found a net reduction in scheduled set points of 0.50°F per targeted participant, equal to 0.79°F per opt-in (63% opt-in rate for customers in the analysis). For executed set points, the reduction averaged 0.40°F per targeted participant and 0.63°F (±0.07°F) per opt-in participant.

Table 3 shows the net changes in scheduled and executed setpoints by climate zone per opt-in participant. The 95% confidence intervals indicate that the differences are estimated fairly precisely for the larger climate zones and the overall average.

Table 3. Changes in Heating Setpoints per opt-in by Climate Zone (with 95% c.i.)

Climate Zone	Scheduled Setpoint	Actual Executed Setpoint
6	0.82 ±0.10°F	0.66 ±0.08°F
8	0.73 ±0.11°F	0.55 ±0.09°F
9	0.80 ±0.10°F	0.63 ±0.07°F
10	0.77 ±0.10°F	0.66 ±0.08°F
14	0.80 ±0.27°F	0.87 ±0.20°F
15	0.51 ±0.18°F	0.49 ±0.16°F
16	0.85 ±0.52°F	0.60 ±0.35°F
Average (weighted)	0.78°F ±0.11°F	0.62°F ±0.08°F

In most deployments of Seasonal Savings, reasonable estimates of the heating savings can be derived using a two step approach where step one is analyzing the net change in executed setpoint and step two is analyzing the change in HVAC runtime per degree change in setpoint. These two results are then multiplied together to calculate HVAC runtime savings. In this instance the mild climate limited the reliability of the two step approach -- the post deployment period averaged just 2.9 HDD60 per day. Two different modeling approaches to estimating HVAC runtime savings per degree change in setpoint led to widely differing estimates, indicating that the two step approach was inappropriate for this deployment and the evaluation should rely on the primary approach of analyzing HVAC runtime directly.

Runtime Analysis

The heating runtime recorded by the thermostats can be used to directly assess the impact of Seasonal Savings. Figure 5 shows the average daily heating run time for the target participant group and the matched controls with a vertical line marking the date the deployment began.

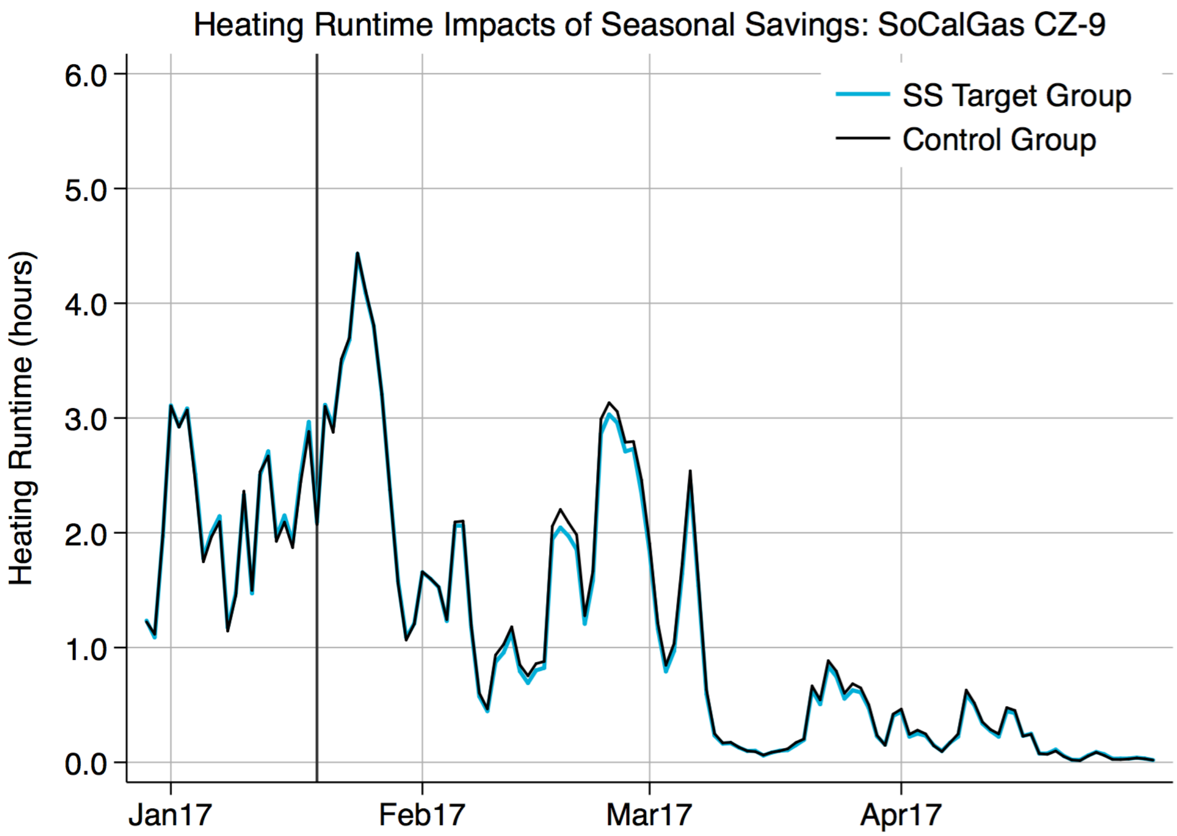

Figure 5. Average Daily Heating Runtime by week: Target and Control Groups

The heating runtime is nearly identical for the two groups in the three weeks prior to the deployment with the target participant group looking slightly higher. A few weeks after the deployment starts there is a period of colder weather with larger runtimes and the participant line can be seen slightly below the control group line. Figure 6 better illustrates the impact on runtime by directly plotting the difference in average daily heating runtime between the two groups -- i.e., the difference between the two lines of Figure 5 -- and aggregates them by week.

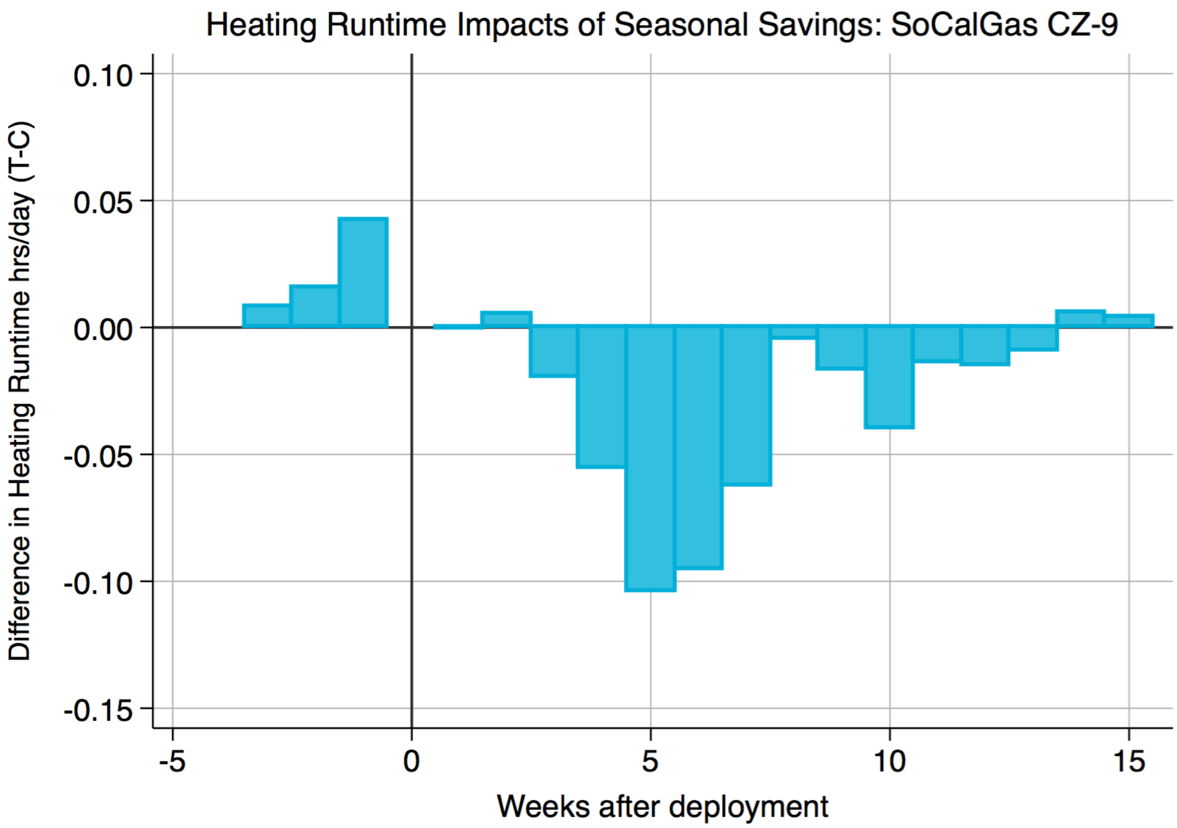

Figure 6. Difference in Average Daily Heating Runtime: Target minus Control Group

The target participant group had slightly higher heating runtime in the few weeks prior to the deployment but then the usage difference reversed and grew quickly during the deployment as the algorithm adjusted the schedules. The savings are clear in weeks 4 through 7 which correspond to the only period with significant heating runtime after deployment. The runtime difference drops back near zero later in the season because there was very little heating to save.

The impacts shown in Figure 6 can be better quantified using regression analysis similar to methods commonly employed to analyze utility meter data. Nest has been using two primary regression modeling specifications for analyzing Seasonal Savings -- a pre/post degree day model with thermostat fixed effects and a post-only difference model with pre-deployment runtime as an explanatory variable and date fixed effects. Both models calculate standard errors that account for clustering by thermostat. Appendix A has more details on the model specifications.

The degree day model is typically effective in colder climates. For climate zone 9, the dataset included 8,299,738 daily observations from 43,228 target participants (including 24,511 opt-ins) and 3,542 controls. The model estimated heating savings per target participant of 4.7% which translates to net savings per opt-in participant of 8.2% ±2.7% (95% confidence interval).

The second regression analysis modeled the post deployment daily runtime data and included pre-deployment runtime data as an explanatory variable and a simple indicator variable for the treatment group. This post-only model used date-specific fixed effects instead of thermostat fixed effects because the thermostats effects are incorporated by using the pre-deployment runtime as an explanatory factor. For climate zone 9, this model estimated 3.9% savings per targeted participant which equals net savings of 6.9% ±2.1% per opt-in participant.

The very mild weather led to fairly wide confidence intervals even with a large sample. The post-only model savings estimate was 1.3% less than the degree day model but this difference was well within the confidence intervals of the two estimates. The post-only model was selected as the better estimator overall due to the smaller reported standard errors and mild weather of this deployment. Table 4 shows the results from the two modeling approaches by climate zone and an overall weighted average.

Table 4. Heating Runtime Savings per opt-in participant by Climate Zone (with 95% c.i.)

Climate Zone	Post-Only Model	Pre/Post HDD model
6	13.5% ±3.2%	12.2% ±4.1%
8	7.6% ±3.0%	4.1% ±4.3%
9	6.9% ±2.1%	8.2% ±2.7%
10	9.3% ±2.3%	8.0% ±3.6%
14	6.6% ±3.8%	5.6% ±6.8%
15	2.8% ±9.0%	12.1% ±15.0%
16	12.1% ±7.8%	2.4% ±8.8%
Average (weighted)	8.4% ±2.7%	8.2% ±3.8%

The two different modeling approaches ended up with very similar overall average savings for the deployment -- 8.2% and 8.4%, lending further confidence to the estimate.

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 (January 19, 2017 through April 30, 2017) and using estimated heating system natural gas and electric input rates. We estimate the gas furnace input rates based on DEER averages by climate region. These estimates ranged from 45 to 61 kBtu/hr wth a weighted average of 49.8 kBtu/hr. 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 furnace power draw at 8 watts per kBtu/hr which worked out to 400W on average. In addition, 6.7% 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 3.15 kW. The energy savings were then calculated based on these input rates, the 8.4% percent savings from the runtime analysis, and the average post-deployment heating runtime for the gas furnaces and the heat pumps. Table 5 shows the resulting savings by climate zone per opt-in participant and in aggregate.

Table 5. Energy Savings by Climate Zone (per opt-in participant)

	Savings: Gas Heated					Savings: Heat Pumps		
Climate Zone	N opt-in	therms /opt-in	Total therms	kWh/ opt-in	Total kWh	N opt-in	kWh/ opt-in	Total kWh
6	8,366	7.2	60,841	5.8	48,673	738	32.4	23935
8	8,699	3.2	27,802	2.6	22,241	400	17.7	7072
9	22,579	4.2	95,956	3.4	76,764	1897	26.0	49357
10	5,552	4.5	24,827	3.6	19,862	207	38.2	7901
14	491	6.0	2,960	4.8	2,368	13	32.5	425
15	1,284	0.5	695	0.4	556	121	4.7	572
16	303	10.1	3,085	8.1	2,468	4	151.7	610
Total	47,274	4.6	216,166	3.6	172,932	3,380	26.6	89,872

This savings per gas heated opt-in participant averaged 5 therms of natural gas (actually 4.6 ±1.5 therms) and 4 kWh of electricity (3.6 ±1.2 kWh). Savings per opt-in heat pump participant averaged 27 kWh (26.6 ±8.7 kWh). The aggregate savings from the deployment are estimated at 216,166 therms of natural gas and 262,804 kWh (172,932 kWh in gas heated homes and 89,872 kWh in heat pump homes).

These savings results do not include any savings achieved after April 2017 (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 Southern California Gas customers during the 2016-17 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 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

β_1 is the net impact of Seasonal Savings on set points estimated by the regression model

ε_{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

The heating 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. Nest employs two main model specifications:

1) 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;
2) a fixed effects model of post-only runtime that includes pre-deployment runtime as an explanatory variable and date specific fixed effects

The two models tend to provide similar results for large sample RCT/RED studies with substantial pre and post deployment runtime data available. The degree day model tends to provide less consistent results in smaller samples and data sets with more limited pre or post deployment HVAC runtime (e.g., milder climates with late deployments). Some potential advantages of the degree day model include: the ability to estimate savings for periods other than the exact post deployment period analyzed; familiarity in the energy program evaluation community with standard specifications available; the ability to account for differences in weather patterns between the treatment and control groups that could result from any imbalance in the randomization or in the matching process for synthetic control groups, especially if geographically dispersed. But the post-only model tends to produce more consistent results for smaller data sets and/or milder climates and also produces standard errors that are usually a little smaller.

The degree day model specification is:

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

where:

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

HDD_{it} is the heating degree days (base 60°) 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

β_1 is the estimated change in HVAC runtime per heating degree day

β_2 is the estimated additional change in HVAC runtime per HDD for thermostats in the target treatment group

β_3 is the estimated change in HVAC runtime in the post deployment period

β_4 is the estimated additional change in HVAC runtime per heating degree day in the post deployment period

β_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

β_6 is the estimated change in HVAC runtime per heating degree day in the post deployment period for thermostats in the target treatment group – which is an estimate of runtime savings per heating degree day for the treatment

ε_{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 β_5 and β_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.

The second regression analysis modeled the post deployment daily runtime data and included pre-deployment runtime data as an explanatory variable and a simple indicator variable for the treatment group. This post-only model used date-specific fixed effects instead of thermostat fixed effects because the thermostats effects are incorporated by using the pre-deployment runtime as an explanatory factor. This model is based on a similar approach used to evaluate home energy report RCTs[1]. The model specification is:

(Eq. 3) $Runtime_{it} = \beta_1 * Treat_i + \beta_2 * PreRuntime_i + Date_t + \varepsilon_{it}$

where:

$Runtime_{it}$ is the hours of HVAC runtime for thermostat i on day t, where t is after program deployment

$Treat_i$ is a dummy variable equal to 1 if thermostat i is in the target treatment group and 0 for the control group

$PreRuntime_i$ is the average daily HVAC runtime for thermostat i in the pre-deployment period. A pre-deployment period of two weeks is most commonly used to maximize the likelihood of sufficient data across thermostats, although longer periods can be used.

$Date_t$ is the date-specific fixed effect for date t

β_1 is the net impact of Seasonal Savings on runtime estimated by the regression model

β_2 is the estimated change in HVAC runtime associated with a one hour per day change in average daily pre-deployment runtime for thermostat i

ε_{it} is the random error term for thermostat i on date j. The variance is calculated accounting for clustering within thermostat

The savings from this model are directly shown from the coefficient β_1. The estimated standard errors of the savings are calculated using the variance covariance matrix from the regression that accounts for clustering within thermostat.

[1] see H. Alcott and T. Rogers, "The Short-Run and Long-Run Effects of Behavioral Interventions: Experimental Evidence from Energy Conservation", American Economic Review 2014, 104(10): 3003–3037

ATTACHMENT B

Advice No. 5204

**Nest White Paper - Energy Savings from the
Nest Learning Thermostat: Energy Bill Analysis Results**

WHITE PAPER

Energy Savings from the Nest Learning Thermostat: Energy Bill Analysis Results

Nest is committed to being an industry leader in measuring and sharing energy savings results. This white paper is one in a continuing series of such empirical reports. The results reported here are averages across broad populations and are not intended as an estimate of savings that any specific user will obtain. Actual savings will vary with a number of factors including occupancy and behavior patterns, energy use, utility rates, and weather. Savings numbers are not a guarantee

February 2015
Nest Labs

Executive Summary

This white paper summarizes the results from three studies of Nest Learning Thermostat energy savings based on comparisons of utility bills from before and after installation. Two of the studies were each independently funded, designed and evaluated -- one conducted in Oregon and the other in Indiana. The third study was performed by Nest using a national sample of Nest customers across 41 states in the U.S. who had also enrolled in Nest's MyEnergy service.

The energy savings results of all three studies were similar -- showing Nest Learning Thermostat savings equal to about 10%-12% of heating usage and electric savings equal to about 15% of cooling usage in homes with central air conditioning. Furthermore, the Oregon study noted that the majority of participants reported feeling more comfortable after the Nest Learning Thermostat was installed.

Although the average savings were similar across the three studies, it's important to note that thermostat savings in any given home can vary significantly from these averages due to differences in how people used their prior thermostat and how they use their Nest Learning Thermostat, as well as due to occupancy patterns, housing characteristics, heating and cooling equipment, and climate. Savings for any given customer may be much higher or lower than the average values. Results from future studies by Nest or third parties may also find higher or lower average savings due to differing characteristics of the populations studied.

Prior Nest analysis based on thermostat data estimated savings of up to 20% of heating use compared to the standard assumed behavior -- used by government and industry -- of maintaining a constant temperature setting all winter. The 10%-12% heating savings in this white paper are consistent with that estimate because survey results indicated that many Nest customers had previously programmed their thermostat or manually adjusted heating and cooling temperature settings. Calculations based on the survey responses suggested that Nest customers averaged about 8%-10% more efficient schedules than just maintaining a constant temperature -- implying expected additional savings in the 10%-12% range.

Nest is committed to being an industry leader in measuring and sharing energy savings results. We expect to have industry-leading measured energy savings, but we prioritize keeping people comfortable and in control of their homes. Our thermostat is designed to capture as much energy savings as feasible without compromising comfort or convenience.

Background

Programmable thermostats have been promoted as an energy savings product for many years. The real world energy savings provided by programmable thermostats has been an area of controversy. The Energy Star program of the US Environmental Protection Agency summarized the issue in 2003:

> *"Consumers are often advised that installing a programmable thermostat can save them anywhere from 10 to 30% on the space heating and cooling portion of their energy bills. While reliant on proper use of the programmable thermostat, such savings are easily true in theory; however, there needs to be more field-tested data to better substantiate savings claims. Analyses from recent field studies have suggested that programmable thermostats may be achieving considerably lower savings than their estimated potential." [EPA 2003]*

The energy savings are primarily expected to come from automatically turning down the heating set point temperature (or turning up the cooling set point) when people either aren't at home or are sleeping (known as "setback"). The magnitude of the savings depends on the how much the temperatures are changed compared to before installing the thermostat.

Field research [see Peffer et al, 2011] has found that many programmable thermostats aren't actually programmed due to usability and design problems, leading to set points that aren't much more efficient than manual thermostat set points and therefore to uncertain energy savings. This research led EPA to end the Energy Star designation for all programmable thermostats in 2009.

Still, the government and manufacturers have continued to explain the energy savings potential of well-programmed thermostats in terms of the possible savings relative to previous set point assumptions. The U.S. Department of Energy (DOE) lists heating savings of 5%-15% for a single eight hour temperature setback per day compared to a constant temperature setting [DOE 2015]. The EPA, although having ended Energy Star certification for programmable thermostats, lists savings of $180 per year for a programmable thermostat [EPA 2015]. The Nest web site states that customers "could cut 20% off your heating and cooling bill" compared to maintaining a constant temperature [Nest Labs 2015], where the constant temperature is based on customer-specific set points. Other thermostat manufacturers make a variety of savings estimates:

- "customers in the US saved an average of 23% on their heating and cooling costs" based on a comparison to an assumed 72°F constant heating set point [Ecobee 2015]
- "homeowners saved an average of 20% on their heating and cooling energy costs" based on a comparison to an assumed 72°F constant heating set point [Carrier 2014]
- "cut your heating bill by up to 31%" compared to a constant set point [Tado 2015]

All of the thermostat savings estimates are based on models of how set points affect energy use and calculate the savings compared to an assumed constant temperature set point. It's been common practice to assume a constant set point as the baseline setting behavior because it provides a clear reference condition, data on prior set points are rarely available, and because field research has found that many programmable thermostats aren't running any program [Meier et al, 2010].

The savings estimates based on the constant set point assumption are a useful guide but may not reflect actual expected savings in a specific home or average savings in a group of homes if the assumptions aren't met -- for example, if people had already been turning down the heating set point at night. Although the methods and assumptions are usually stated with the savings estimates and often include qualifiers like "save up to", it can still differ from actual consumer experience.

To assess the actual savings that customers achieved requires analyzing energy usage from before and after the thermostat installation for large groups of homes. Because such energy usage data is not usually available -- especially to thermostat manufacturers -- there have been very few such studies performed.

In May 2013, Nest acquired MyEnergy -- a company that helps customers track and analyze their utility usage and bills. The tools Nest took over from MyEnergy allow customers to gather all of their utility usage and bills in one place, providing them with the ability to monitor usage and costs month over month, year over year, and can compare performance to friends and other homes in their neighborhood. Nest also uses these insights to help analyze energy usage patterns. By comparing energy use before and after Nest Learning Thermostat installation we are able to evaluate the energy savings achieved in a sample of customers. It is this comparison, presented in a de-identified and aggregated manner, that forms the basis for this white paper. Unlike prior estimates based on assumed pre-thermostat behavior, this evaluation allows an empirical assessment of energy savings by actual consumers based on changes in their energy usage.

Methodology

Evaluating the energy savings achieved by a thermostat (or any efficiency improvement) using energy usage data might appear to be straightforward -- just calculate the difference in usage from the year before the installation to the year after the installation. But the reality is not that simple. A major challenge to evaluating energy savings is that energy usage changes from year to year for many reasons unrelated to the thermostat installation, for example:

- Weather: the winter may be colder or the summer may be milder from one year to the next, causing increased or decreased energy use. Energy savings evaluations employ statistical methods to adjust energy usage for weather variations
- Occupancy patterns: babies are born; children enter school, become teenagers, and may eventually go off to college; people get jobs, lose jobs or start or stop working from home; vacation schedules and holiday hosting vary from year to year. All of these changes can affect thermostat set points and also affect how people use their appliances, lighting, and other energy end uses.
- Home/Equipment/Appliances: people replace heating and cooling systems and appliances, build additions, add insulation, replace windows, and make other physical changes in their homes. Each of these changes can affect energy usage.

Things people do and how they live causes energy use to vary from year to year (see Figure 1 on page 8). Two main approaches are used to deal with these variations in energy use. First, energy savings studies are based on large groups of homes rather than taking results for any one home at face value. The use of larger samples allows random usage variations to average out -- with some homes increasing their energy usage due to these factors while others decrease their energy usage. Second, to account for any general trends towards increasing or decreasing energy usage (e.g. changes in energy prices, employment rates, birth rates, etc.) a control group[1] of homes not installing the thermostat is analyzed in a parallel manner to adjust the results.

In performing this energy savings analysis, we followed industry standard practices as defined by the US DOE Uniform Methods Project [DOE 2013] -- specifically, the guidelines found in "Whole-Building Retrofit with Consumption Data Analysis Evaluation Protocol" [Agnew and Goldberg 2013]. The protocol describes two primary approaches for analyzing utility energy usage data -- the "two stage" approach and the "pooled" approach.

The "two stage" approach involves analyzing the energy usage data for each customer from before and after the installation using a weather normalization procedure (a variable-base degree day regression model) and then summarizing the annualized usage and savings across homes for both the installation group and a control group of non-participant homes.

The "pooled" approach involves fitting a single linear regression model to all of the energy usage data across all homes. The model includes variables to account for degree days and variables to estimate the changes in energy use after installation (interacted with degree days). In addition, these models include customer-specific fixed effects and often include time period specific effects as well. The overall average energy savings are calculated directly from the model coefficients.

1 actually, more appropriately called a "comparison group" as the term "control group" is often reserved for only randomized experiments.

In this analysis, we employed both the “two stage” and “pooled” approaches. The analysis involved the following steps (see appendix for more details):

1. assemble and prepare the utility usage data collected through MyEnergy
2. identify Nest customers and parse energy use data into pre and post Nest Learning Thermostat installation periods
3. parse the control group (i.e., non-Nest MyEnergy customers) energy use data into comparable pre and post ”installation” periods by randomly assigning installation dates to each customer from the Nest customer sample
4. calculate heating and cooling degree days for each meter reading for each Nest customer
5. calculate weather normalized energy usage for the pre and post installation periods for each customer and fuel using variable-base degree day regression models. The electric analysis involved fitting models with and without heating and cooling terms to select the best model type for each home.
6. fit pooled time-series cross-sectional fixed effects regression models to the monthly gas and electric usage data using degree day terms and interactions and with month-specific indicator variables for the gas analysis to account for the polar vortex (an extreme cold weather system that affected the eastern half of the US in January 2014).

The electric analysis focused on homes with central air conditioning loads (defined as >500 kWh/yr in estimated cooling use) and without electric heat (there were too few electrically heated homes in the sample to reliably evaluate). The gas analysis excluded homes where electric heating usage was also detected.

A reliable savings analysis requires about a year of energy use data from before and after the installation. Due to the limited amount of historical energy usage data maintained online by most utilities and the timing of the MyEnergy acquisition and Nest customer enrollments, the vast majority of MyEnergy+Nest customers did not have sufficient pre-Nest energy use data for reliable analysis or had installed their Nest Learning Thermostats too recently to be included in the current analysis.

These data requirements led to the final sample sizes of 735 homes for the gas usage analysis and 624 homes for the electric analysis. Although these samples are large enough to estimate average overall savings, they’re not large enough to provide for more detailed analyses, especially given the heterogeneous nature of a national sample. The natural gas sample includes customers from 36 different states. California was the most common state with 15% of the sample and Illinois, Massachusetts Oregon, Texas, and Utah each represented more than 5% of the sample. The average heating season climate across these homes was moderately cold -- 4,533 heating degree days (HDD65) per year, comparable to Baltimore, MD. The electric sample included customers from 39 different states with California again being most common (19% of sample), and Texas and Massachusetts each at 10% of the sample. The electric sample homes averaged 1,729 cooling degree days (CDD65), comparable to Charlotte, North Carolina.

Findings: Gas and Electric Savings

The two energy usage analysis approaches -- pre/post and pooled -- yielded similar savings estimates (differences between approaches were not statistically significant), but the potential bias in weather normalization from the 2014 polar vortex (see more details in the appendix), led us to select the pooled approach as the best estimate of savings. The results of the analysis are summarized in Table 1.

Table 1. Gas and Electric Savings Results

		Pre-Nest Usage		Energy Savings	
Fuel	N	Total	HVAC	Total	**% of HVAC**
Natural Gas (therms/yr)	735	774	584	56 ±12	**9.6% ±2.1%**
Electricity (kWh/yr)	624	12,355	3,351	585 ±97	**17.5% ±2.9%**

Natural gas savings averaged 56 therms per year equal to 9.6% of pre-Nest heating use. Electricity savings averaged 585 kWh per year equal to 17.5% of pre-Nest HVAC[2] usage.

Most of the homes in the analysis had just a single Nest Learning Thermostat, but 19% of the gas analysis homes and 25% of the electric analysis homes had two or more Nest Learning Thermostats. We ran the analysis for just the homes with a single thermostat and found average savings of 11.0% for gas heating (60 th/yr out of 547 th heating use) and 15.5% of electric HVAC (448 kWh out of 2,897 HVAC use). The differences between these values and the overall values in the table are not statistically significant.

We calculated the estimated value of the energy savings using two approaches. In the first approach, we applied the most recent (October 2014) average U.S. residential electric and natural gas prices of 12.6¢/kwh and $13.15/mcf ($1.28/therm), as reported by the EIA [EIA 2014a], to the average therm and kWh savings, which yields $145 in annual savings. In the second approach, we applied the percent heating and cooling savings to the most recent average annual U.S. heating and cooling costs according [EIA 2014b, EIA 2015]. This calculation estimates the annual savings at $131 (9.6% of $988 for heating and 15% of $240 for cooling). The two approaches provide similar estimates. Of course both of these figures are just rough estimates of savings because energy prices vary between energy providers and change over time and marginal costs may differ from average costs. In addition, these savings are estimates for homes that have gas heating and also use central air conditioning and have average energy use consistent with the values found here. Dollar savings vary with energy savings as well as with fuel type and local energy costs.

Energy Usage and Savings Variability

Figure 1 shows the distribution of percent natural gas "savings" for the comparison group of homes that did not install Nest Learning Thermostats. This distribution is approximately symmetric around zero (no change in usage) and also shows a wide range of usage changes -- 34% of the homes experienced a change in weather normalized total natural gas use of more than 10% from year to year.

2 Although we screened out homes that were electrically heated, most homes have some winter seasonal electricity usage -- some of which is related to furnace fan power draw. To account for the savings and usage not related to cooling we expressed electric savings as a percent of HVAC use.

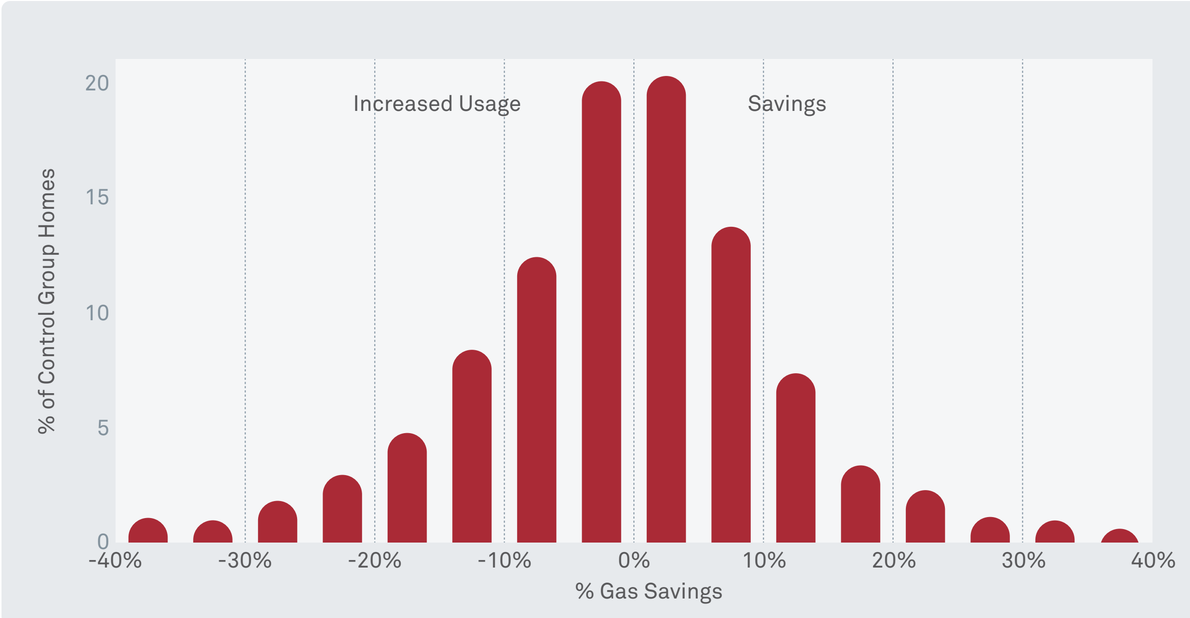

Figure 1. Distribution of Natural Gas "Savings" for non-Nest comparison group

Figure 2 shows the same graph for the Nest customers in the analysis. The peak is clearly to the right of the 0% vertical line -- indicating savings, but there's a lot of variability - including many homes where the gas usage seemed to increase.

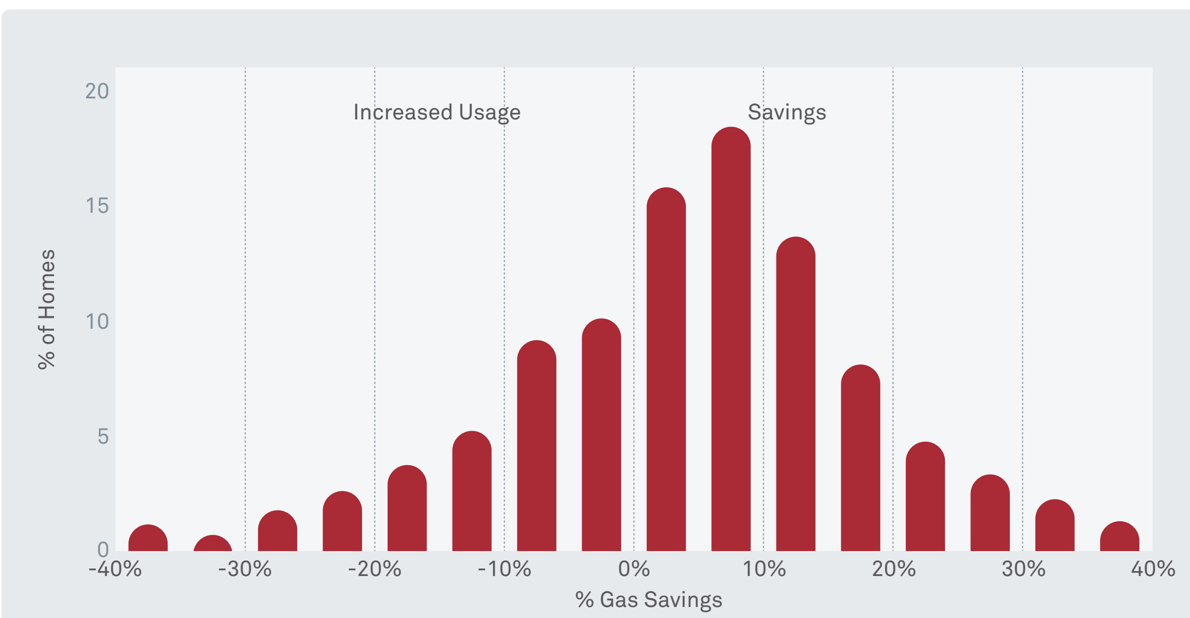

Figure 2. Distribution of Natural Gas Savings for Nest MyEnergy customers

These graphs illustrate that the change in energy use for a given home after installing a Nest Learning Thermostat (or making any other change) is not just the energy savings from the Nest Learning Thermostat but is the total change in energy usage from everything that happened over the period -- including all other changes in people's homes and how they use them. The true energy savings attributable to the thermostat is the difference between the actual energy use with the Nest Learning

Thermostat and the energy use a customer *would have had* if they hadn't installed the Nest Learning Thermostat. But what we can actually observe in people's bills is the change in usage from the year before to the year after, which includes a host of factors unrelated to the Nest Learning Thermostat.

If a thermostat saved every customer exactly 10% of their total gas usage then the savings in Figure 2 would look just like Figure 1 above, except shifted over by 10%. We would still see homes that increased their energy usage while we would see other homes with larger decreases in usage.

While Nest would love to be able to take credit for all of the energy savings when a customer's usage drops by 40% we know that there's a good chance that other things changed in their home or how they use it that may be responsible for some of that savings. Similarly, when the energy use of some customers stays the same or increases, the blame could be due to many other things that changed over time.

Thus, the actual savings we ascribe to Nest is, in essence, the difference between the results of Figure 1 (i.e., the natural year-to-year variability of energy usage) and the results of Figure 2 (i.e., the year-to-year variability of energy usage in homes installing a Nest Learning Thermostat).

Assessment of Potential Bias: Evaluating MyEnergy Customers

Like most evaluations of energy efficiency upgrades, this study is not a designed experiment or randomized control trial but is instead an "observational study". Observational studies need to consider potential sources of bias since the participants may not represent the larger population of customers or the comparison group may differ from the participants. In addition, extraneous factors such as extreme weather or energy price changes may have affected energy use in ways that differ between groups or aren't otherwise accounted for properly in the analysis.

In this study, the analysis group comprises people who purchased a Nest Learning Thermostat and also chose to sign up for MyEnergy. People who enroll in MyEnergy are interested in tracking their energy use and so they tend to be more energy conscious and efficient than the average Nest customer. Although it may seem counterintuitive, this greater interest in energy efficiency may lead to lower energy savings from a Nest Learning Thermostat. The most energy conscious customers are the ones more likely to have had efficient thermostat settings -- either because they put in the effort to properly use their old programmable thermostat or they consistently set back temperatures whenever feasible prior to having a Nest. The prior behavior has a large impact on savings potential.

We explored the potential bias from the sample composition through an email survey and an analysis of Nest settings. Table 2 summarizes some key findings from the survey.

Table 2. MyEnergy Customers compared to average Nest customers

	MyEnergy	Other Nest	Difference
Customer Survey Findings			
Had Programmable Thermostat	74%	65%	+9%
Most Efficient: Programmable with double setback	37%	28%	+9%
Least Efficient: No Regular Setback	26%	36%	-10%

Nest Device Settings			
Average Heating Set Point	66.2°F	67.2°F	-1.0°F
Average Night Setback	4.9°F	4.0°F	+0.84°F

note: Survey results are based on 657 MyEnergy and 763 other Nest customers.

The table shows that the MyEnergy customers reported having more efficient set points prior to installing the Nest than the average Nest customer surveyed. Compared to the other Nest customers, MyEnergy customers were more likely to have a programmable thermostat, more likely to employ two or more setbacks per day, and less likely to have practiced no setbacks prior to having the Nest. These differences all suggest that MyEnergy Nest customers have less potential for saving energy since they were already more efficient. We assessed the magnitude of this effect using energy modeling and estimate that the MyEnergy customers have about 2% lower savings potential than the average Nest customer -- their set points were calculated to be about 10% more efficient than a constant baseline compared to about 8% more efficient for the average Nest customer.

The last two rows of the table summarize the actual Nest Learning Thermostat customer set points during February and March 2014 for the survey homes. The MyEnergy Nest customers maintained a lower average heating set point than the average Nest customer and also had greater night temperature setbacks (primarily more frequent rather than deeper). Differences were also found for other settings, such as daytime setbacks, and for the use of Nest features such as Heat Pump Balance (more than twice as likely to select “Max Savings”). We used energy modeling to estimate the impact of these differences and calculated that the MyEnergy customers were about 2% more efficient with their Nest set points than the average Nest customer.

Based on this analysis, it appears that the MyEnergy customers were more efficient than the average Nest customer both before and after installing their Nest and the magnitude of these differences was about the same -- implying no significant bias between the groups.

It’s also worth noting that both groups of Nest customers reported more efficient prior thermostat practices compared to studies of typical US household thermostat use. A literature review [Peffer et al, 2011] reported that 42% of US households had programmable thermostats in 2008 and 47% of programmable thermostats were running a program. In contrast, 65% of non-MyEnergy Nest customers reported having a programmable thermostat and 71% of those were running a program. These results indicate that Nest customers tended to have more efficient set points than the average U.S. household, which reduced the potential for savings.

Another potential source of bias is the comparison group. The comparison group of non-participants comprises people who signed up for MyEnergy on their own. The fact that they chose to enroll on their own implies that they may differ from the MyEnergy customers that were recruited by Nest. This difference could introduce a downward bias on savings if, for example, the non-Nest MyEnergy customers were more likely to pursue other efficiency upgrades on their own -- which may have led them to sign up for MyEnergy.

Overall, our analysis did not uncover any evidence of a large bias from having the study focus on MyEnergy customers, although the comparison group issue suggests any likely bias would lead toward finding lower energy savings than the average Nest customer might achieve.

Other Recent Studies of Nest Learning Thermostat Savings

Two studies have been released recently by independent third parties that evaluated the energy savings from Nest Learning Thermostat installations -- one in Oregon and one in Indiana.

Energy Trust of Oregon Heat Pump Pilot

The Oregon study [Apex Analytics, 2014] was a pilot project designed, funded, and overseen by the non-profit Energy Trust of Oregon. In the fall of 2013, the Energy Trust had a contractor install Nest Learning Thermostats in 185 homes heated by heat pumps. The Energy Trust hired an independent firm to analyze changes in energy bills and also survey participants about their experiences. The main findings from the energy billing data analysis and final customer survey included:

- customers experienced an average 12% reduction in electric heating use (781 kWh/year per home) relative to their pre-Nest usage
- 89% of customers were satisfied with their Nest Learning Thermostat
- 66% of participants reported feeling more comfortable after the Nest Learning Thermostat was installed
- 34% of participants reported that they thought the Nest Learning Thermostat was worth the full retail price even if it had provided no energy savings at all

The report cited the Nest Learning Thermostat's unique "Heat Pump Balance" feature as a key element in providing the savings. The 12% heating savings for heat pumps in Oregon is especially noteworthy given that programmable thermostats are typically not recommended for heat pumps.

The US DOE web page on thermostats (http://energy.gov/energysaver/articles/thermostats accessed 21-Jan-2015) notes:

> *"Programmable thermostats are generally not recommended for heat pumps... when a heat pump is in its heating mode, setting back its thermostat can cause the unit to operate inefficiently, thereby canceling out any savings achieved by lowering the temperature setting"*

But it goes on to note that "some companies have begun selling specially designed programmable thermostats for heat pumps, which make setting back the thermostat cost-effective". The study suggests that the Nest Learning Thermostat algorithms have succeeded in this challenge of achieving savings from setback for heat pumps.

The study findings about high customer satisfaction and improved comfort listed above are particularly noteworthy. Given the importance of behavior in energy savings from thermostats, user satisfaction with the technology and their feeling that their energy savings have not come at the expense of comfort mean that the Nest Learning Thermostat can serve its dual role as a comfort control device and an energy control device without putting those objectives in conflict. This has not always been the case with new energy-saving technologies, which can become ineffective if they force users to choose between comfort and efficiency.

Indiana Utility Pilot

The Indiana study [Aarish et al, 2015] was a pilot project designed to assess the energy savings of Nest Learning Thermostats. The project was designed, funded, and overseen by Vectren Energy, a gas and electric utility in Indiana. In the fall of 2013, Vectren hired a contractor to install Nest Learning Thermostats in 300 homes and standard programmable thermostats (Honeywell TH211 Pro 2000 series) in 300 homes. Vectren hired the Cadmus Group to perform the evaluation. The main findings from the evaluation included:

- Homes that received a Nest Learning Thermostat had average natural gas savings of 69 therms/year, equal to 12.5% (±1.5%) of the heating use
- Nest homes had average electricity savings of 429 kWh/yr, equal to 13.9% (±5%) of cooling use
- Homes that received a standard programmable thermostat averaged savings of 30 therms/yr equal to 5.0% (±1.3%) of heating use. In terms of electricity usage, they saved 332 kWh/yr equal to 13.1% (±6%) of cooling use

The Nest customers saved more than twice as much heating energy as the standard programmable thermostat customers and this difference was statistically significant. The electricity savings estimates had much larger uncertainty than the gas results and pre-existing differences in cooling use and occupancy between the groups makes it hard to draw any firm conclusions about the difference in cooling savings.

There were two aspects of the pilot that may have affected the savings comparison:

- The pilot offered thermostats for free and the resulting sample of customers were much less likely to install and use the Nest phone or tablet apps or connect to WiFi than typical Nest customers -- potentially lowering the savings from Nest Learning Thermostat features.
- Both types of thermostats were professionally installed and set up by a contractor. One of the key features of the Nest Learning Thermostat compared to standard thermostats is the ease of creating a program through the learning feature. The pilot design created a best case scenario for a standard programmable thermostat in terms of being programmed.

Furthermore, thermostat research has found that many standard programmable thermostats eventually end up with no program or set to "hold" and the Indiana study found some evidence of this behavior already. The study reported that "only 37% of participants appear to have relied on their thermostat program by the end of the study period". Therefore, savings from a standard programmable thermostat could be expected to degrade over time as more users override their schedules.

Real World Thermostat Energy Savings

The results from the MyEnergy customer analysis and the two independent studies suggest that Nest customers are saving about 10%-12% of heating use. Although these savings are less than the 20% projected by Nest from energy modeling, the results are consistent once the different baseline behaviors are taken into account. The 20% projection was based on the standard assumption of a constant temperature setting without the Nest Learning Thermostat, but the email survey found that Nest customers reported having set points that were about 8%-10% more efficient than the constant baseline (and also more efficient than the average U.S. home). Therefore, the 10%-12% heating savings are in fact consistent with the 20% projection when adjusted for the more efficient baseline. This suggests that the modeling itself was accurate and the baseline assumption is responsible for the difference in savings.

The MyEnergy and Indiana studies found electric savings in homes with central air conditioning (and not electric heat) of about 15% of cooling use. Due to the inherently greater variability a electric use, these savings have greater uncertainty than the gas savings and larger samples and more studies would help to draw stronger conclusions about the impacts.

The real energy savings achieved from installing a Nest Learning Thermostat is expected to vary based on many factors. Table 3 lists some of the behaviors and characteristics associated with higher or lower heating savings potential from installing a Nest Learning Thermostat. A similar list would apply to cooling savings.

Table 3. Factors Associated with Higher or Lower Thermostat Savings

Larger Savings Potential	Behavior / Characteristic	Smaller Savings Potential
Rarely or never used setback, but willing to	Nighttime setback: before installing Nest	Always used setback
Often away during the day but didn't use setback	Daytime occupancy / prior setback	Home during the day or already used setback regularly
Often go away for days or weekends or vacations and forget to turn down heat; vacation homes	Vacations and other away periods	Never go away or always remember to turn down heat when away
Keep nest features enabled: auto-schedule, auto-away; set heat pump balance to max savings	Nest settings	Disable energy saving features; select less efficient settings (heat pump balance max comfort)
Colder climates (but % savings may be less)	Climate	Milder climates (but % savings may be greater)
Heat pumps with typical or excess auxiliary heat use	HVAC type	Heat pumps with little auxiliary heat use, heat pumps due to limits on setbacks from aux. Heat requirements; condensing boilers if often running in condensing mode
Leakier, less insulated homes lose heat faster during setback, save more	Building shell efficiency	Tighter, better insulated homes lose heat slowly and save less from setback
Low mass homes cool down more quickly and save more from setback	Building mass	High mass homes (e.g., Masonry) cool down more slowly and save less from setback

The dominant factor affecting energy savings will often be the efficiency of the prior schedule / set points combined with the Nest Learning Thermostat's ability to create a more efficient schedule.

Higher energy savings would be expected for a customer who would like to have night and day setbacks but can't figure out (or doesn't want to bother to figure out) how to do it automatically with his or her current thermostat and can't remember or be bothered with manually adjusting the thermostat multiple times each day.

Lower energy savings would be expected for a customer who already sets back the temperature every night and day and always remembers to turn down the heat when leaving for an extended period. Such households are already operating their HVAC efficiently and provide less opportunity for savings, but they may still want a Nest Learning Thermostat for the convenience, functionality, and design in addition to the energy savings from other Nest features.

Conclusions

This white paper has presented results from three studies of Nest Learning Thermostat energy savings based on comparisons of energy bills from before and after installation of a Nest Learning Thermostat. The results of the studies were generally similar -- showing Nest Learning Thermostat heating savings of about 10%-12% and electric savings of about 15% of cooling use in homes with central air conditioning. Although the average savings were similar across the three studies, savings can be expected to vary significantly between homes due to variations in how people set their temperatures before installing the Nest Learning Thermostat as well as due to occupancy patterns, house characteristics, and climate. Future studies by Nest or other third parties may find higher or lower average savings due to differing characteristics of the populations studied. Nest is committed to being an industry leader in measuring and sharing energy savings results. We will continue to highlight new results as they become available.

At Nest, we expect to achieve industry-leading measured energy savings, but we prioritize keeping people comfortable and in control of their homes. If we didn't care about our customers' comfort, we could probably achieve greater energy savings, but we would have failed in our primary mission. Instead, we designed our thermostat to capture as much energy savings as feasible without compromising our customers' comfort or convenience.

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