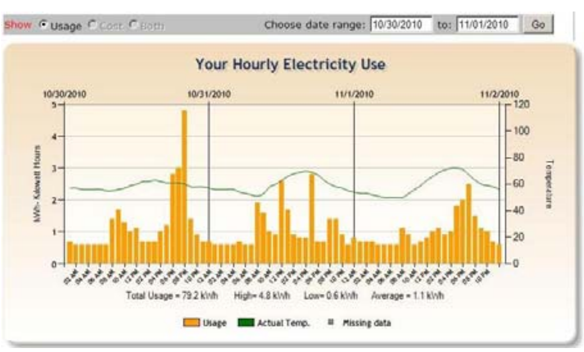
SMUD's Low Income Weatherization & Energy Management Pilot – Load Impact Evaluation



Promoting residential energy and peak savings for low-income customers through enhanced information, education, and smart thermostats

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Herter Energy
RESEARCH SOLUTIONS

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CONTENTS

FIGURES

Tables

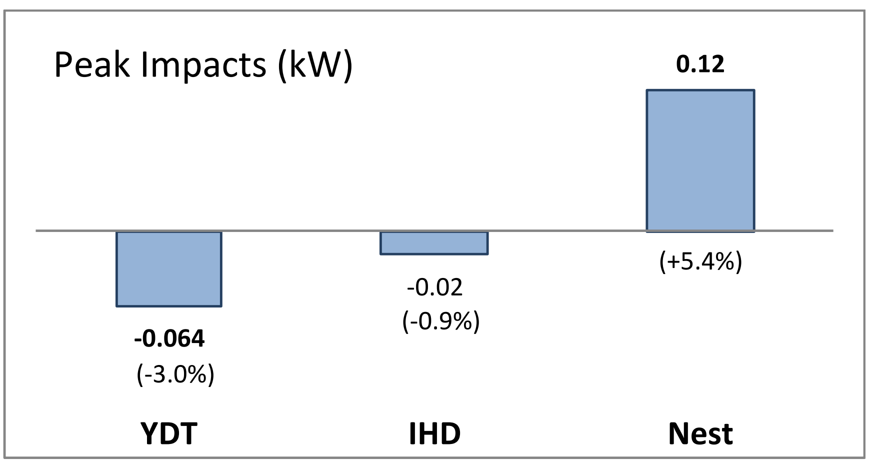
Executive Summary

This study investigates whether the provision of measures beyond SMUD's standard Low-Income Weatherization program – smart thermostats (Nest), in-home energy displays (IHD), and training on web-based hourly electricity use summaries, known internally at SMUD as Yesterday's Data Today (YDT) – might help low-income customers further reduce their energy use and peak loads. To this end, SMUD offered and implemented these three treatment measures in about 400 homes on the low-income Energy Assistance Program Rate (EAPR). All three treatment groups received SMUD's standard Low-Income Weatherization Audit.

A fourth group receiving only the audit (Audit) was used as the control for the load impact analysis. On average, participants in the Audit group saved a statistically significant 490 kWh annually – 310 kWh in the summer and 170 kWh in the winter – for a total of 4.8% of their annual energy use. During the summer peak hours of 4 to 7 p.m., participants in the Audit group saved a statistically significant 220 watts on average, or 9.2% of their peak load.

During the summer peak hours of 4 to 7 pm, the YDT treatment saved an additional 3.0% of peak demand relative to the Audit group, while the Nest treatment increased peak demand by 5.4%, and the IHD treatment had no statistically significant effect (Figure 1).

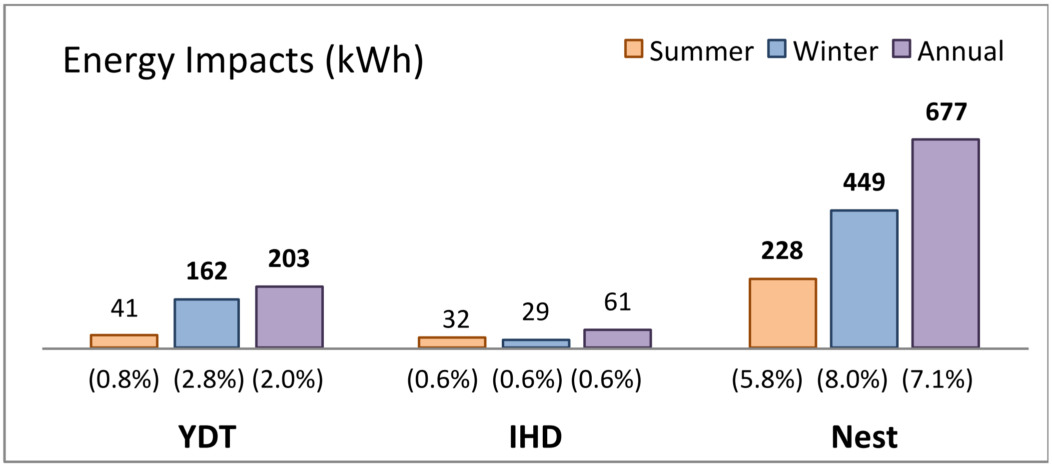
Figure 1. Peak impacts relative to the Audit group



Values in bold are statistically significant (α=0.05)

Relative to the Audit group, the YDT, IHD, and Nest treatments did not show additional seasonal or annual energy savings (Figure 2). Both the YDT and Nest treatments showed statistically significant *increases* in annual energy use, at +2.0% and +7.1% respectively, while the IHD treatment had no statistically significant effect.

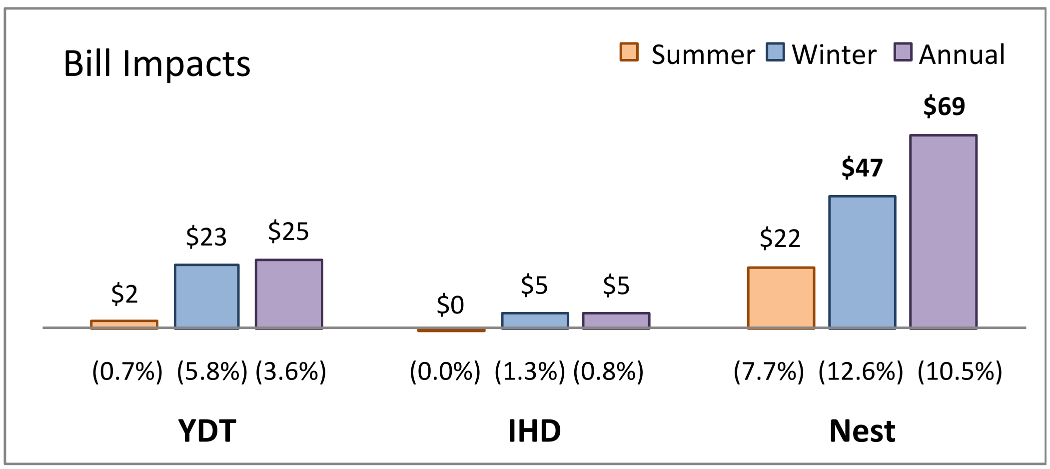
FIGURE 2. ANNUAL AND SEASONAL ENERGY IMPACTS RELATIVE TO THE AUDIT GROUP



Values in bold are statistically significant (α=0.05)

Similarly, the treatments of interest did not reduce electricity bills relative to the Audit group (Figure 3). Statistically significant bill increases were evident in the Nest group.

FIGURE 3. BILL IMPACTS



Values in bold are statistically significant (α=0.05)

In summary, the results of this load impact evaluation indicate that SMUD's Low-income Weatherization Audit effectively reduced energy use and bills for low-income customers. Beyond the Audit, however, training on SMUD's Yesterday's Data Today website (YDT), the provision of a real-time energy display (IHD), and the installation of a Nest Learning thermostat (Nest) were not effective in reducing energy use or bills further. The 7.1% annual energy *increase* for the low-income customers provided with a Nest thermostat suggests that future programs that involve the Nest, or perhaps any other smart thermostat, might consider the low-income population separately from the standard population.

1. Introduction

Problem Statement

A recent report by the Smart Grid Consumer Collaborative indicates that low-income customers are less likely to benefit from Smart Grid technologies for two reasons. First, low-income customers are less likely to have access to utility web portals where they can review their energy data. Second, many low-income customers are renters, so energy efficiency upgrades are less likely to be allowed by landlords or cost-effective when they are allowed (Smart Grid Consumer Collaborative 2014).

SMUD's low-income weatherization program provides low-income customers with the opportunity for a free home energy assessment and installation of simple efficiency measures at no cost. Of interest to SMUD is whether the provision of measures beyond weatherization – such as smart thermostats, in-home energy displays, and hourly energy data training – would help low-income customers further reduce their energy use and peak loads.

Study Overview

The main goal of this study is to provide SMUD with empirical data to support decisions about future residential programs that promote energy efficiency in the low-income sector. The objective of this study was to estimate the energy, summer peak, and bill impacts associated with the following three measures, which were implemented in 393 homes on the Energy Assistance Program Rate (EAPR):

- Yesterday's Data Today (YDT) online energy use summaries and training
- In-Home Display (IHD) of real-time energy use
- Nest Learning Thermostat

All treatment groups also received SMUD's standard Low-Income Weatherization Audit, such that a fourth group, which received *only* the audit, could be used as a baseline to filter out exogenous and Hawthorne effects. Available audit measures included attic, water heater and water pipe insulation; ceiling fans, weather-stripping, fluorescent lighting, refrigerators, low-flow showerheads, faucet aerators, and microwaves. Measures were installed as appropriate for each home.

This report describes the evaluation of electric load impacts for these four groups (Figure 4). The evaluation makes use of SMUD's hourly interval meter data to determine annual and seasonal energy impacts, summer peak load impacts, and customer bill impacts.

Study Design

The Energy Insights Weatherization Study involved 3 treatment groups, a Baseline group, and a control group as shown in Figure 4 and described below. All participants in the YDT, IHD, and Nest treatment groups received an in-home weatherization audit in addition to the treatment specified below. The Audit baseline group received only the low-income weatherization audit.

YDT = Yesterday's Data Today. All SMUD customers have access to their electricity use data through My Account on SMUD's website, where they can view interval data by hour, day or billing period. YDT participants were trained on using this analytical data at the time of the low-income weatherization audit.

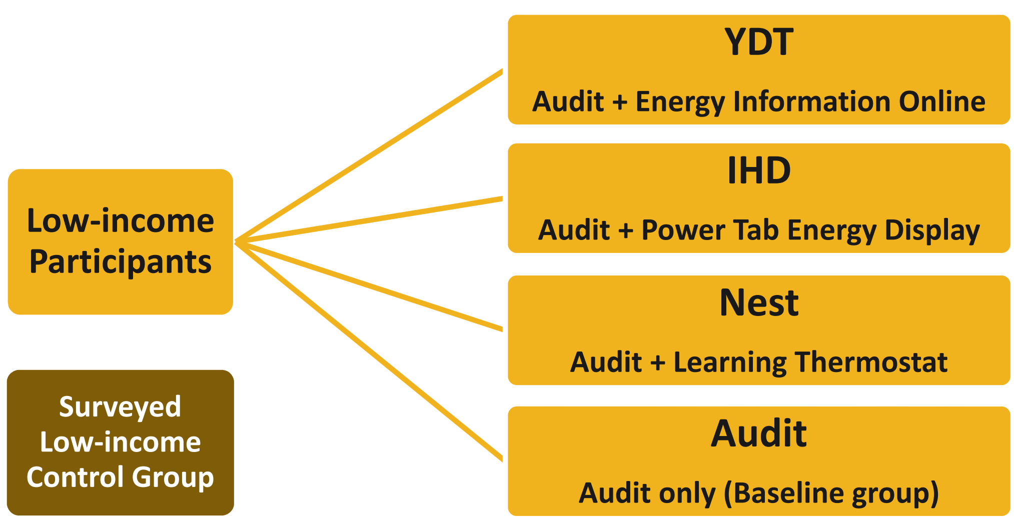
IHD = In-Home Display. IHD participants received an In-Home Display that linked with their smart meter to provide real-time energy use and cost data. The IHD was professionally installed during the audit and returned to SMUD after two months.

Nest = Nest Learning Thermostat. Nest participants received a Nest Learning Thermostat, a unit with integrated optimization services out of the box and optional remote connection for software upgrades and customer remote control. The Nest was professionally installed during the audit and became the property of the homeowner.

Audit = Low-income Weatherization Audit. The Audit participants received an in-home energy assessment along with prescribed energy efficiency upgrades from a list of limited options as determined by the audit results.

Surveyed Control Group. Participants in the surveyed control group responded to a survey but were unaware of the larger study.

Figure 4. Basic Sample Design



Evaluation Period

The pretreatment period for the Energy Insights Weatherization Study spans from August 2011 to May 2012, while the treatment period starts in February 2013 and ends in January 2014. For the analysis, the summer months of August and September 2011 are used to construct the baseline loads to which the June through September 2013 loads are compared. Loads from the summer of 2012 could not be used because they were affected by recruitment efforts.

While the months of June and July are missing from the pretreatment period due to a lack of meter data prior to August 2011, this is not expected to have a substantial effect on final results because they are corrected for temperature effects; i.e. the baseline loads estimated from pretreatment data are adjusted to reflect outdoor temperatures during the treatment period.

Study Timeline

Table 1 outlines the major phases of project activity and corresponding research tasks.

Table 1. Energy Insights Weatherization Study schedule

Task	Dates	Activities
Recruitment & Preparation	Mar 2012 – Jan 2013	• Prepare education and marketing materials • Prepare IT and billing • Mail invitation letters and follow up • Create participant database • Site visits and audits • Pre-pilot surveys
Field Study	Jan 2013 – Jan 2014	• Interval data collection period
Interim Data Collection	Sep 2012 - Jan 2013	• Collect survey data two months after all treatments are implemented
Data Collection & Final Evaluation	Jan 2014 – May 2014	• Satisfaction surveys • Retrieve load database • Data analysis → Final Report

Implementation

Electricity Rates

SMUD's Energy Assistance Program Rate (EAPR) offers eligible low-income customers a discount of about 30% on monthly energy costs. In addition to lower rates (Table 2), EAPR customers paid just $3.50/month in fixed charges during the study period– a 65% discount from the standard rate.

Table 2. SMUD's 2013 Energy Assistance Program Rate Pricing ($/kWh)

Rate Code	Summer Base	Summer Base+	Winter Base	Winter Base+
Electric Heat	<= 700 kWh $0.0643	>700 kWh $0.1262	<= 1120kWh $0.0492	>1120 kWh $0.1010
Gas Heat			<= 620 kWh $0.0592	>620 kWh $0.1217
Electric Heat with Well	<= 1000 kWh $0.0643	>1000 kWh $0.1262	<= 1420 kWh $0.0492	>1420 kWh $0.1010

Participant Offerings

Table 3 summarizes the study measures offered to each treatment group. The following sections describe each offering in more detail.

Table 3. Treatment Group measures

Treatment Group	Energy Assessment + Efficiency Measures	SMUD Website Tutorial	PowerTab Energy Display	Nest Learning Thermostat
YDT	✔	✔		
IHD	✔		✔	
Nest	✔			✔
Audit (control)	✔			

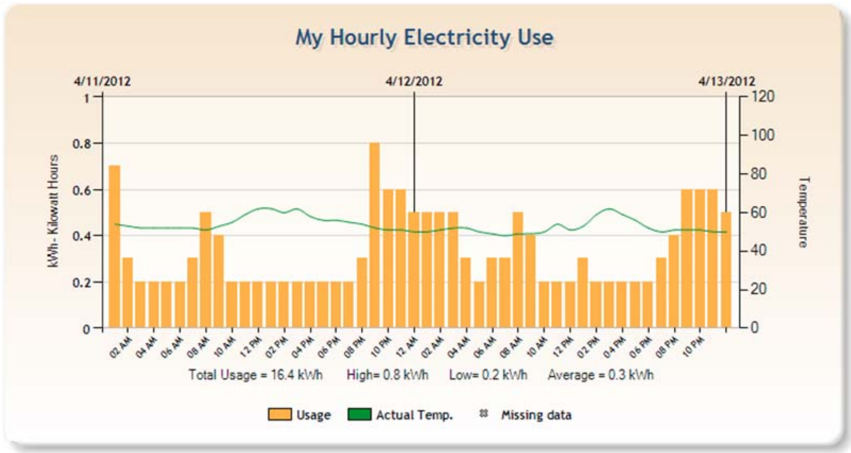
Home Energy Assessment

All participants received a free on-site energy assessment, including installation of weatherization and energy efficiency measures for their homes as appropriate.

SMUD Website Tutorial - Energy Information Online

All SMUD customers have access to their electricity usage data through an account on SMUD's website, where they can view interval data by billing period, day, or hour (Figure 4). During the audit, participants in the YDT group were provided a portable DVD player to view a video that provided an overview of how to use My Account Energy Information data to learn about their energy use and track the effects of the actions they take. Many YDT participants watched this video while the low-income energy assessments were being conducted.

FIGURE 4. YESTERDAY'S DATA TODAY ONLINE: MY HOURLY ELECTRICITY USE



POWERTAB IHD

IHD participants received an EnergyAware PowerTab IHD capable of displaying real-time electricity use data received wirelessly from the electricity meter (Figure 5). Available screens included Current Use in units of instantaneous demand (kW) and dollars per hour, daily Running Total in cumulative energy use (kWh) and dollars, and price per kWh of electricity. Like most IHD's, the PowerTab was not capable of displaying SMUD's inclining block rates as they came into effect for each customer. Instead, the unit displayed the Base rate at all times, regardless of whether the customer was paying this lower rate or the higher Base Plus rate.

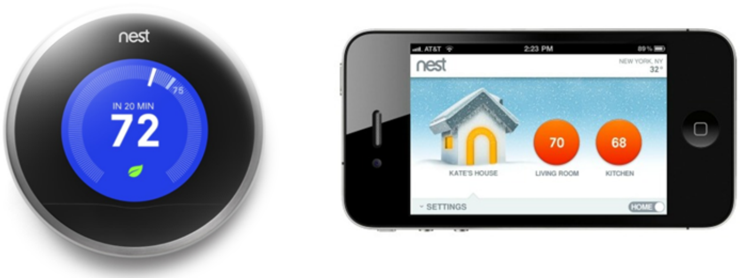
FIGURE 5. THE POWERTAB IN-HOME DISPLAY

After two months, customers were required to mail back the IHD device in a prepaid envelope, provided at the time of the energy assessment.

Nest Learning Thermostat

The Nest Learning Thermostat is an advanced thermostat that uses WiFi for remote access and programming (Figure 6). The main advanced features of the Nest Learning Thermostat include: Auto-Schedule, Auto-Away, Airwave, Energy History, the Efficiency Leaf, and Remote Control. All work equally well in the absence of a web connection with the exception of Remote Control, the only feature requiring that the thermostat be connected to the Internet.

Figure 6. The Nest Thermostat and smartphone app



Auto-Schedule. The automated schedule learning requires a seven-day process of manual thermostat interaction, from which the Nest defines a customized schedule. After the first seven days of "aggressive learning", the resulting schedule can be modified on the thermostat, the computer, or the smartphone app. Pattern matching optimizes the schedule whenever it recognizes similar temperature settings on two consecutive days, weekdays, or days of the week. Occupants can disable the Auto-Schedule feature in the Nest Settings menu.

Auto-Away. The Auto-Away feature is intended to save energy by initiating energy-efficient temperature settings when the Nest motion sensors do not sense movement for a period of time. Like Auto-Schedule, the Auto-Away feature can be disabled.

Airwave. Airwave™ uses software algorithms aimed at lowering air-conditioning costs by automatically turning off the compressor a few minutes before the scheduled run-time end and keeping the fan running to deliver the cool air still inside the ducts.

Energy History. The Nest displays information about heating and air-conditioning use compared to historical use, including estimates of how weather, Auto-Away and manual adjustments affected energy use.

The Leaf. The Nest Leaf appears on the main screen when the target temperature is set to an energy-efficient level.

Remote Control. Temperature settings can be modified remotely via connected devices.

Thermostat Installation

An outside contractor with HVAC and networking installation experience was responsible for scheduling appointments, installing thermostats, maintaining inventory, and servicing the thermostats after installation. During installation, the customer filled out the Pre-pilot Survey and watched a video designed to educate participants on the smart thermostat technology. The installer collected the completed surveys from the participants and returned them to SMUD.

Market Research

All pilot participants were required to fill out paper surveys while the energy advisor conducted the energy assessment. This Pre-Pilot Survey collected participant information in the following categories:

- Household demographics
- Dwelling structural characteristics and appliances (collected by auditor)
- Energy saving strategies
- Energy knowledge

At the end of the study, participants were asked to complete the Post-Pilot Survey, which measured post-treatment energy literacy, possible changes in energy-related behavior, perceived effort and savings, evaluation of technology, frequency of interaction, and attitudes toward program and SMUD.

A summary and analysis of market research data can be found in Energy Insights Weatherization Pilot Program Final Report (True North Research 2014).

2. DATA

EVALUATION PERIOD

Table 4 provides the start and end dates for which hourly load and temperature data were collected for the evaluation. Note that the pretreatment summer includes only August and September because many participants did not have smart meters installed before August 2011.

TABLE 4. EVALUATION PERIOD START AND END DATES

Evaluation period	Start date	End date
Pretreatment	8/1/11	5/31/12
Treatment	2/1/13	1/31/14

SAMPLE POPULATION

SCREENING

The Energy Insights Weatherization Pilot was originally designed to accommodate 156 customers in each treatment group. Each treatment was offered in isolation to a group of screened but otherwise randomly chosen customers, so the results for any one of the treatments can safely be extrapolated to the subset of SMUD's residential customers that meet the same screening criteria, at the same rate of participation as occurred for that treatment, assuming the same marketing effort[1]. Initial screening of SMUD's residential customer population involved exclusion of all customers with any of the following characteristics:

- Move in date after July 2011 or plans to move within 12 months
- Smart Meter data unavailable or not clean starting August 2011
- Dwelling is an apartment, a condominium, or a townhome
- Master meter, net meter, or bottom-fed meter
- On TOU, PV, Well, Medical (life support)
- On the "Do not call" or "Do not mail" list
- SMUD executive or Board member
- Meter without HAN certificate
- Renter or third party notification (indicating a renter)
- Operates a child or convalescent care facility from home
- Does not pay electricity bills

[1] SMUD's standard Weatherization program permits only all-electric homes to participate. This pilot did not screen out customers who also had gas service to the home.

- No access to the Internet
- Participant in the ACLM program, Smart Pricing Options, EV Innovators pilot, Summer Solutions study, solar, Smart Meter Acceptance Test Group, or smart meter opt-out

The 10,000 customers in the screened database were randomly assigned to one of five groups such that roughly 6,600 customers were assigned to the participant groups and about 3,300 customers were assigned to the control group sample. Of the 1,650 customers in each participant group, 1,500 randomly chosen customers were invited to participate in one of the four treatment groups.

The 2,250 customers that submitted an application for participation (37.5% of those invited) were further screened to ensure that each: lived at the dwelling and paid the bill; did not have an energy assessment conducted after 6/12/2012; lived in a single-family or mobile home; did not plan to move before 12/31/2013; did not operate a child or convalescent business from the home; had central heating and air conditioning; had access to the Internet via home, work, mobile, or library; had at most two thermostats; and were able to read and speak English (or have a family member interpret). At the end of this secondary screening, about 160 customers remained in each treatment group. By the end of the summer, the Nest treatment group had dropped to about 120 participants, due mainly to incompatible air-conditioning equipment, while the YDT, IHD, and Audit groups each maintained about 150 participants each.

Evaluation Sample

The database received from SMUD by the load impact evaluation team contained 563 active participants. A total of 38 participants were removed from the database – 9 customers who moved out during the treatment period, and 29 customers who were no longer on the EAPR rate by the end of the treatment period – leaving a total of 525 participants to include in the load impact analysis, as shown in Table 5.

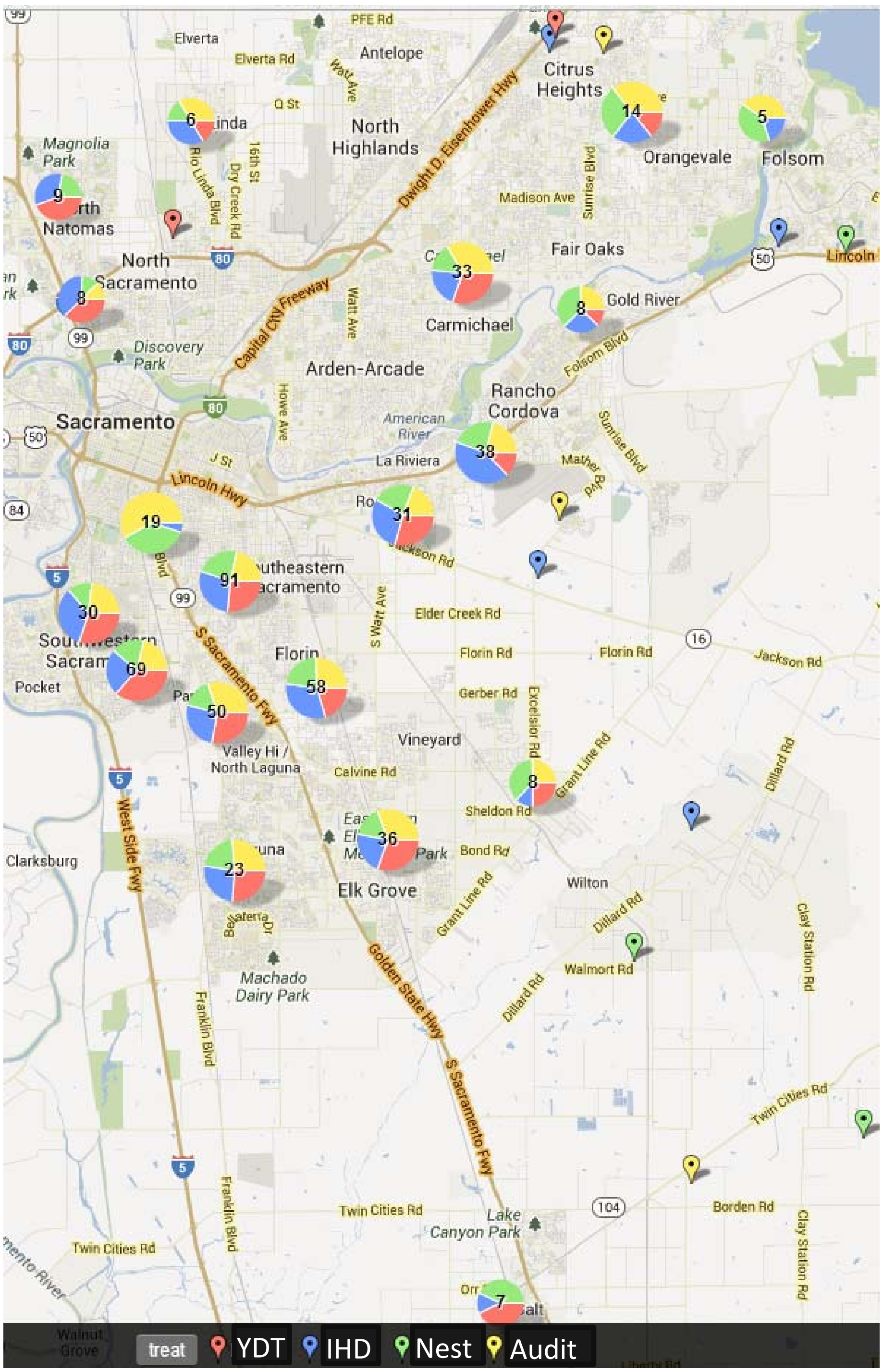
Table 5. Final Sample Sizes

Group	Description	Homes
YDT	Yesterday's Data Today = education on SMUD's online electricity use data	137
IHD	In-home display = real-time electricity use on a handheld device	141
Nest	Nest Learning Thermostat = automated scheduling of temperature settings	115
Audit (control)	Low-income weatherization audit = energy-saving measures installed	132
Total		**525**

Geographic Locations

The location of treatment group homes are mapped in Figure 7, with YDT in red, IHD in blue, Nest in green, and Audit in yellow. The reasonably even distribution provides evidence that a strong geographic bias is not present.

Figure 7. Map of participants, by treatment



Potential Sources of Bias

This section discusses some of the most likely sources of bias for this study.

Selection Bias in the Invited Group

Selection bias occurs as a result of limitations or errors in sampling. Evidence of selection bias can be detected by comparing load data for the group of invited customers to load data for a group that represents the program target market. A comparison of pretreatment summer energy use indicates that the invited group – which was screened for many variables, as described previously – had significantly higher loads than the general EAPR population. This suggests that the results presented here may not be valid if all EAPR customers will be eligible for the final program offering. If the EAPR population will be screened for the same variables as were the invited customers, then this bias may be reduced or eliminated.

Self-selection Bias in the Participant Groups

This study was designed to offer the participants the same self-selection criteria as might ultimately be offered to program participants. Assuming *selection* bias is not present (as described above), the customers who self-select into this pilot should be similar to those who would self-select into a full rollout of any of the individual treatments, meaning the results presented here do not suffer from self-selection bias as long as they are interpreted correctly.

Importantly, extrapolation of the results for any *one* of the treatments is valid as long as only *one* of the treatments studied here is offered to the broader low-income population. Load impacts for any combination of treatments not tested here – for example a Nest thermostat combined with an IHD, or a Nest offered separately but in the same invitation as an IHD – cannot be predicted in the absence of an in-depth understanding of customer choices and synergistic effects of treatments.

The results of this evaluation can be extrapolated to the target market by assigning the load impacts estimated for each treatment to the expected *participating* fraction of the program population – based on the pilot participation rate – and assuming zero load impacts for the *nonparticipating* fraction of the program population. In practice, this means that the *per-participant* load impacts provided in this evaluation report cannot be applied to the entire target population. Instead, *per-customer* impacts must be calculated as the product of the participation rate and the per-participant load impacts and then applied to the target population. For example, if 5% of invited customers participated in a given treatment, and annual energy savings are estimated at 2%, the expected savings of a larger rollout would be (0.05)(0.02) = 0.001 = 0.1% savings in the invited program population.

Control Group Bias

For experimental integrity and validity, a study should be designed from the outset as a random control trial (RCT) or randomized encouragement design (RED). Where these are not possible, other control group options must be considered. For this study, multiple control group options are available. All have the potential to introduce bias in the results because the self-selection criteria (pilot offerings) differ between the participants and control group members.

Control for Treatment Effects

For this evaluation, the Audit group is used to correct for exogenous effects in the treatment group loads. This group received all of the interventions experienced by the three treatment groups with the exception of the treatments themselves; i.e. the Audit group did not receive online training, an IHD, or a Nest thermostat. Use of the Audit group as the control has the potential to introduce bias in the results because the self-selection criteria (pilot offerings) differ between the Audit and treatment group participants.

Control for Audit Effects

To assess the load impacts of the Audit group, a separate control group was needed. Three non-mutually-exclusive groups were assessed, each drawn from the original randomly selected control group sample described previously.

> **Geographically matched.** A subset of customers was geographically selected to match the participating customer locations by street. Since these customers were not invited to participate and did not sign up for the study, variables of intention and willingness to participate are likely to differ from those of the participants. In addition, central air-conditioning ownership is unknown for these customers, while participants were required to have central air-conditioning.
>
> **Surveyed.** Another subset of the full control group completed a phone survey. These survey respondents were screened for central air-conditioning, which was one of the survey questions. The potential for bias is further reduced due to the fact that there is evidence of a willingness to participate by virtue of agreeing to answer the survey questions by phone. Even so, there is uncertainty about whether the same types of customers who answer a phone survey would sign up for the study, had they been offered the opportunity to participate.

The potential impact of bias in the control group depends on its intended use. In the load impact model used for this evaluation, the control group is used to correct for year-over-year exogenous effects. Thus, if the year-over-year differences are the same for the full and surveyed control groups, it matters little which group is used.

A review of loads and load impacts for the matched and surveyed control groups was conducted to consider this issue. Table 6 shows the observed summer weekday load impacts for the two different control groups: the geographically matched group of 651 customers and the 192 survey respondents with central air-conditioning. All results are calculated as actual differences between treatment and pretreatment periods.

The average peak, pre-peak, and post-peak load impacts shown in Table 6 are calculated as the average across the three hours for each period. In each case, an analysis of mean differences indicates that the year-over-year changes of the two control groups are statistically the same, indicating that it makes little difference which control group is used for the load impact evaluation. However, since the surveyed control group was screened for the presence of central air-conditioning, as were the participants, the surveyed control group will be used in the load impact analysis for the Audit-only treatment.

TABLE 6. CONTROL GROUP LOAD IMPACT COMPARISON

Control group	N	Pre-peak ΔkW (hours 14-16)	Peak ΔkW (hours 17-19)	Post-peak ΔkW (hours 20-22)
Geo Matched Control	651	-0.09	-0.23	-0.10
Surveyed	192	-0.10	-0.15	0.01

Load Data

Average Pretreatment and Treatment Loads – Actual

Figure 8 and Figure 9 show the average *observed* loads for summer 2011 and winter 2011-12, respectively. After correction for weather and exogenous effects through regression analysis and modeling, the dotted pretreatment load shapes will provide the baseline for each treatment group. In each case, the Treatment loads will be compared to their respective baselines through hourly load modeling, and treatment effects will be calculated as the difference between the Treatment and Baseline loads minus the effect seen in the Audit group.

Figure 8. Average summer loads 2011

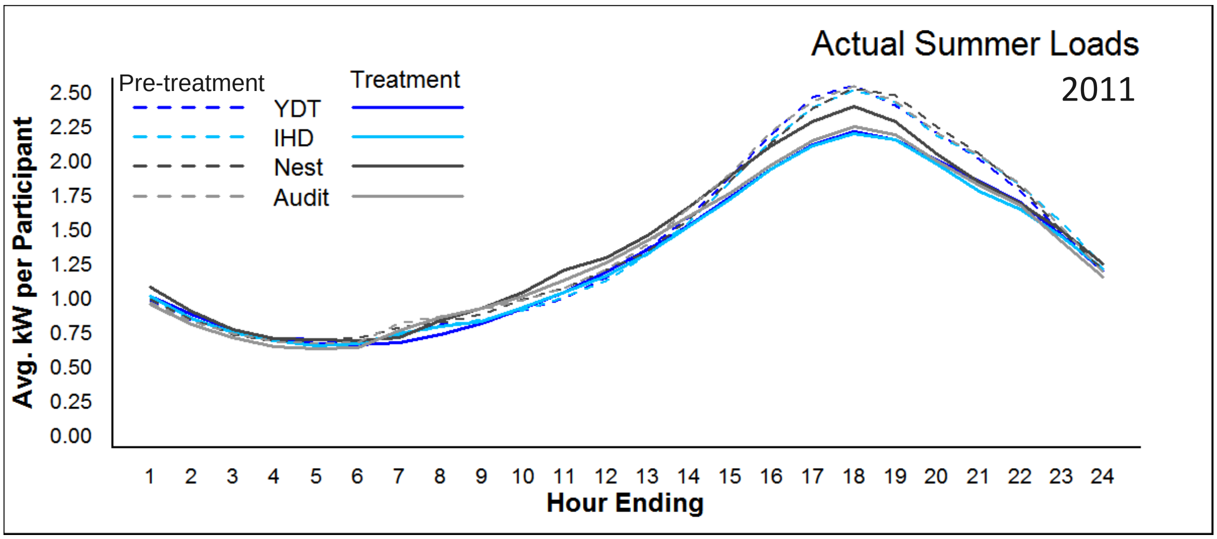
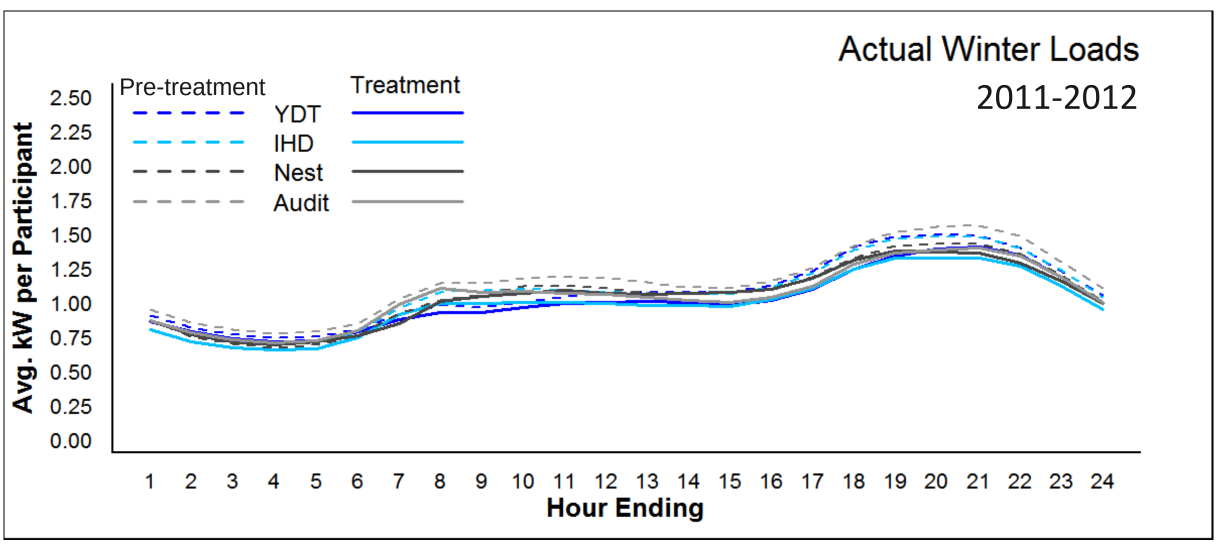


Figure 9. Average winter loads 2011-2012



Pretreatment Load Data Comparisons

The following sections consider the differences in pretreatment energy and peak demand between the treatment groups, as well as differences between the general, invited and participant populations. While differences between pre-treatment loads could indicate self-selection into treatment groups, we would expect the results to be unbiased and valid for a voluntary program with the same offerings.

Treatment and Control Groups

Figure 10 and Table 7 indicate that there are no statistically significant differences in pretreatment energy use between treatment groups.

Figure 10. Pretreatment average energy use

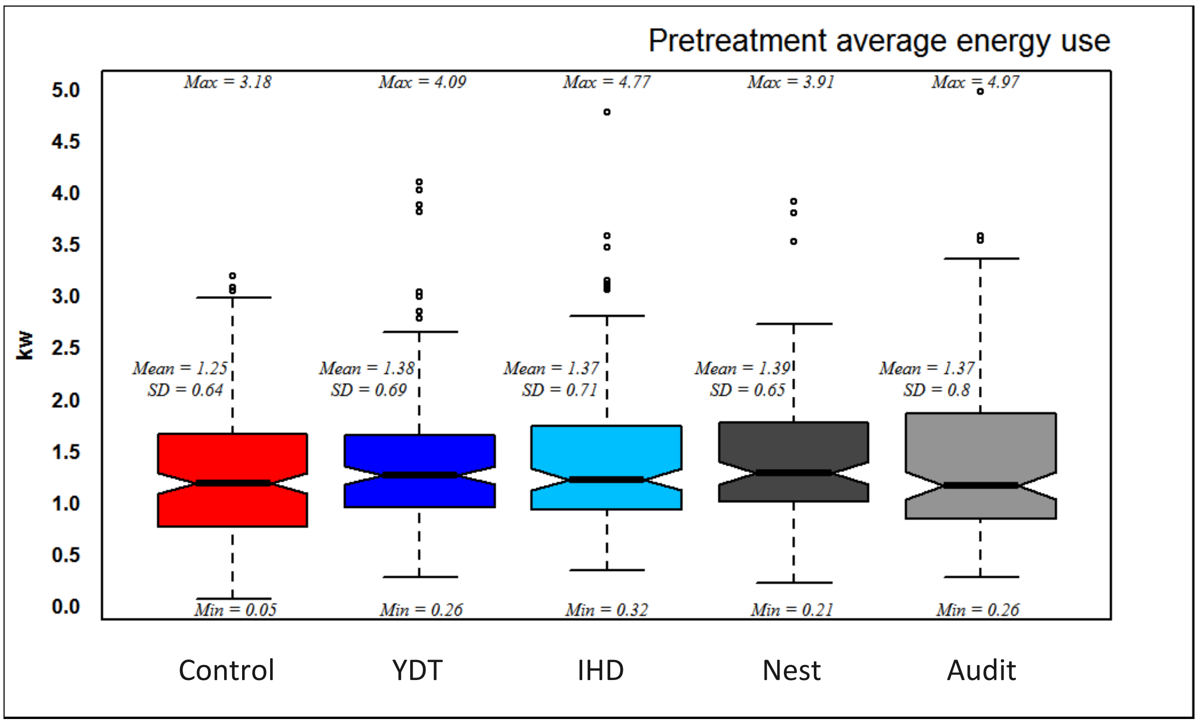


Table 7. Pretreatment average energy use comparisons (p-values)

Group	YDT	IHD	Nest	Audit
Control	0.4281	0.4380	0.3514	0.4683
IHD	0.9999			
Nest	0.9996	0.9993		
Audit	0.9999	1.0000	0.9999	

Figure 11 and Table 8 indicate that there are no statistically significant differences in pretreatment peak demand between treatment groups.

Figure 11. Pretreatment average peak demand

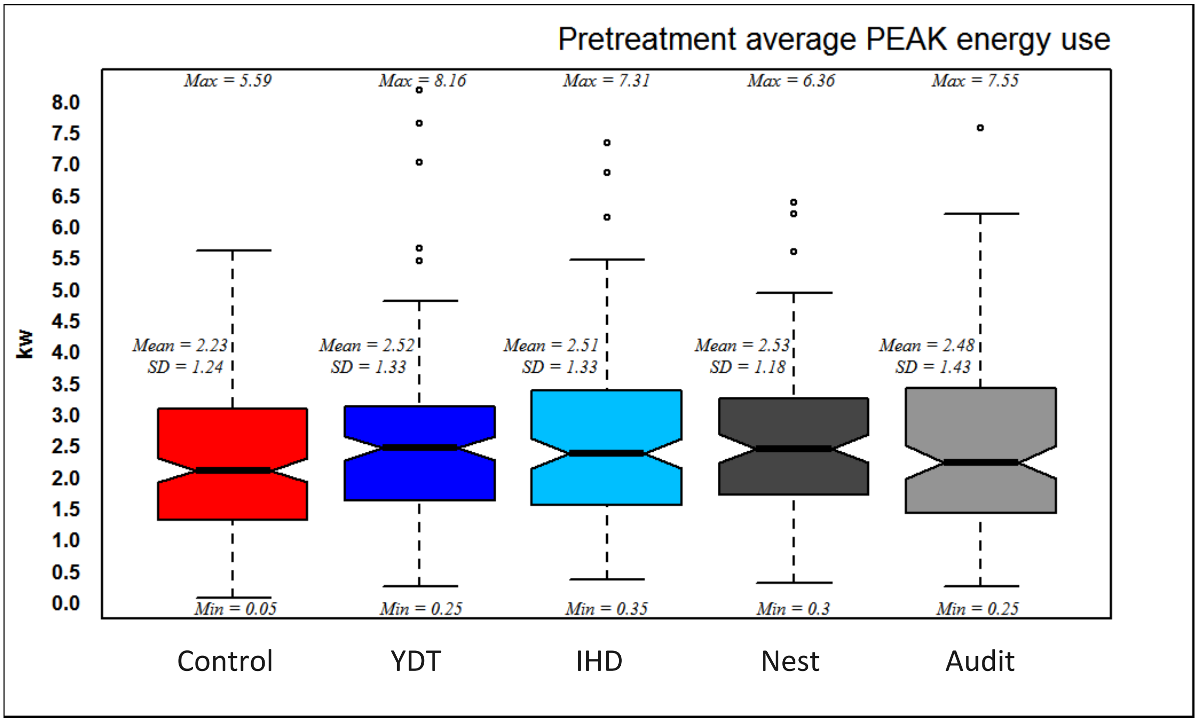


Table 8. Pretreatment average peak demand comparisons (p-values)

Group	YDT	IHD	Nest	Audit
Control	0.2172	0.2519	0.2498	0.3825
IHD	1.0000			
Nest	1.0000	0.9999		
Audit	0.9984	0.9996	0.9978	

General, Invited and Participant Populations

Figure 12 and Table 9 indicate that there are statistically significant differences in pretreatment energy use between the general, invited and participant groups.

The small difference (60 kWh) between the participant and invited populations may be the result of self-selection – customers with higher August 2011 energy use being somewhat more likely to participate. This self-selection is likely to be present in a full rollout of a similar voluntary program, and so does not bias the load impact estimates.

The larger difference (160 kWh) between the invited and general EAPR populations is likely the result of screening – customers with higher than average energy use were invited to participate. Given the strong correlation between pretreatment energy use and savings (Table 16), these results indicate that a rollout of this program to the general EAPR population (unscreened) would have a smaller impact that what is reported here.

FIGURE 12. PRETREATMENT AUGUST ENERGY USE, GENERAL AND INVITED POPULATIONS

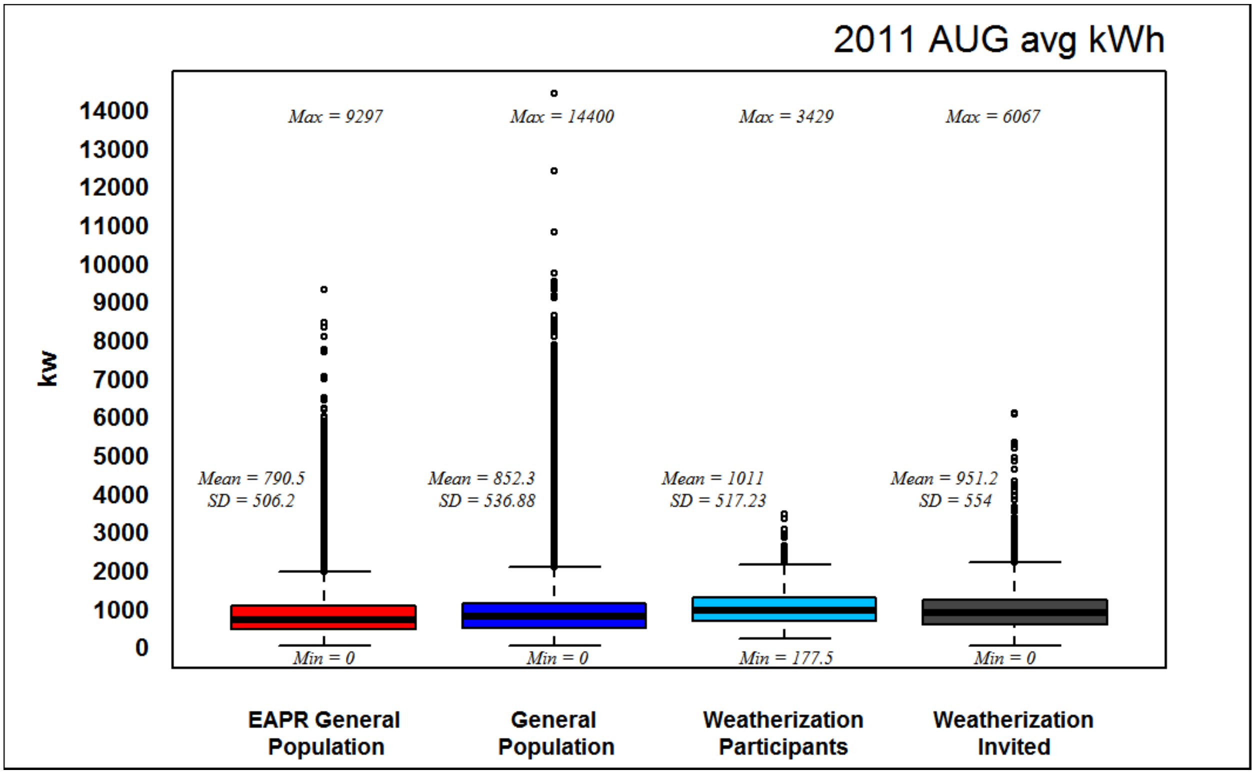


TABLE 9. PRETREATMENT AUGUST ENERGY USE COMPARISON, GENERAL AND INVITED POPULATIONS

Linear Hypotheses:	Estimate	Std. Error	t value	Pr(>|t|)
General.Population - EAPR.General.Population == 0	61.78	1.971	31.34	<0.001
WZN - EAPR.General.Population == 0	220.201	23.298	9.451	<0.001
WZN.invited - EAPR.General.Population == 0	160.624	7.246	22.168	<0.001
WZN - General.Population == 0	158.422	23.242	6.816	<0.001
WZN.invited - General.Population == 0	98.844	7.063	13.996	<0.001
WZN.invited - WZN == 0	-59.577	24.265	-2.455	0.05

Figure 13 and Table 10 indicate that there is a statistically significant 0.384 kW difference in pretreatment August peak demand between the invited and participant groups – likely the result of self-selection, such that customers with higher August 2011 peak demand were more likely to participate. The same type of self-selection is expected to be present in a full rollout of a voluntary program, and so is not an indication of bias in the load impact estimates.

FIGURE 13. SUMMER PEAK DEMAND, INVITED POPULATION

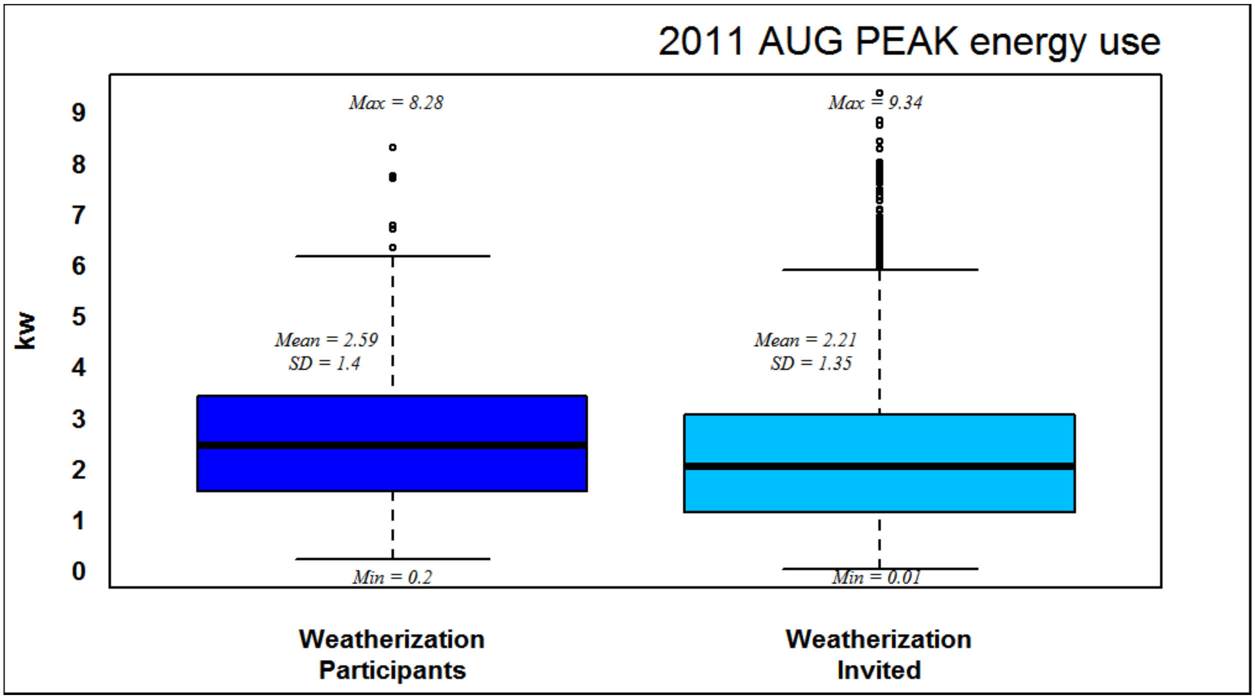


TABLE 10. SUMMER PEAK DEMAND COMPARISON, PARTICIPANTS AND INVITED

Linear Hypotheses:	Estimate	Std. Error	t value	Pr(>|t|)
WZN.invited - WZN == 0	-0.384	0.06186	-6.208	5.69E-10

Temperature Data

Figure 14 maps the ten weather stations in the SMUD service territory – charted using unique identifiers in the green boxes – for which hourly temperature data were downloaded. To ensure as-accurate-as-possible outdoor temperatures, participants were each assigned to the data recorded at the station closest to their home.

Figure 14. Weather stations used for load impact evaluation

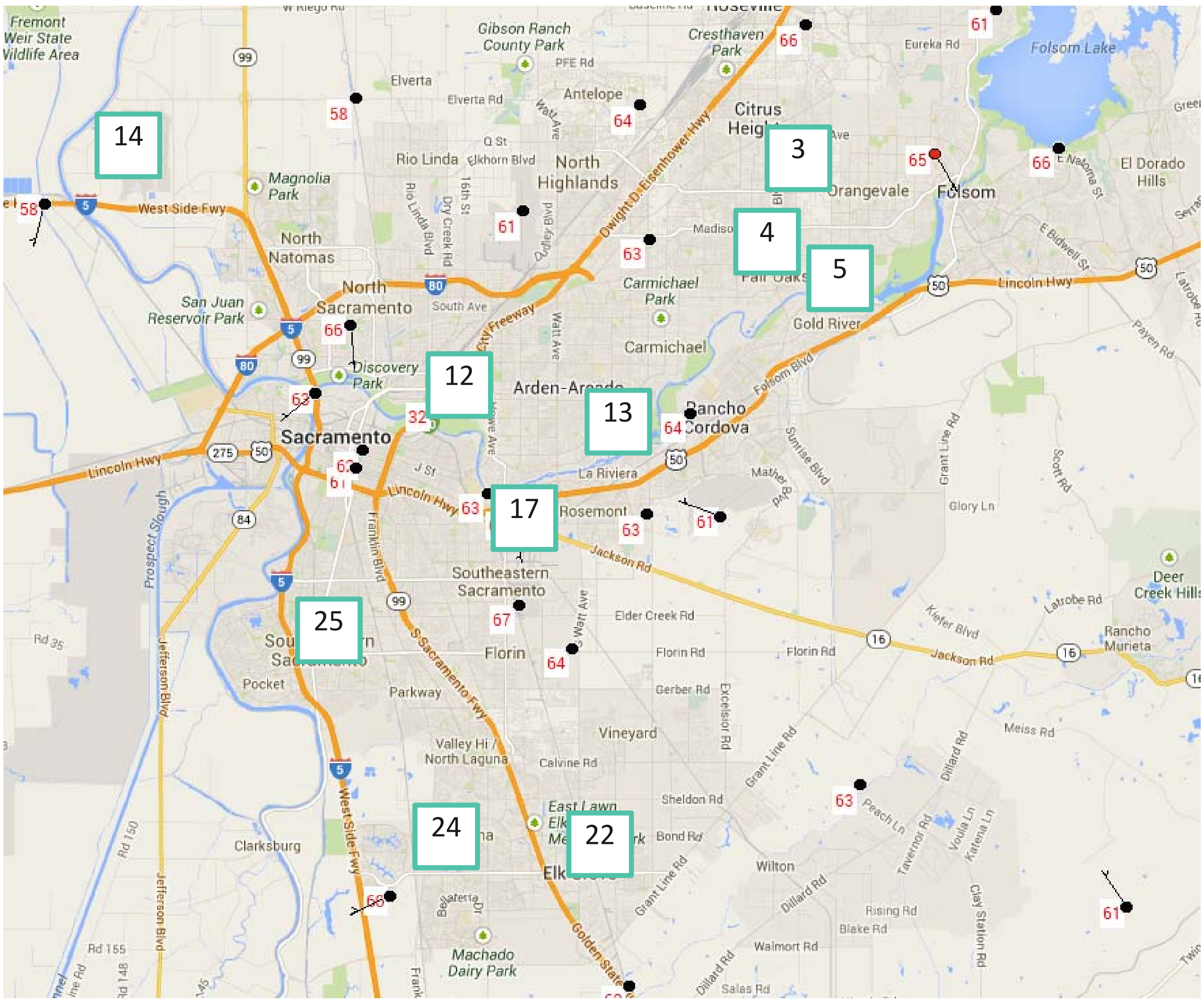


Figure 15 plots the average hourly summer temperatures at each of the 10 weather stations used in this analysis. Note that there are visible differences in temperatures across stations due to local microclimates, thus justifying the multiple-station approach.

FIGURE 15. AVERAGE HOURLY TEMPERATURE READINGS, SUMMER 2013

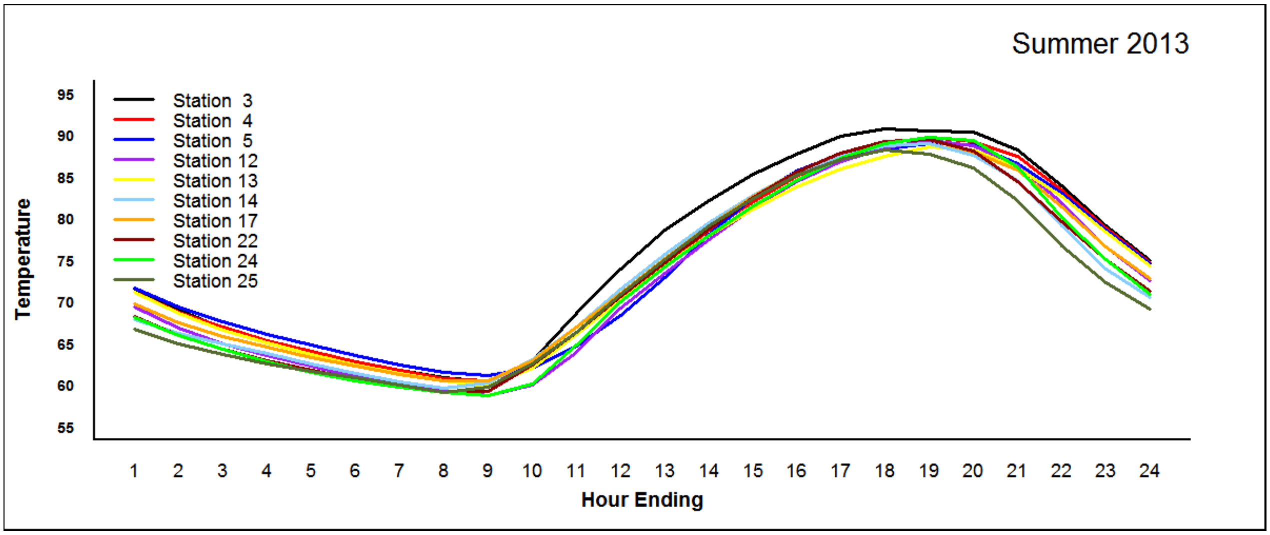
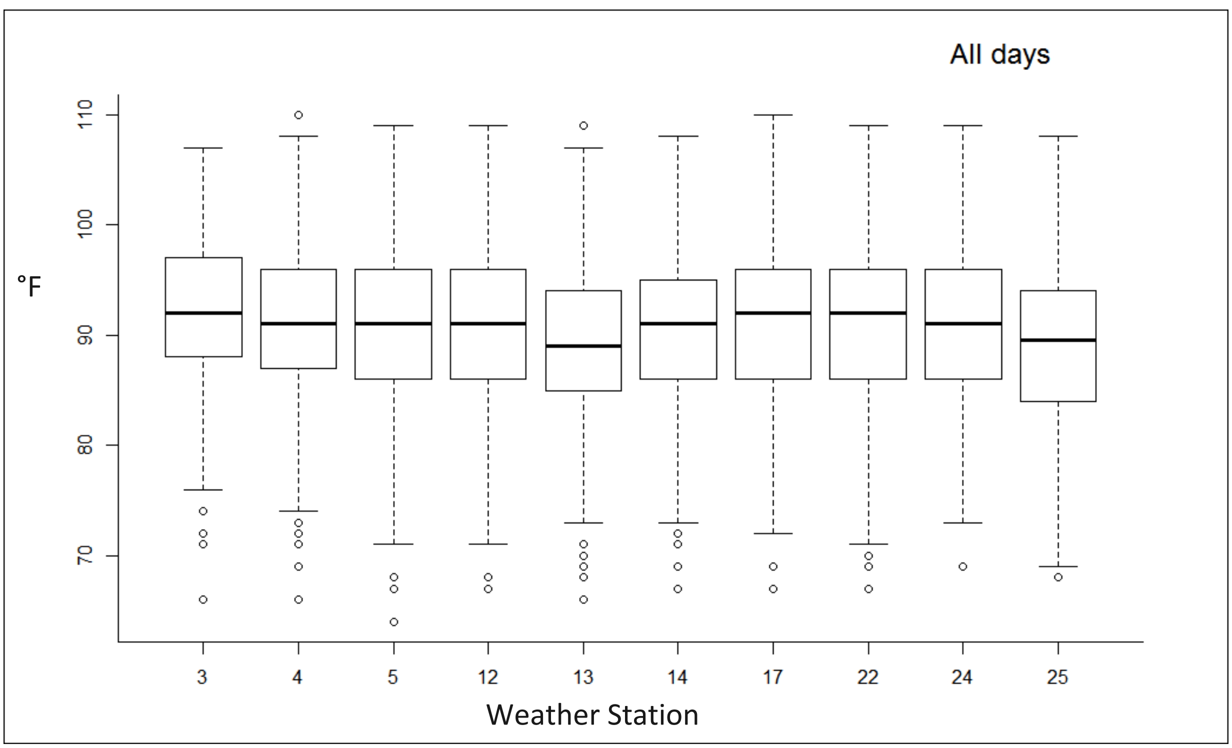


Figure 16 provides the distribution of maximum daily temperature measurements at each weather station for the summer of 2013, with the centerline of each box indicating the median, and the bottom and top edges of the boxes the first and third quartiles, respectively. Whiskers extend to the most extreme data point that is no more than 1.5 times the interquartile range. All points beyond the whiskers are outliers.

FIGURE 16. BOXPLOTS OF MAXIMUM DAILY TEMPERATURE READINGS, SUMMER 2013



3. Analysis and Results

Approach

Load Impact Estimation

Load impacts are estimated using the standard hourly load data collected by SMUD's existing metering infrastructure. The summer weekday, monthly, and seasonal load impact model equations are given in Appendices B, C and D, respectively.

The model coefficients allow calculation of load values, while impact values are then calculated as the difference-in-differences (DID) of the four load shapes as described in Equation 1. The basic premise of DID evaluation is to compare the measure of interest at two points in time – before and after treatment – in both the treatment and control groups, where the pretreatment loads are normalized to treatment period temperatures.

Equation 1. Calculation of load impacts

$$Load\_Impact_{ijk} = (Part.treat_{ijk} - Part.pretreat_{ijk}) - (Control.treat_{ijk} - Control.pretreat_{ijk})$$

Where, for customer *i* on day *j* at hour *k*:

- $Load\_Impact_{ijk}$: estimate of hourly load change resulting from the treatment
- $Part.treat_{ijk}$: modeled average participant loads during the treatment period
- $Part.pretreat_{ijk}$: modeled average participant loads during the pretreatment period
- $Control.treat_{ijk}$: modeled average control loads during the treatment period
- $Control.pretreat_{ijk}$: modeled average control loads during the pretreatment period

This technique can be thought of as a *within-subjects* estimate of the treatment effect corrected for exogenous effects using the changes seen in the Audit control group, where both are corrected for temperature differences between the pretreatment and treatment periods using standard regression techniques. Without exogenous effects correction, a within-subjects comparison can overestimate or underestimate impacts by associating non-treatment effects with the treatment. For example, a downturn in the economy might cause an overall reduction in residential electricity use. These exogenous energy savings must be removed from the treatment group impacts using the control group impacts as a proxy for exogenous effects. Otherwise, savings attributable to the treatment would be overestimated, when in fact much of the savings was simply a result of the floundering economy.

An unbiased DID methodology requires that the composition of and exogenous inputs to the treatment and control groups are as similar as possible. A standard method for accomplishing this is a random control trial, whereby portions of the recruited population are randomly assigned to treatment and control groups. For the control group, treatment is then deferred to a later date or denied altogether. Where a random control trial is not practical, as was the case for this study, a control group can be selected to closely resemble the treatment group along a subset of relevant variables. Such a control group, chosen or recruited under different circumstances, is not without bias, however, because “willingness to participate” in the same program as the participants is difficult or impossible to measure without putting the control group through the same solicitation and recruitment process. In addition, Hawthorne effects likely prevalent in the treatment group will not be seen in the control population.

The following sections provide the modeled loads and load impacts using this approach. For consistency and ease of comparison, all loads and impacts are presented in units of average kilowatt-hours per hour (kWh/h), abbreviated in most cases to kW, where positive impact values indicate an increase in energy use relative to the baseline, and negative impact values indicate savings. Note that these hourly kW values are easily converted to kWh through multiplication by the number of hours across the desired time period.

Bill Impact Estimation

Bills are estimated for each customer by applying their individual electricity rate to their modeled treatment and baseline loads as follows. Recall that 2011 summer loads are used as the baseline because 2012 summer loads were affected by recruitment.

Step 1: Calculate actual 2013 standard rate bills (treatment)

1. Aggregate kWh by month
2. If kWh <= tier1.allowance then monthly.bill = monthly.kWh*tier1.price
   else monthly.bill = (tier1.allowance*tier1.price) +
   (monthly.kWh - tier1.allowance)*(tier 2 price)
3. Avg. Summer Bill = (sum of June-September bills from step 2)/4
   Avg. Winter Bill = (sum of October-May bills from step 2)/8

Step 2. Estimate 2011 Standard rate bills (baseline)

1. Model: kWh = CDH + CDD + month + hour*year
2. Estimate the average daily.kWh for each summer month in 2011 (1 daily value for each of the 4 summer months) using month-specific temperatures
3. Monthly.kWh = (daily.kWh)*(number of days in the month)
4. If Monthly.kWh <= tier1.allowance then monthly.bill = (kWh* tier1.price)
5. Else monthly bill = (tier1.allowance*tier1.price) + ((Monthly.kWh - tier1.allowance)*tier2.price)
6. Avg. Summer Bill = (sum of June-September bills from step 4)/4
7. Avg. Winter Bill = (sum of October-May bills from step 4)/8

NULL HYPOTHESES

The purpose of the load impact evaluation is to estimate the energy, peak demand, and bill impacts for each treatment group, and to determine how these impacts differ across customer segments. The following null hypotheses were tested:

1. *Treatment loads are not different from baseline loads (adjusted for weather and exogenous effects)*

Equation 1

$$H_0: (\mu_{part.treat_i} - \mu_{part.base_i}) - (\mu_{control.treat} - \mu_{control.base}) = 0$$

$$H_a: (\mu_{part.treat_i} - \mu_{part.base_i}) - (\mu_{control.treat} - \mu_{control.base}) \neq 0$$

$\mu_{part.treat_i}$ = average participant loads during the treatment period for $(Treatment\_Period)_i$

$\mu_{part.base_i}$ = average participant loads during the pretreatment period for $(Treatment\_Period)_i$

$\mu_{control.treat}$ = average control group loads during the treatment period

$\mu_{control.base}$ = average control group loads during the pretreatment period

2. *Treatment type has no effect on impacts (adjusted for weather and exogenous effects)*

Equation 2

$$H_0: \left[(\mu_{part.treat_i} - \mu_{part.base_i}) - (\mu_{control.treat} - \mu_{control.base})\right] - \left[(\mu_{part.treat_{i'}} - \mu_{part.base_{i'}}) - (\mu_{control.treat} - \mu_{control.base})\right] = 0$$

$$H_a: \left[(\mu_{part.treat_i} - \mu_{part.base_i}) - (\mu_{control.treat} - \mu_{control.base})\right] - \left[(\mu_{part.treat_{i'}} - \mu_{part.base_{i'}}) - (\mu_{control.treat} - \mu_{control.base})\right] \neq 0$$

$\mu_{part.treat_i}$ = average participant loads during the treatment period for $(Treatment\_Period)_i$

$\mu_{part.treat_{i'}}$ = average participant loads during the treatment period for $(Treatment\_Period)_{i'}$

$\mu_{part.base_i}$ = average participant loads during the pretreatment period for $(Treatment\_Period)_i$

$\mu_{part.base_{i'}}$ = average participant loads during the pretreatment period for $(Treatment\_Period)_{i'}$

$\mu_{control.treat}$ = average control group loads during the treatment period

$\mu_{control.base}$ = average control group loads during the pretreatment period

Load Impacts of the Audit only

Although the main purpose of this evaluation is to determine the effects of the YDT, IHD, and Nest treatments, SMUD is also interested in estimating the load impacts of the Audit group, which received only the Low-Income Weatherization Audit. Because gas-heat customers have been excluded from the pre-existing weatherization program, results for gas and electric homes are differentiated from each other.

Table 11 shows the average summer peak load reduction for participants that received the low-income weatherization audit. During the 4-7 pm peak period, where savings are most beneficial, the gas heat participants shaved 260 watts (11%) off their pre-weatherization peak load. In contrast, electric heat participants showed no statistically significant savings.

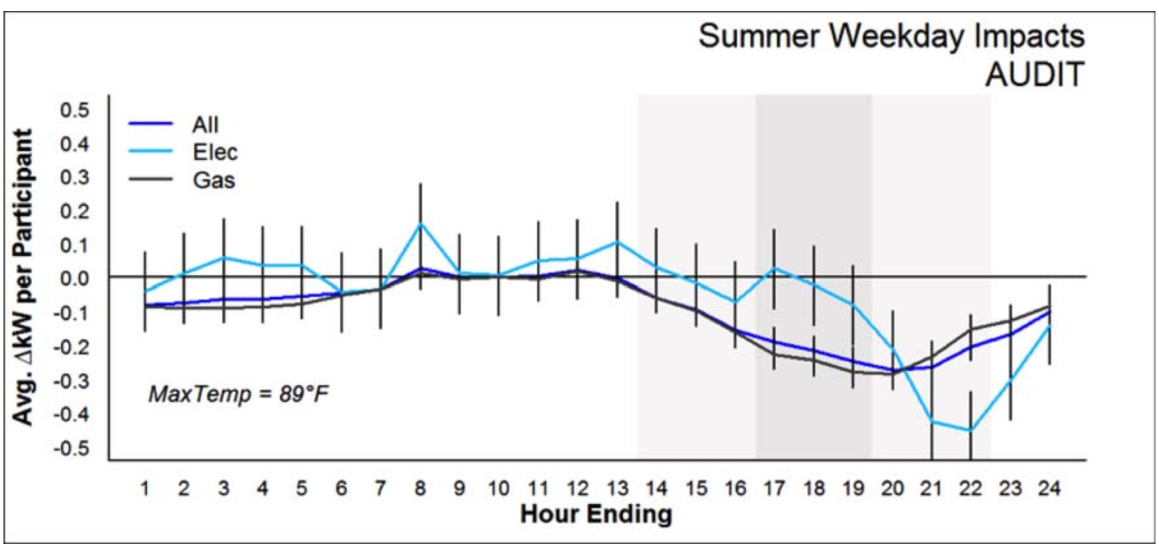
Table 11. Average Summer weekday impacts for the Audit group

Treatment	N	Pre-peak (hours 14-16)	Peak (hours 17-19)	Post-peak (hours 20-22)
Audit – electric heat	30	-0.012 (-0.6%)	-0.014 (-0.5%)	-0.35* (-13%)
Audit – gas heat	102	-0.11* (-6.4%)	-0.26* (-11%)	-0.22* (-12%)
Audit – all	132	-0.10* (-5.8%)	-0.22* (-9.2%)	-0.24* (-12%)

* Statistically significant, α=0.05.

A closer look at the hourly loads on summer weekdays for the Audit group, shown in Figure 17, indicates that unlike the gas customers, the savings for the electric heat customers appear almost exclusively between 7 pm and midnight.

Figure 17. Actual vs. modeled standard rate bills, winter 2013



The Audit group exhibited statistically significant annual electricity savings of 0.055 kWh/h or about 490 kWh per year (Table 12). Annual energy savings for the gas customers exceeded 400 kWh per year (4.4%) and electric customers saved about 560 kWh (4.0%) per year. Given the high costs of electricity during the summer months, however, the gas customers might be more cost-effective, having more than twice the summer energy savings (330 kWh/summer) of the electric customers (150 kWh/summer).

TABLE 12. AVERAGE ENERGY IMPACTS FOR THE AUDIT GROUP[2]

Treatment	N	Summer Energy Impact *kW (%)*	Winter Energy Impact *kW (%)*	Annual Energy Impact *kW (%)*
Audit – electric heat	30	-0.050 (-3.1%)	-0.072* (-4.4%)	-0.064* (-4.0%)
Audit – gas heat	102	-0.114* (-8.5%)	-0.012* (-1.3%)	-0.046* (-4.4%)
Audit – all	132	-0.107* (-7.6%)	-0.029* (-2.8%)	-0.055* (-4.8%)

* Statistically significant, α=0.05.

TREATMENT EFFECTS – YDT, IHD, AND NEST

SUMMER WEEKDAY PEAK IMPACTS

Summer weekday results are presented in this section as average daily loads and impacts accompanied by tabular values covering three periods of interest:

- Pre-peak = the 3-hour period immediately preceding the peak = hours ending 14-16
- Peak = the 3-hour peak period = hours ending 17-19
- Post-peak = the 3-hour period immediately following the peak = hours ending 20-22

Figure 18 plots the summer load impacts for each treatment at the average summer 2013 maximum daily temperature of 89°F. Since these impacts are relative to those of the Audit control group, the Audit impacts can be thought of as coinciding with the x-axis, having a value of zero in all hours. Loads for the YDT and IHD treatment groups closely match those of the Audit group, while the Nest group shows marked increases in energy use from 2 to 6 pm.

[2] The "Audit – all" values are not necessarily equal to the weighted average of the seasonal values because separate models were run for each row in Table 12. Baseline loads and other details of these calculations can be found in Table 41.

FIGURE 18. SUMMER WEEKDAY IMPACTS, RELATIVE TO THE SURVEYED CONTROL GROUP

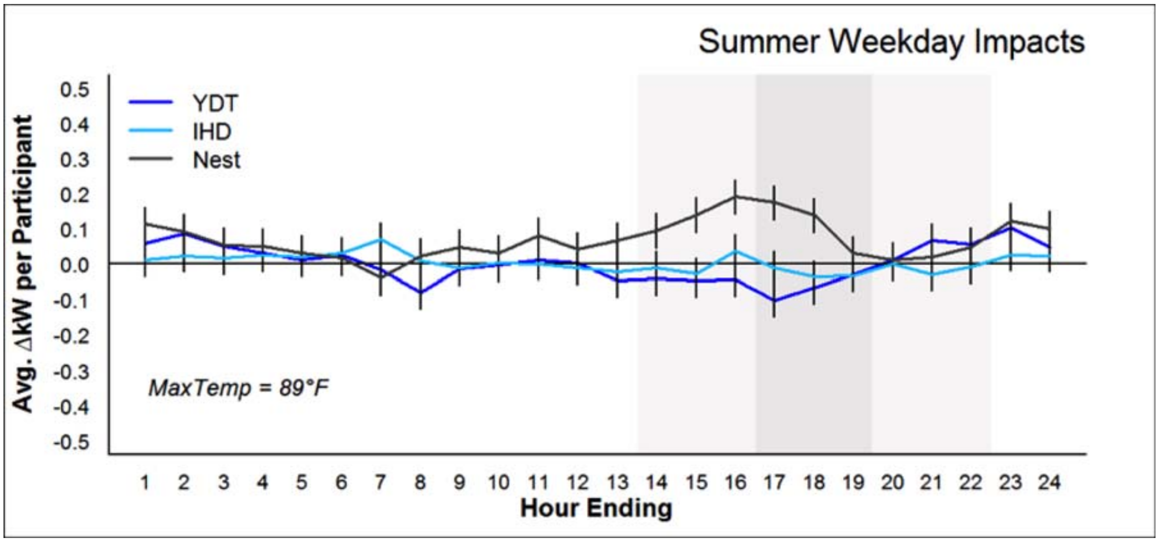


Table 13 shows these load impacts in the peak, pre-peak and post-peak periods. Compared to the audit alone, the IHD treatment had no statistically significant effect in any of the three periods considered here. The YDT treatment reduced energy use by 3% during the peak period, and the Nest treatment increased loads in the pre-peak and peak periods by 8.8% and 5.4%, respectively.

TABLE 13. SUMMER WEEKDAY DEMAND IMPACTS, RELATIVE TO THE AUDIT GROUP

Treatment	N	Pre-peak (hours 14-16) *kW (%)*	Peak (hours 17-19) *kW (%)*	Post-peak (hours 20-22) *kW (%)*
YDT	137	-0.041 (-2.4%)	-0.064* (-3.0%)	+0.043 (+2.4%)
IHD	141	+0.006 (0.3%)	-0.020 (-0.9%)	-0.013 (-0.7%)
Nest	115	+0.15* (8.8%)	+0.12* (+5.4%)	+0.023 (+1.3%)

* Statistically significant, α=0.05.

Seasonal Energy and Bill Impacts

Table 14 summarizes the annual and seasonal energy impacts for each of the treatments relative to the Audit baseline. Of the three treatments – YDT, IHD, and Nest – none saved energy or money on their bills. The IHD treatment had no statistically significant effect on annual energy use, while the YDT treatment increased energy use by over 2% and the Nest thermostat increased overall annual energy use by more than 7%.

Table 14. Average energy impacts of treatments, relative to the Audit group

Treatment	N	Summer Energy Impact		Winter Energy Impact		Annual Energy Impact	
		kW	*(%)*	*kW*	*(%)*	*kW*	*(%)*
YDT	137	+0.011	(+0.8%)	+0.029*	(+2.8%)	+0.022*	(+2.0%)
IHD	141	+0.008	(+0.6%)	+0.007	(+0.7%)	+0.006	(+0.6%)
Nest	115	+0.076*	(+5.8%)	+0.078*	(+8.0%)	+0.077*	(+7.1%)

* Statistically significant, α=0.05.

Customer-specific bill impacts are estimated as the difference between the baseline and treatment period bills for each customer, adjusted by the mean impact seen in the Audit group. A summary of bill impacts relative to the Audit group is provided in Table 15. Only the Nest group exhibited a statistically significant average bill impact, increasing winter bills by an average of just under $6 per month in the winter months.

Table 15. Average monthly bill impacts of treatments, relative to the Audit group

Treatment	N	Summer		Winter		Annual	
		$/month	*(%)*	*$/month*	*(%)*	*$/month*	*(%)*
YDT	137	+$0.51	(+0.7%)	+$2.82	(+5.8%)	+$2.05	(+3.6%)
IHD	141	-$0.01	(-0.0%)	+$0.65	(+1.3%)	+$0.43	(+0.8%)
Nest	115	+$5.51	(+7.7%)	+$5.93*	(+12.6%)	+$5.79	(+10.5%)

* Statistically significant, α=0.05.

The following sections provide further detail on the seasonal energy and billing results.

Summer (June – September)

Figure 19 plots the hourly energy impacts for each treatment, calculated as the difference between the hourly baseline and treatment load values. Summed across the 24 hours, only the Nest group exhibited load impacts that were statistically different from the Audit group, increasing summer energy use by 5.8% as shown in Table 14.

Figure 19. Average summer energy impacts, relative to the Audit group

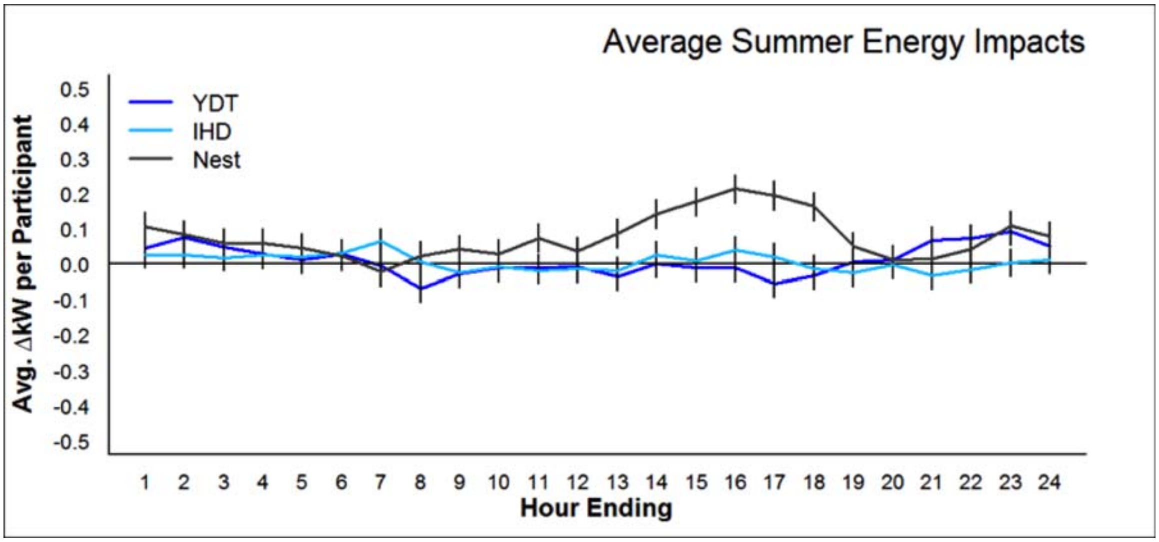
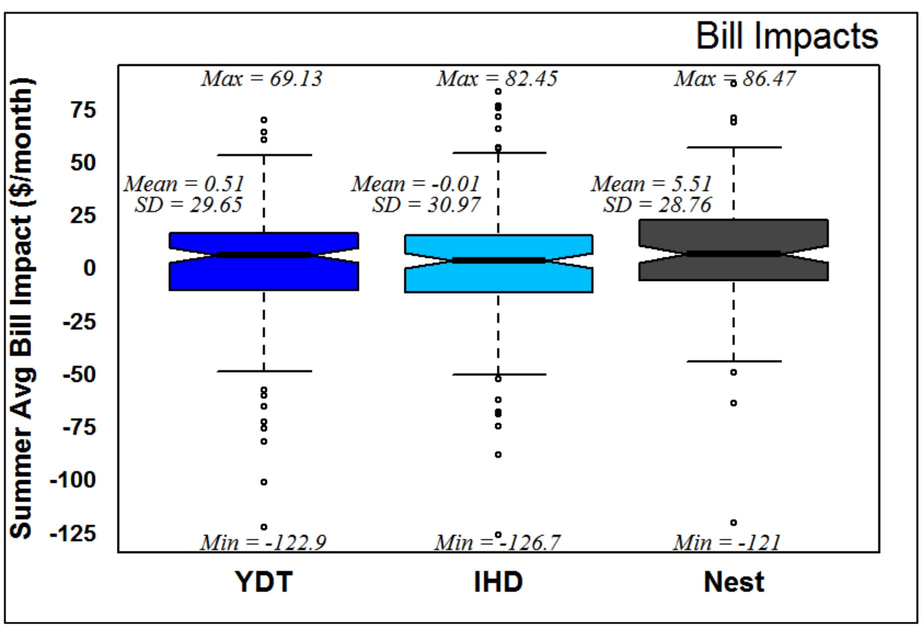


Figure 20 shows that the distributions of summer bill impacts for the three treatment groups are very similar.

Figure 20. Boxplot of average summer bill impacts ($/month)



WINTER (OCTOBER – MAY)

Figure 21 plots the winter energy impacts for each treatment, calculated as the difference between the hourly baseline and treatment load values. Summed across the 24 hours, both the YDT and Nest groups exhibited load impacts that were statistically different from the Audit group, increasing winter energy use by 2.8% and 8.0%, respectively, as shown in Table 14.

FIGURE 21. AVERAGE WINTER ENERGY IMPACTS, RELATIVE TO THE SURVEYED CONTROL GROUP

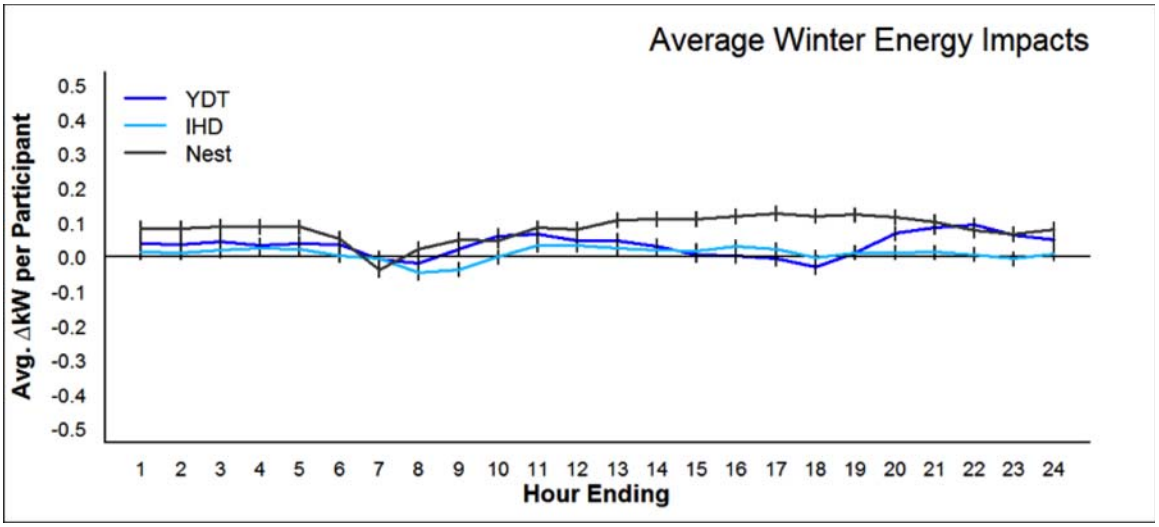
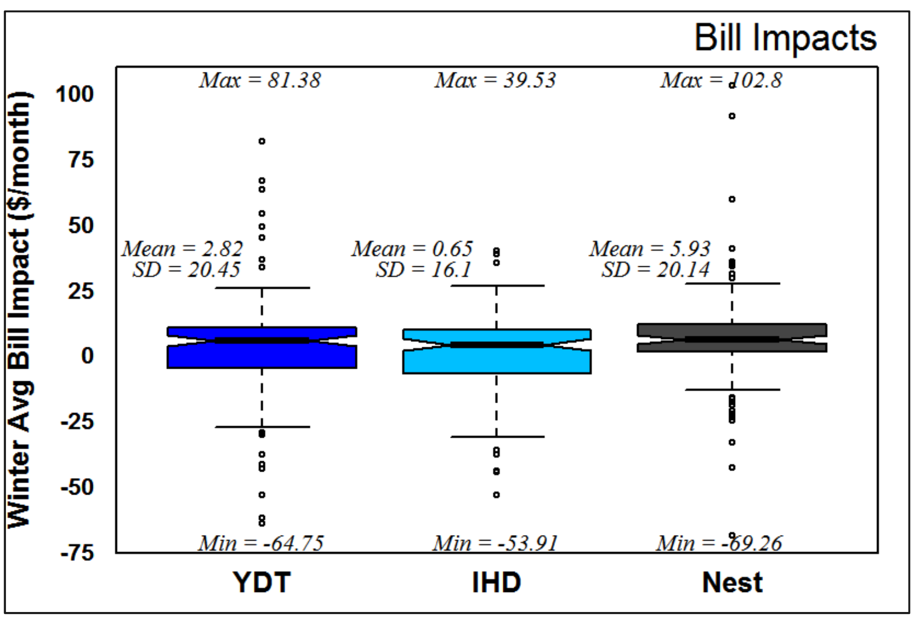


Figure 22 shows that the distributions of summer bill impacts for the three treatment groups are fairly similar, although the IHD group indicates a slightly narrower distribution.

FIGURE 22. BOXPLOT OF AVERAGE WINTER BILL IMPACTS ($/MONTH)



Segmentation Effects

Customer-specific energy impacts estimated using fixed-effects regression analysis were correlated with demographic variables collected in the pretreatment survey to investigate which customer characteristics are likely to lead to higher energy impacts. Results show that pretreatment energy use is significantly correlated with energy impacts for all groups, meaning that in all cases, higher users are likely to save more than lower users. For the YDT and Audit groups, larger homes also saved significantly more energy than did their smaller counterparts.

For Audit customers, participant age and education were significant factors in how much energy was saved, with older participants saving more energy, and more educated participants saving less energy. Interestingly, this relationship was reversed for those in the Nest group, where more education resulted in better savings.

For the YDT treatment, the size and ownership of the home were significant factors, with homeowners and those in larger homes saving more energy.

Table 16. Correlations with annual energy impact (Pearson's R)

Variable	YDT	IHD	Nest	Audit
Annual Pretreatment kWh	**-0.45***	**-0.42***	**-0.22***	**-0.51***
Respondent Age	-0.08	+0.11	-0.04	**-0.21***
Respondent Education	-0.04	-0.00	-0.17	**+0.24***
House Age	+0.18	+0.01	+0.11	+0.02
House Size	**-0.23***	-0.07	+0.08	**-0.29***
Number of Persons in Home	-0.04	+0.02	-0.04	-0.11
Number of Persons < 18	+0.10	+0.10	-0.05	+0.05
Number of Persons Home at Peak	+0.07	+0.02	-0.09	+0.06
Home Ownership	**-0.20***	+0.07	-0.08	+0.04

* Statistically significant, α=0.05.

See Appendix D (Figure 53 through Figure 56) for plots of correlations between energy impacts and demographic variables for each treatment.

4. Conclusions

This study investigated whether advanced smart grid devices and training would help low-income customers reduce their energy use and peak loads beyond what was saved under SMUD's standard Low-Income Weatherization program. To this end, SMUD provided three measures – smart thermostats (Nest), in-home energy displays (IHD), and training in hourly energy data use (YDT) – to about 400 homes on the low-income Energy Assistance Program Rate (EAPR). The three treatment groups – YDT, IHD, and Nest – received SMUD's standard Low-Income Weatherization Audit in addition to the treatment of interest, while a fourth group (Audit) received just the low-income audit without smart grid devices or training.

During the summer peak hours of 4 to 7 p.m., participants in the Audit group saved a statistically significant 220 watts on average, or 9.2% of their peak load. Relative to this value, the YDT treatment saved an additional 64 watts (-3.3%), the Nest treatment increased peak loads by 120 watts (+5.4%), and the IHD treatment had no statistically significant effect.

Relative to the Audit alone, none of the three treatments saved energy. The YDT treatment increased annual energy use by over 2%, and the Nest thermostat increased overall annual energy use by more than 7%. Both of these increases are statistically significant. The IHD treatment had no statistically significant effect on annual energy use.

Overall, the results of this study indicate that SMUD's Low-income Weatherization Audit effectively reduced both summer and winter energy use for low-income customers, resulting in an annual energy savings of 4.8% and bill savings of about $50. Beyond the Audit, however, training on SMUD's Yesterday's Data Today website (YDT), the provision of a real-time energy display (IHD), and the installation of a Nest Learning thermostat (Nest) were not effective in reducing energy use, and in some cases showed evidence of increasing energy use.

The 7.1% annual energy *increase* for the low-income customers provided with a Nest thermostat are surprising given the 1.6% energy *savings* enjoyed by participants on the standard rate who received Nest thermostats under SMUD's Smart Thermostat pilot (Herter & Okuneva 2014b).

REFERENCES

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5. Appendices

Appendix A. Summer Weekday Load Model

This section provides conditional R^2 values for each model along with plots of the modeled and actual average load values. In all cases, the dotted line representing the 24 modeled load values are nearly identical to those of the solid lines representing the actual loads. All days except weekends and holidays were included in the analysis.

- Baseline = Aug 1, 2011 – September 30, 2011
- Treatment = June 1, 2013 – September 30, 2013

Model Equation

$$kw_{ijk} = \beta 1_k hour_{ijk} + \beta 2 CDH_{ijk} + \beta 3 CDD_{ij} + \beta 4_{m-1} Treatment\_Period_m + \beta 5_{k-1}(CDD_{ij} * hour_{ijk}) + \beta 6_{m-1}(CDD_{ij} * Treatment\_Period_m) + \beta 7_{(k-1):(m-1)}(hour_{ijk} * Treament\_Period_m) + \beta 8_{(k-1):(m-1)}(CDD_{ij} * hour_{ijk} * Treatment\_Period_m) + r_i + r_{ij} + \varepsilon_{ijk}$$

kw_{ijk}: kilowatt load for customer i on day j at hour k

$hour_{ijk}$: indicator variable for hour of the day (1-24, or 14-16, or 17-19, or 20-22)

CDH_{ijk}: cooling degree hour for customer i on day j at hour k . If Temperature > 75 for customer i on day j at hour k, then CDH for customer i on day j at hour k is Temperature – 75; otherwise, CDH for customer i on day j at hour k is 0.

CDD_{ij}: Cooling degree day = Sum of 24 CDH values for customer i on day j

$Treatment\_Period_m$: indicator variables for treatment and treatment period (YDT.baseline=reference level, YDT.treatment, IHD.baseline, IHD.treatment, Nest.baseline, Nest.treatment, Audit.baseline, Audit.treatment, control.baseline, control.treatment)

r_i: random effects for customer $\sim N(0, \varphi_1)$, assumed to be independent for different i

r_{ij}: random effects for day $\sim N(0, \varphi_2)$, assumed to be independent for different i or j and to be independent of r_i

ε_{ijk}: error terms $\sim N(0, \delta^2 I)$, assumed to be independent for different i or j and to be independent of random effects

Model Fit

Figure 23 through Figure 26 show that the modeled average hourly loads are nearly identical to the average of the actual hourly loads.

Figure 23. Actual and modeled summer loads, YDT

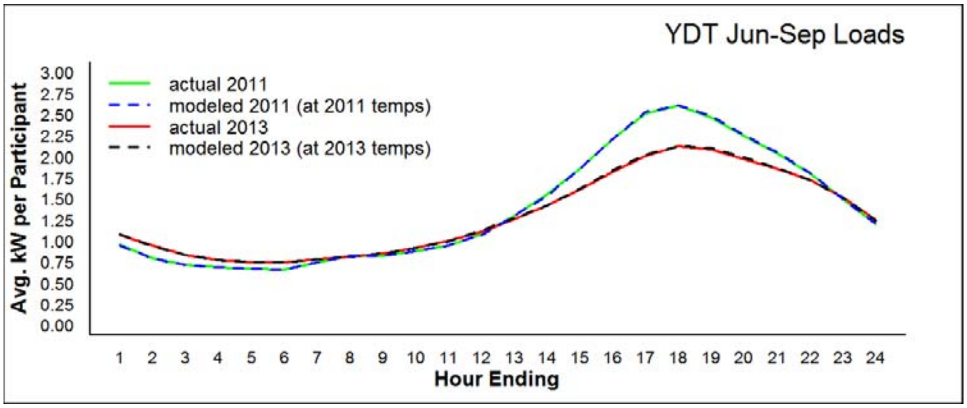


Figure 24. Actual and modeled summer loads, IHD

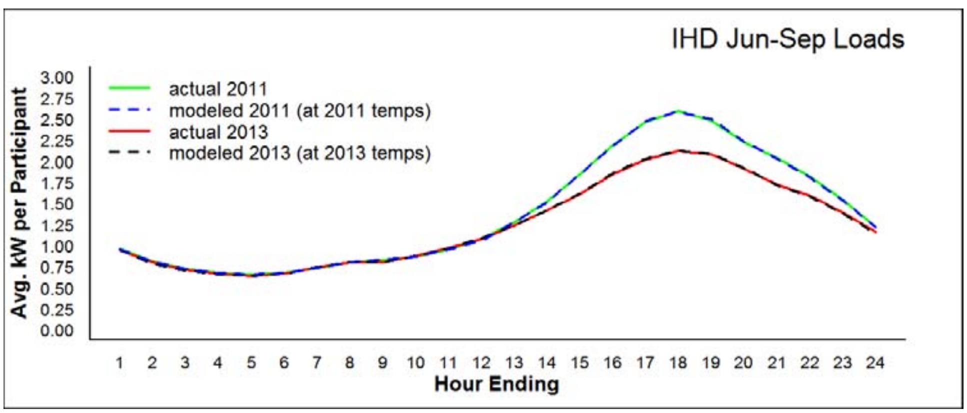


Figure 25. Actual and modeled summer loads, Nest

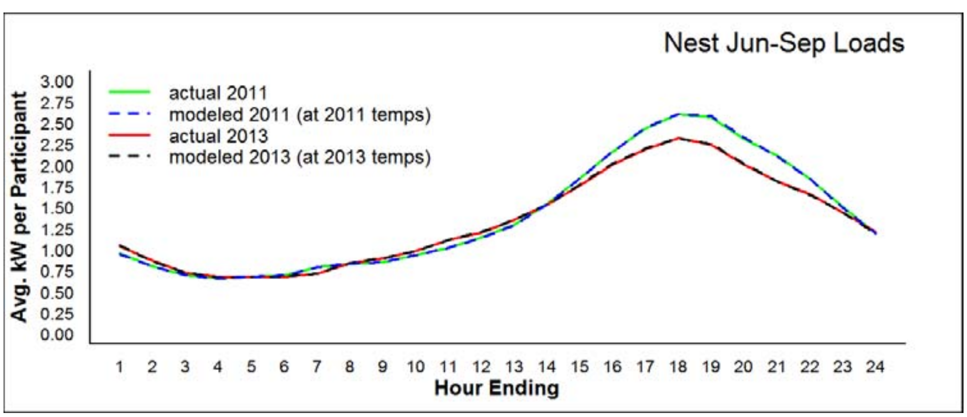
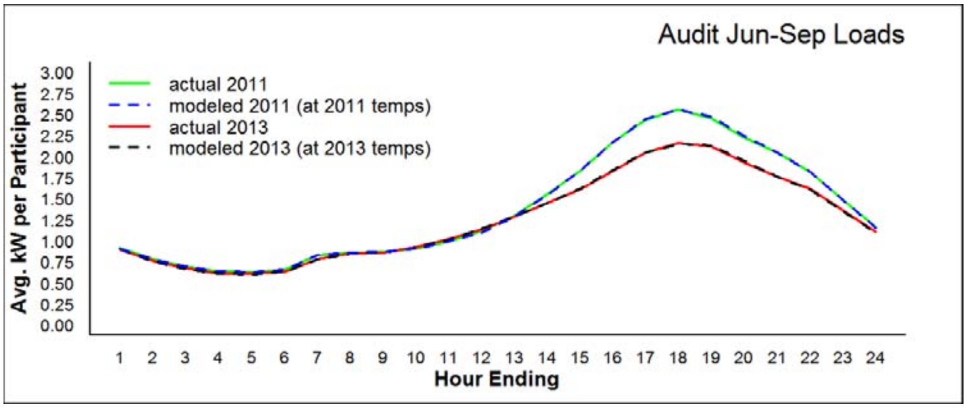


FIGURE 26. ACTUAL AND MODELED SUMMER LOADS, AUDIT



Model Diagnostics

PRE peak model

Figure 27 provides scatter plot of normalized residuals versus fitted values for PRE peak model.

Figure 27.Scatter plot of normalized residuals versus fitted values for PRE peak model

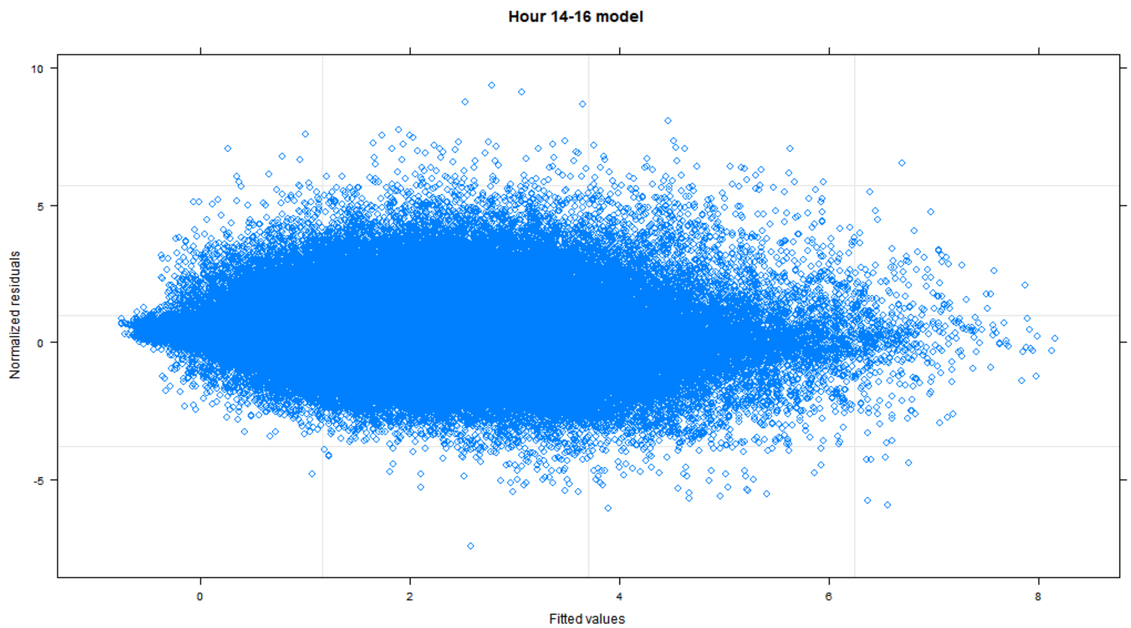


Figure 28 provides normal plot of estimated random effects at customer level for PRE peak model.

Figure 28.Normal plot of estimated random effects (customer level), PRE peak model

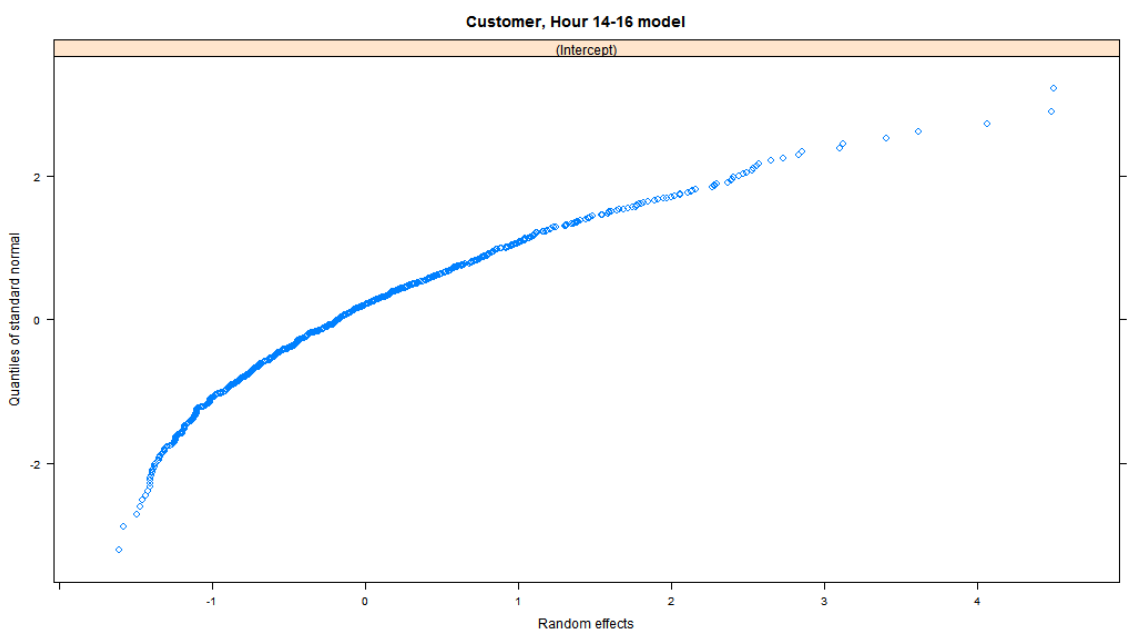


Figure 29 provides normal plot of estimated random effects at day level for PRE peak model.

FIGURE 29. NORMAL PLOT OF ESTIMATED RANDOM EFFECTS (DAY LEVEL), PRE PEAK MODEL

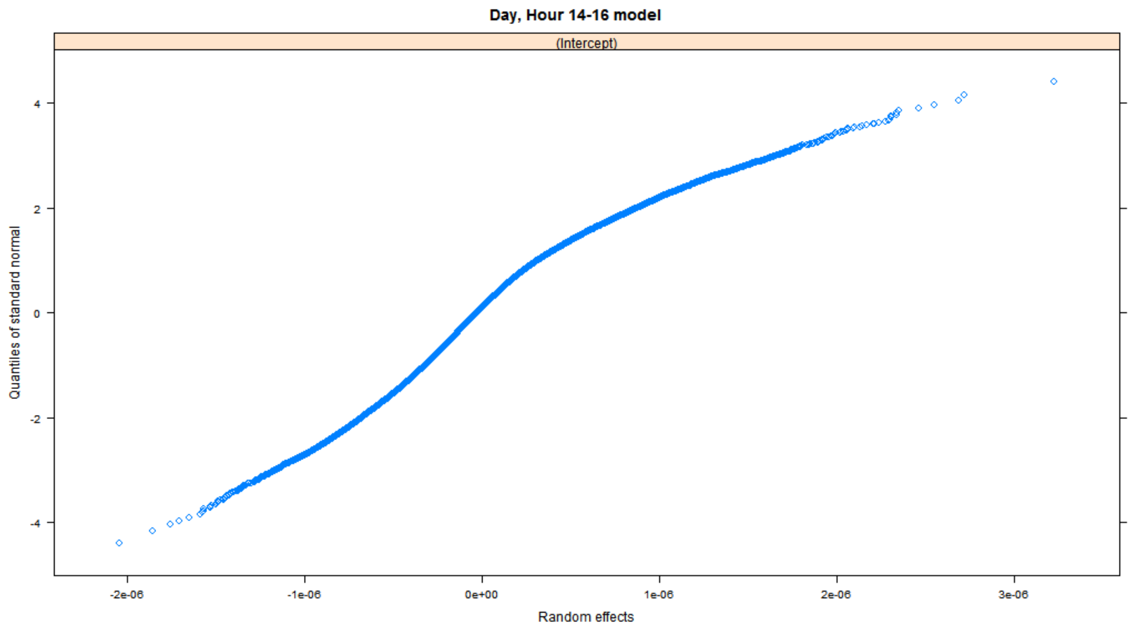


Figure 30 provides normal plot of residuals for PRE peak model.

FIGURE 30. NORMAL PLOT OF RESIDUALS, PRE PEAK MODEL

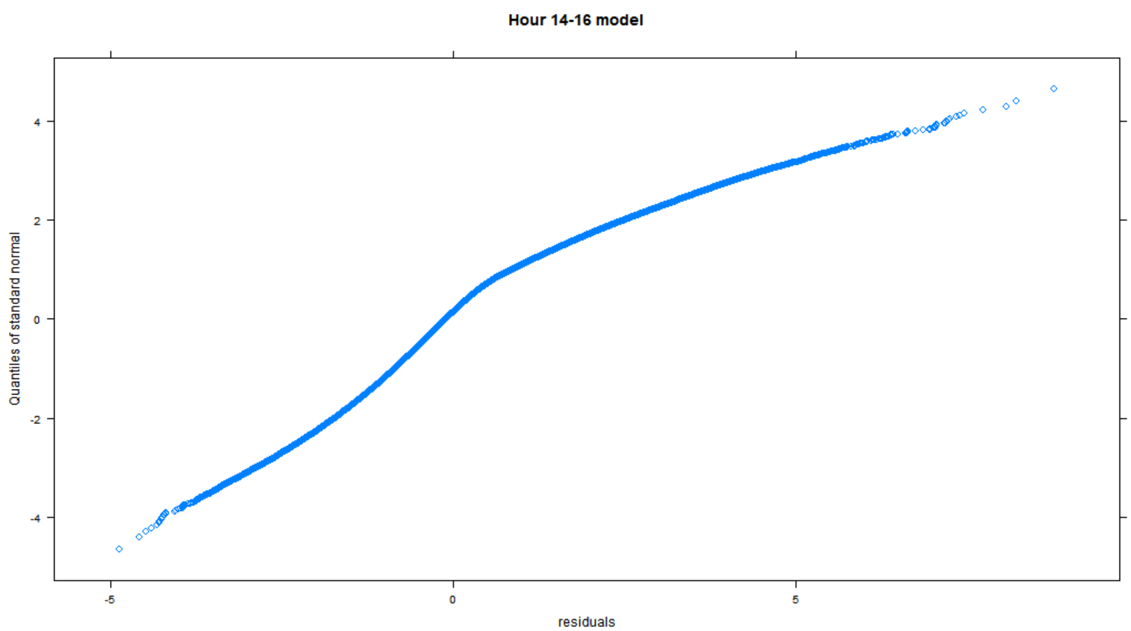


Figure 31 provides a histogram of normalized residuals for PRE peak model.

FIGURE 31.HISTOGRAM OF NORMALIZED RESIDUALS, PRE PEAK MODEL

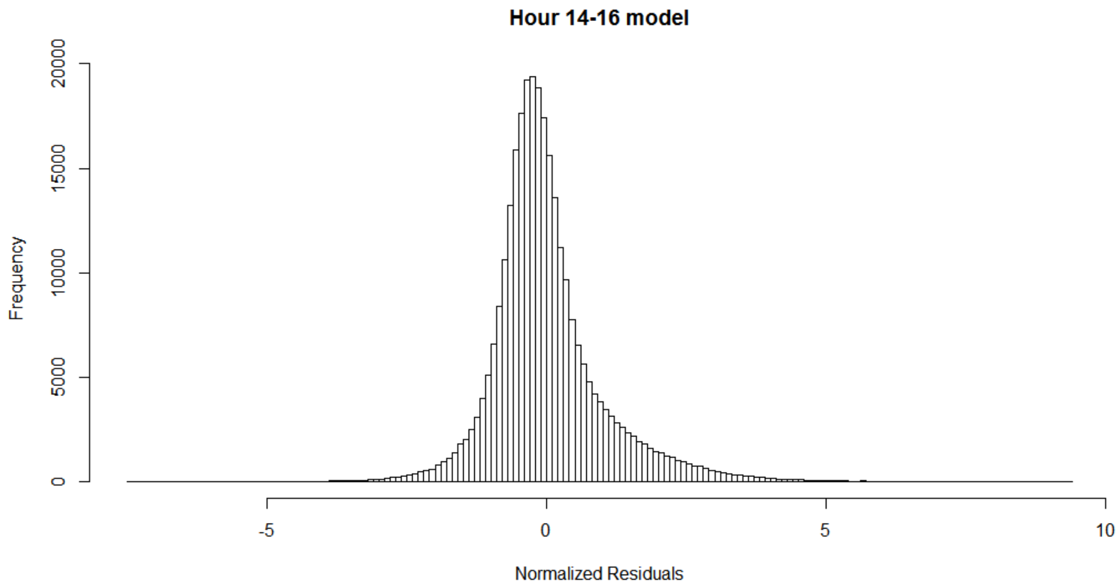


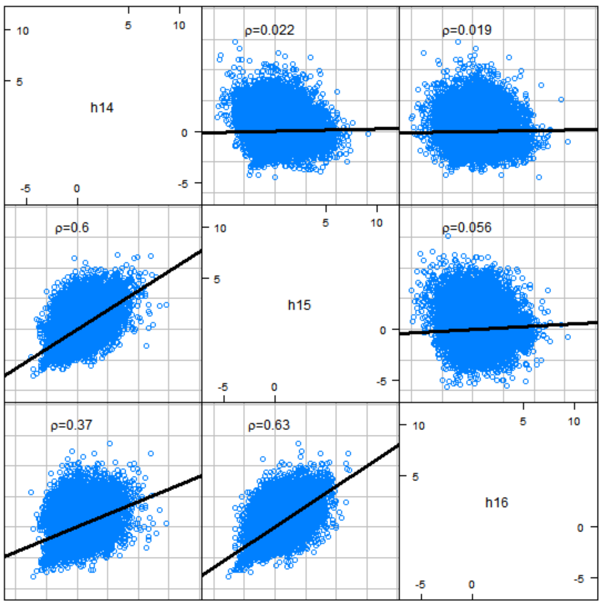
Table 17 provides summary of residuals for PRE peak model.

TABLE 17.SUMMARY OF RESIDUALS, PRE PEAK MODEL

Min	1st Qu.	Median	Mean	3rd Qu.	Max
-7.4150	-0.5484	-0.1521	0.0000	0.3568	9.3460

Figure 32 below the scatter plot of Pearson and Normalized residuals (pearson - lower panel, normalized – upper panel). Pearson residuals show a correlation between the residuals for hours 14-16. Normalized residuals show that the residuals are approximately uncorrelated for hours 14-16.

FIGURE 32.SCATTER PLOT MATRIX OF PEARSON AND NORMALIZED RESIDUALS, PRE PEAK MODEL



PEAK MODEL

Figure 33 provides scatter plot of normalized residuals versus fitted values for PEAK model.

FIGURE 33. SCATTER PLOT OF NORMALIZED RESIDUALS VERSUS FITTED VALUES FOR PEAK MODEL

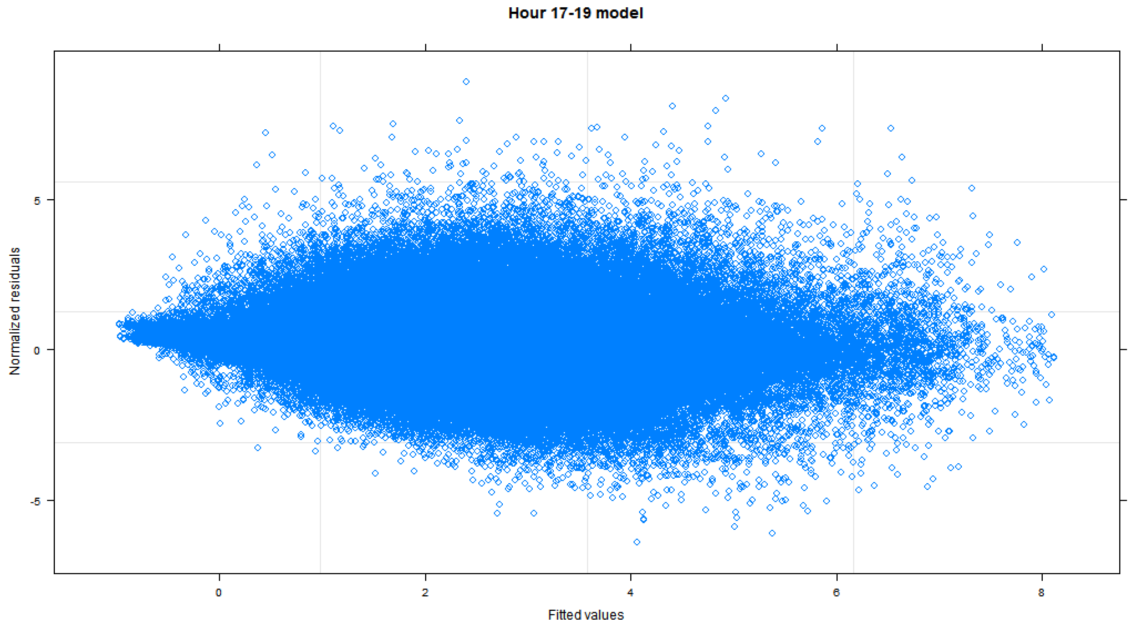


Figure 34 provides normal plot of estimated random effects at customer level for PEAK model.

FIGURE 34. NORMAL PLOT OF ESTIMATED RANDOM EFFECTS (CUSTOMER LEVEL), PEAK MODEL

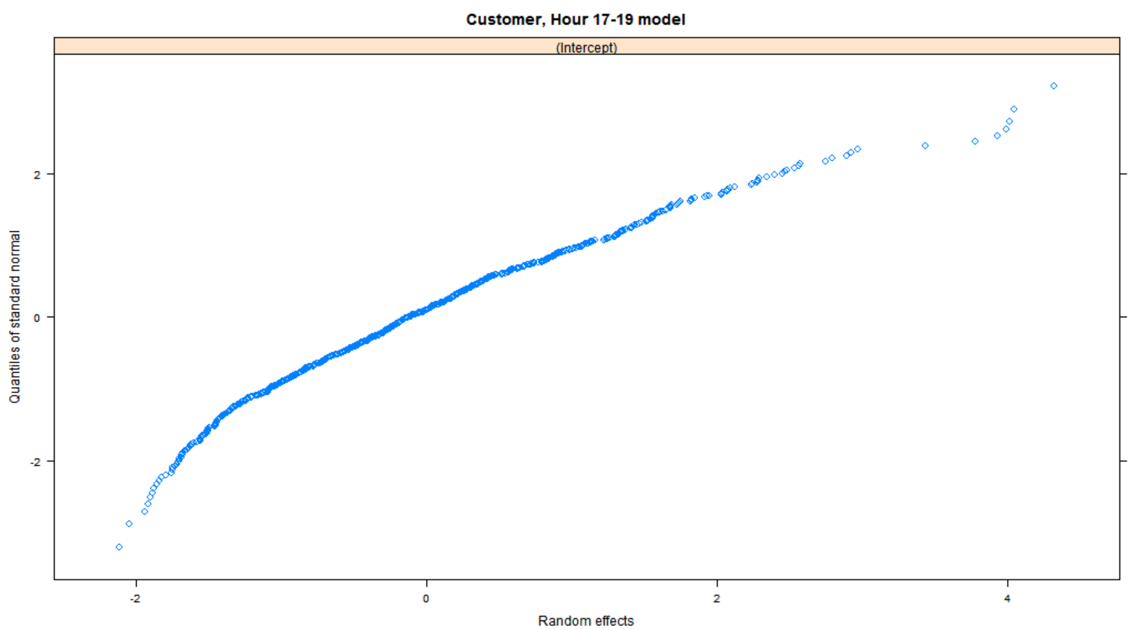


Figure 35 provides normal plot of estimated random effects at day level for PEAK model.

Figure 35. Normal plot of estimated random effects (day level), PEAK model

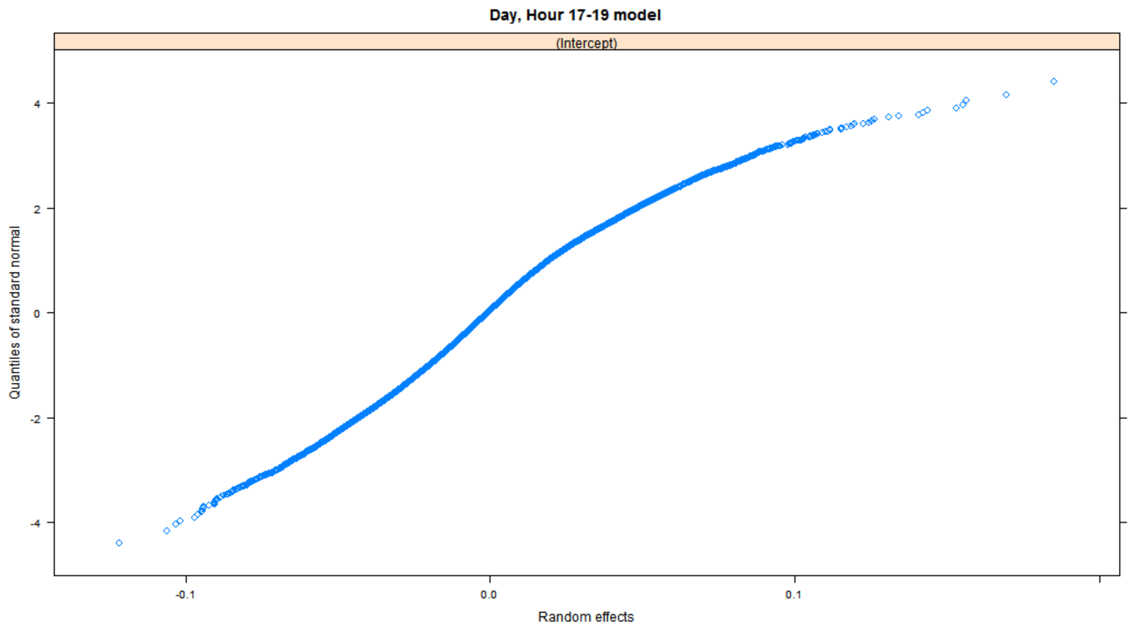


Figure 36 provides normal plot of residuals for PEAK model.

Figure 36. Normal plot of residuals, PEAK model

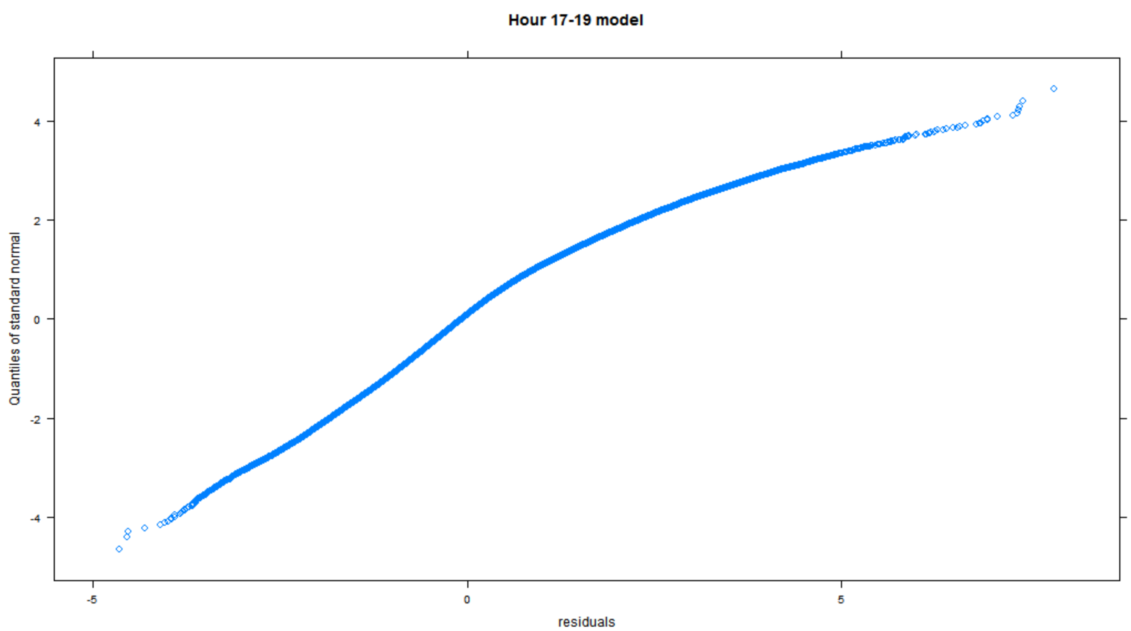


Figure 37 provides a histogram of normalized residuals for PEAK model.

FIGURE 37. HISTOGRAM OF NORMALIZED RESIDUALS, PEAK MODEL

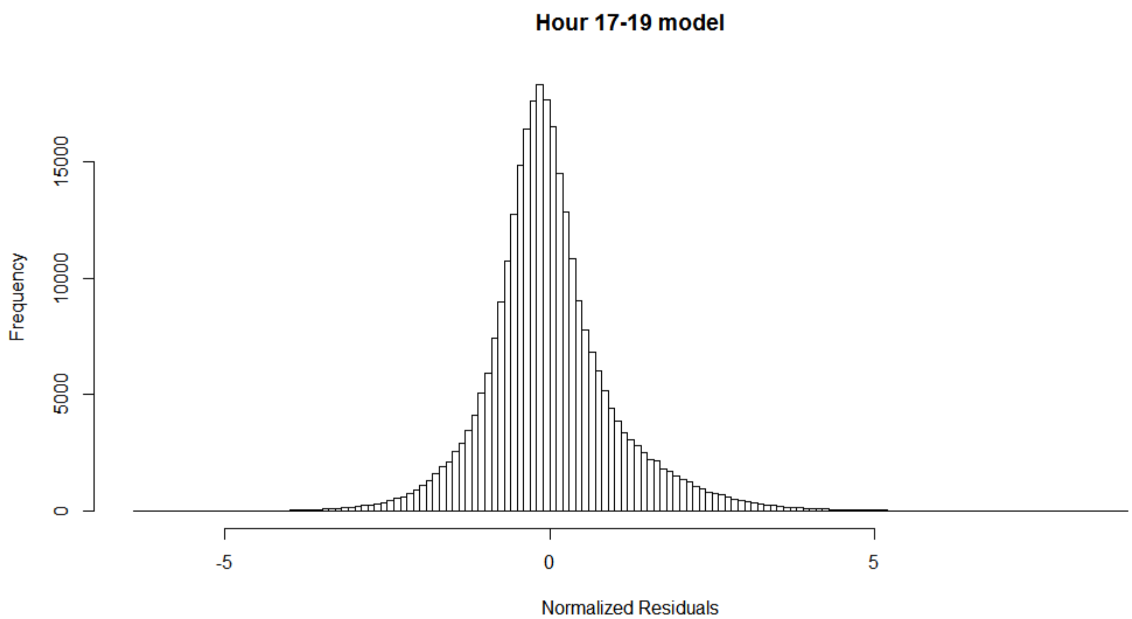


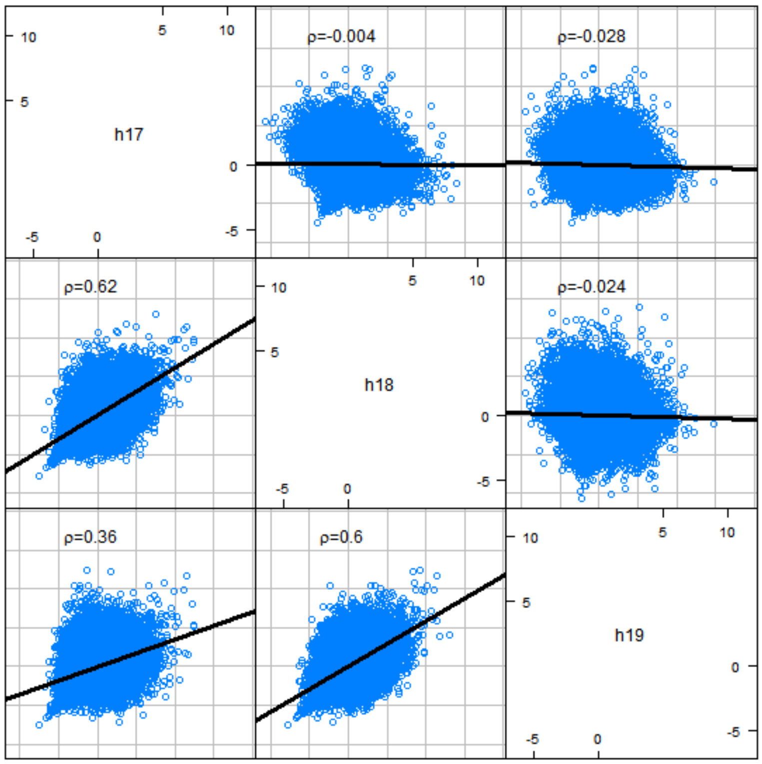
Table 18 provides summary of residuals for PEAK model.

TABLE 18. SUMMARY OF RESIDUALS, PEAK MODEL

Min	1st Qu.	Median	Mean	3rd Qu.	Max
-6.3950	-0.5329	-0.0909	0.00000	0.4270	8.8950

Figure 38 shows the scatter plot of Pearson and Normalized residuals (pearson - lower panel, normalized – upper panel). Pearson residuals show a correlation between the residuals for hours 17-19. Normalized residuals show that the residuals are approximately uncorrelated for hours 17-19.

FIGURE 38.SCATTER PLOT MATRIX OF PEARSON AND NORMALIZED RESIDUALS, PEAK MODEL



POST PEAK MODEL

Figure 39 provides scatter plot of normalized residuals versus fitted values for POST peak model.

FIGURE 39.SCATTER PLOT OF NORMALIZED RESIDUALS VERSUS FITTED VALUES FOR POST PEAK MODEL

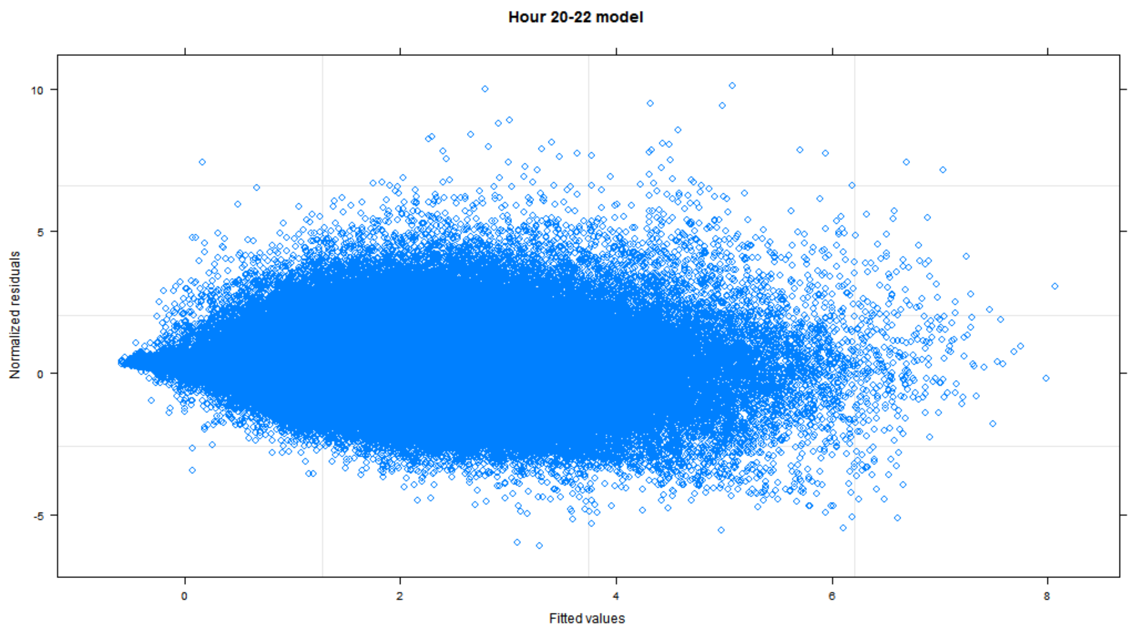


Figure 40 provides normal plot of estimated random effects at customer level for POST peak model.

FIGURE 40.NORMAL PLOT OF ESTIMATED RANDOM EFFECTS (CUSTOMER LEVEL), POST PEAK MODEL

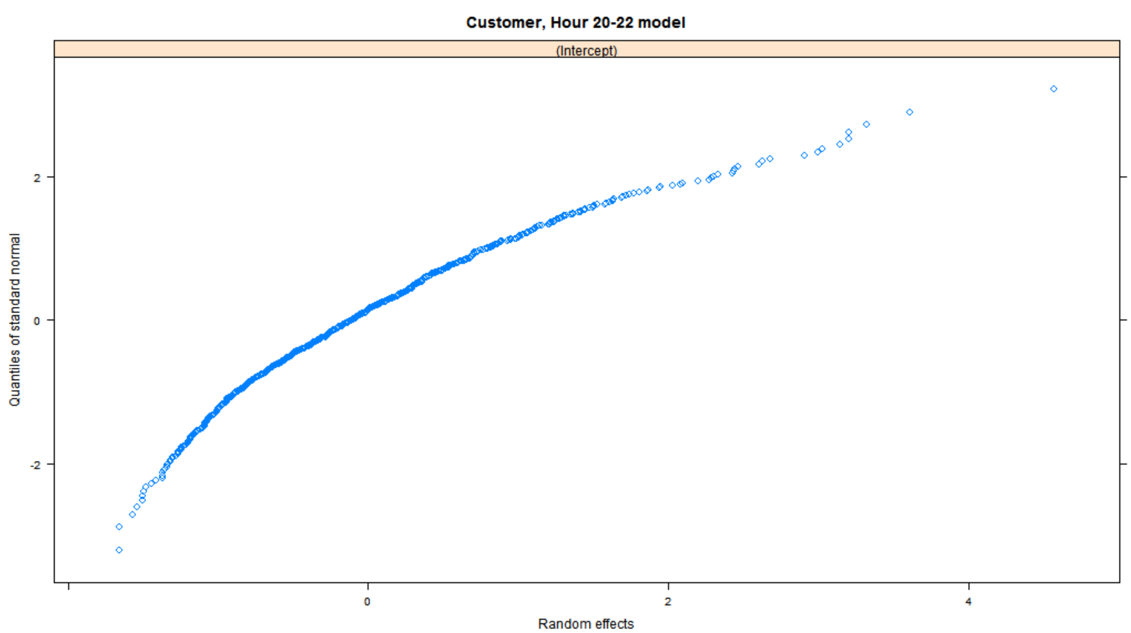


Figure 41 provides normal plot of estimated random effects at day level for POST peak model.

FIGURE 41.NORMAL PLOT OF ESTIMATED RANDOM EFFECTS (DAY LEVEL), POST PEAK MODEL

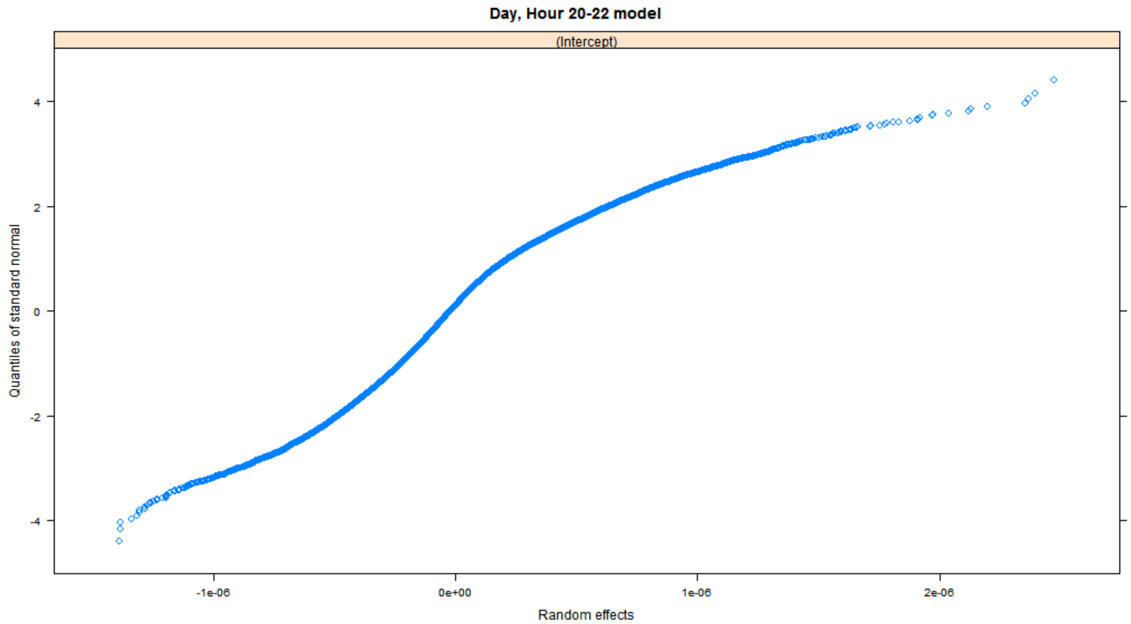


Figure 42 provides normal plot of residuals for POST peak model.

FIGURE 42.NORMAL PLOT OF RESIDUALS, POST PEAK MODEL

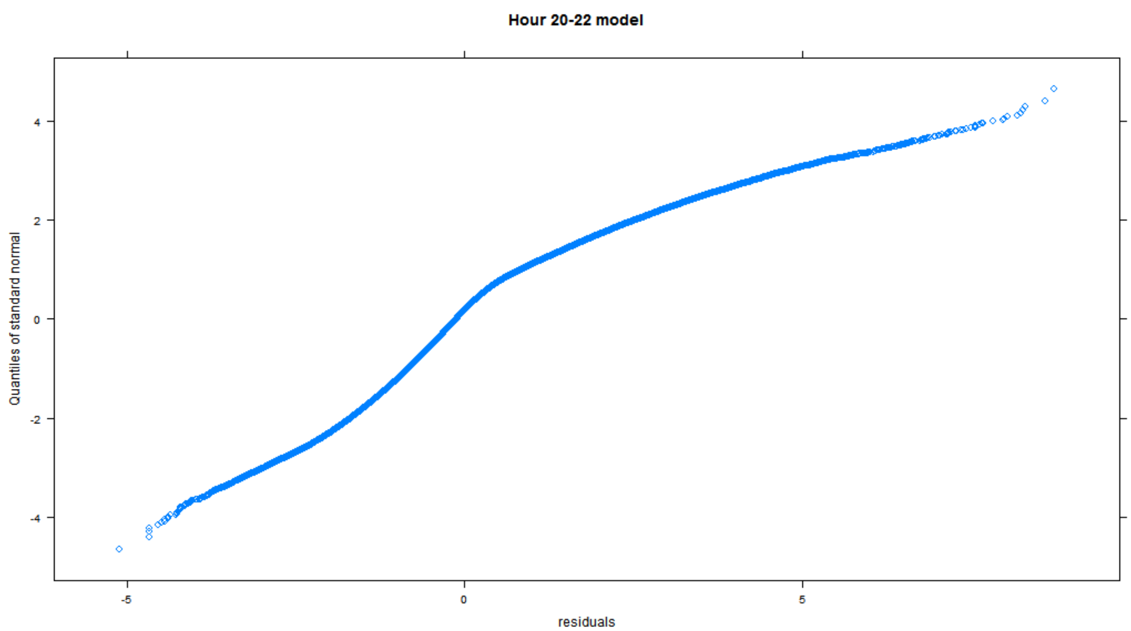


Figure 43 provides a histogram of normalized residuals for POST peak model.

FIGURE 43.HISTOGRAM OF NORMALIZED RESIDUALS, POST PEAK MODEL

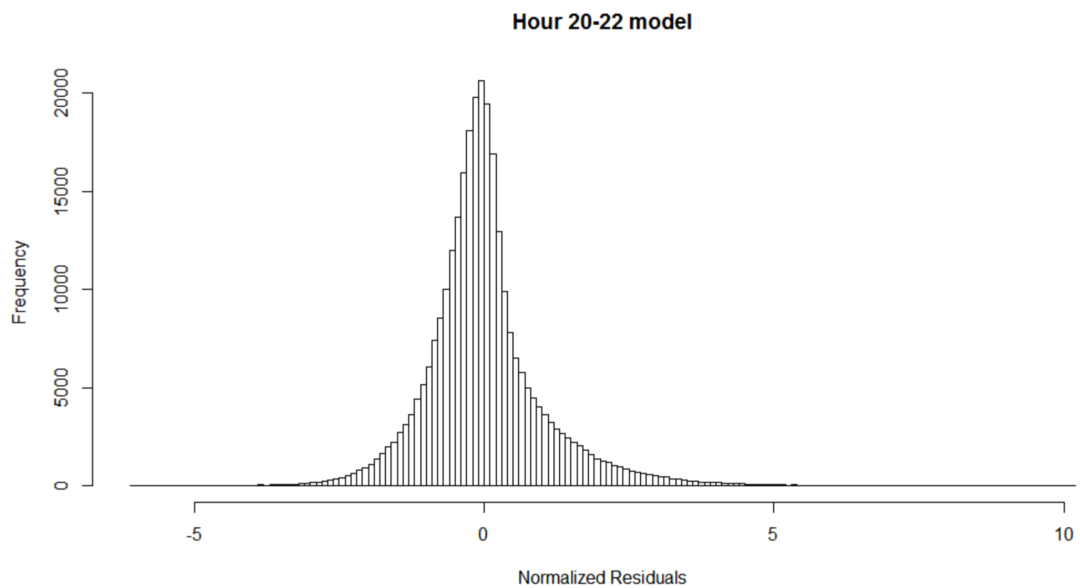


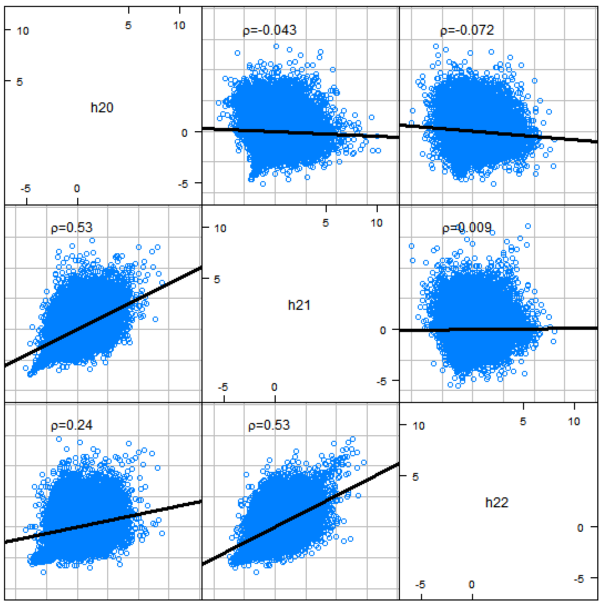
Table 19 provides summary of residuals from POST peak model.

TABLE 19.SUMMARY OF RESIDUALS, POST PEAK MODEL

Min	1st Qu.	Median	Mean	3rd Qu.	Max
-6.0590	-0.5232	-0.0862	0.0000	0.3608	10.1100

Figure 44 below shows the scatter plot of Pearson and Normalized residuals (pearson - lower panel, normalized – upper panel). Pearson residuals show a correlation between the residuals for hours 20-22. Normalized residuals show that the residuals are approximately uncorrelated for hours 20-22.

FIGURE 44.SCATTER PLOT MATRIX OF PEARSON AND NORMALIZED RESIDUALS, POST PEAK MODEL



MODEL DETAILS

CONTRASTS (APPLIES TO ALL 3-HOUR MODELS)

1. *Treatment loads are not different from baseline loads (adjusted for weather and exogenous effects)*

$H_0: L = 0$

$H_a: L \neq 0$

$L = \sum_{i=1}^{12} c_i \mu_i \ where \ \sum_{i=1}^{12} c_i = 0, If \ |t^* = \frac{L}{\sigma^2\{L\}}| \leq t(n-p-q), then \ H_0; otherwise, H_a$ [3]

For peak model, $c_1 through \ c_{12} = {}^1/_3, -{}^1/_3, {}^1/_3, -{}^1/_3, {}^1/_3, -{}^1/_3, -{}^1/_3, {}^1/_3, -{}^1/_3, {}^1/_3, -{}^1/_3, {}^1/_3$

2. *Treatment type has no effect on impacts (adjusted for weather and exogenous effects)*
Same as in 1 above but different set of means.

[3] n=number of observations, p = number of model parameters associated with fixed effects, q = number of covariance parameters with random effects or correlations

CONTRASTS EXAMPLES

YDT peak impact relative to baseline (adjusted for weather and exogenous effects), and comparing YDT and IHD treatments peak impacts (adjusted for weather and pretreatment differences)

1. *Treatment loads are not different from baseline loads (adjusted for weather and exogenous effects)*

$$\hat{L} = \left[\frac{(\hat{\mu}_{YDT.treat.at.hr17} - \hat{\mu}_{YDT.base.at.hr17}) + (\hat{\mu}_{YDT.treat.at.hr18} - \hat{\mu}_{YDT.base.at.hr18}) + (\hat{\mu}_{YDT.treat.at.hr19} - \hat{\mu}_{YDT.base.at.hr19})}{3}\right] - \left[\frac{(\hat{\mu}_{control.treat.hr17} - \hat{\mu}_{control.base.hr17}) + (\hat{\mu}_{control.treat.hr18} - \hat{\mu}_{control.base.hr18}) + (\hat{\mu}_{control.treat.hr19} - \hat{\mu}_{control.base.hr19})}{3}\right]$$

2. *Treatment type has no effect on impacts (adjusted for weather and exogenous effects)*

$$\hat{L} = \left[\frac{(\hat{\mu}_{YDT.treat.at.hr17} - \hat{\mu}_{YDT.base.at.hr17}) + (\hat{\mu}_{YDT.treat.at.hr18} - \hat{\mu}_{YDT.base.at.hr18}) + (\hat{\mu}_{YDT.treat.at.hr19} - \hat{\mu}_{YDT.base.at.hr19})}{3}\right] - \left[\frac{(\hat{\mu}_{IHD.treat.at.hr17} - \hat{\mu}_{IHD.base.at.hr17}) + (\hat{\mu}_{IHD.treat.at.hr18} - \hat{\mu}_{IHD.base.at.hr18}) + (\hat{\mu}_{IHD.treat.at.hr19} - \hat{\mu}_{IHD.base.at.hr19})}{3}\right]$$

Notes:

$\mu's$ are estimated using regression coefficients (provided below) with the temperature profile of interest – average temp weekday summer 2013 days.

Models comparison

Table 20. Model Comparison, PRE peak model

		Model	DF	AIC	BIC	logLik	Test	L.Ratio	p-value
	PRE peak model Random Customer only	1	63	871298.7	871961.8	-435586.4			
	PRE peak model Random Customer & Day	2	64	798920.2	799593.8	-399396.1	1 vs 2	72380.57	<0.0001
Final Model	**PRE peak** model Random Customer & Day AR(1)	3	65	784635.1	785319.2	-392252.5	2 vs 3	14287.07	<0.0001

Table 21. Model Comparison, PEAK model

		Model	DF	AIC	BIC	logLik	Test	L.Ratio	p-value
	PEAK model Random Customer only	1	63	904877.2	905540.3	-452375.6			
	PEAK model Random Customer & Day	2	64	830350.8	831024.5	-415111.4	1 vs 2	74528.38	<0.0001
Final Model	**PEAK** model Random Customer & Day AR(1)	3	65	817306.4	817990.6	-408588.2	2 vs 3	13046.43	<0.0001

Table 22. Model Comparison, POST peak model

		Model	DF	AIC	BIC	logLik	Test	L.Ratio	p-value
	POST peak model Random Customer only	1	63	847159.9	847822.9	-423516.9			
	POST peak model Random Customer & Day	2	64	803250.2	803923.8	-401561.1	1 vs 2	43911.69	<0.0001
Final Model	**POST peak** model Random Customer & Day AR(1)	3	65	789804.0	790488.2	-394837.0	2 vs 3	13448.14	<0.0001

Tests for fixed effects

Table 23.F-tests for variables in the model, PRE peak model

PRE peak model Variable	Numerator DF	Denominator DF	F-value	p-value
CDH	1	183475	39141.93	<0.0001
CDD	1	91023	958.70	<0.0001
hour	3	183475	451.52	<0.0001
Treatment_Period	9	91023	14.27	<0.0001
CDD:hour	2	183475	299.71	<0.0001
CDD:Treatment_Period	9	91023	21.35	<0.0001
hour:Treatment_Period	18	183475	13.70	<0.0001
CDD:hour:Treatment_Period	18	183475	4.32	<0.0001

Table 24. F-tests for variables in the model, PEAK model

PEAK model Variable	Numerator DF	Denominator DF	F-value	p-value
CDH	1	183475	36334.20	<0.0001
CDD	1	91023	1326.49	<0.0001
hour	3	183475	464.99	<0.0001
Treatment_Period	9	91023	58.97	<0.0001
CDD:hour	2	183475	17.71	<0.0001
CDD:Treatment_Period	9	91023	8.04	<0.0001
hour:Treatment_Period	18	183475	8.68	<0.0001
CDD:hour:Treatment_Period	18	183475	1.94	0.0010

Table 25. F-tests for variables in the model, POST peak model

POST peak model Variable	Numerator DF	Denominator DF	F-value	p-value
CDH	1	183470	29373.25	<0.0001
CDD	1	91023	3067.88	<0.0001
hour	3	183470	633.45	<0.0001
Treatment_Period	9	91023	50.16	<0.0001
CDD:hour	2	183470	561.04	<0.0001
CDD:Treatment_Period	9	91023	11.80	<0.0001
hour:Treatment_Period	18	183470	5.90	<0.0001
CDD:hour:Treatment_Period	18	183470	2.64	0.0002

Model Coefficients

Table 26 provides conditional R^2 for PRE peak, Peak, and POST peak models.

Table 26. Conditional R^2 for PRE peak, Peak, and POST peak models

Model	Conditional R^2
PRE peak	0.4778
PEAK	0.5114
POST peak	0.4470

Table 27 through Table 29 provide model coefficients for PRE peak, Peak, and POST peak models. YDT.baseline is the reference level in all 3 models.

Table 27. Model Coefficients, PRE peak model

Variable	Value	Std.Error	DF	t-value	p-value
CDH	0.03269	0.00137	183475	23.83	<0.0001
CDD	0.00217	0.00032	91023	6.76	<0.0001
hour14	1.12830	0.09243	183475	12.21	<0.0001
hour15	1.09051	0.09234	183475	11.81	<0.0001
hour16	1.16662	0.09232	183475	12.64	<0.0001
YDT.treatment	-0.26556	0.04226	91023	-6.28	<0.0001
IHD.baseline	-0.05772	0.12969	91023	-0.45	0.6563
IHD.treatment	-0.27162	0.12530	91023	-2.17	0.0302
Nest.baseline	-0.05211	0.13670	91023	-0.38	0.7031
Nest.treatment	-0.14483	0.13161	91023	-1.10	0.2712
Audit.baseline	-0.08825	0.13178	91023	-0.67	0.5031
Audit.treatment	-0.23624	0.12723	91023	-1.86	0.0633
control.baseline	-0.12976	0.12089	91023	-1.07	0.2831
control.treatment	-0.31595	0.11745	91023	-2.69	0.0071
CDD:hour15	0.00201	0.00027	183475	7.55	<0.0001
CDD:hour16	0.00347	0.00034	183475	10.25	<0.0001
CDD:YDT.treatment	0.00215	0.00034	91023	6.36	<0.0001
CDD:IHD.baseline	0.00022	0.00043	91023	0.52	0.6065
CDD:IHD.treatment	0.00220	0.00034	91023	6.52	<0.0001
CDD:Nest.baseline	0.00047	0.00045	91023	1.05	0.2933
CDD:Nest.treatment	0.00226	0.00034	91023	6.58	<0.0001
CDD:Audit.baseline	0.00122	0.00043	91023	2.82	0.0048
CDD:Audit.treatment	0.00259	0.00034	91023	7.62	<0.0001
CDD:control.baseline	-0.00014	0.00040	91023	-0.34	0.7313

CDD:control.treatment	0.00221	0.00033	91023	6.74	<0.0001
hour15:YDT.treatment	0.02360	0.03699	183475	0.64	0.5236
hour16:YDT.treatment	0.01113	0.04703	183475	0.24	0.8129
hour15:IHD.baseline	0.18088	0.04713	183475	3.84	0.0001
hour16:IHD.baseline	0.13888	0.05989	183475	2.32	0.0204
hour15:IHD.treatment	0.04956	0.03690	183475	1.34	0.1793
hour16:IHD.treatment	0.05551	0.04691	183475	1.18	0.2367
hour15:Nest.baseline	0.09139	0.04964	183475	1.84	0.0657
hour16:Nest.baseline	0.11305	0.06308	183475	1.79	0.0731
hour15:Nest.treatment	0.06329	0.03764	183475	1.68	0.0926
hour16:Nest.treatment	0.11343	0.04785	183475	2.37	0.0178
hour15:Audit.baseline	0.04428	0.04778	183475	0.93	0.3541
hour16:Audit.baseline	0.09239	0.06071	183475	1.52	0.1280
hour15:Audit.treatment	0.02880	0.03712	183475	0.78	0.4378
hour16:Audit.treatment	0.04160	0.04718	183475	0.88	0.3780
hour15:control.baseline	0.03208	0.04391	183475	0.73	0.4650
hour16:control.baseline	0.07848	0.05579	183475	1.41	0.1595
hour15:control.treatment	0.06011	0.03602	183475	1.67	0.0952
hour16:control.treatment	0.07719	0.04580	183475	1.69	0.0919
CDD:hour15:YDT.treatment	-0.00087	0.00030	183475	-2.94	0.0033
CDD:hour16:YDT.treatment	-0.00175	0.00038	183475	-4.66	<0.0001
CDD:hour15:IHD.baseline	-0.00162	0.00037	183475	-4.35	<0.0001
CDD:hour16:IHD.baseline	-0.00151	0.00047	183475	-3.20	0.0014
CDD:hour15:IHD.treatment	-0.00108	0.00029	183475	-3.68	0.0002
CDD:hour16:IHD.treatment	-0.00184	0.00037	183475	-4.92	<0.0001
CDD:hour15:Nest.baseline	-0.00099	0.00039	183475	-2.53	0.0114
CDD:hour16:Nest.baseline	-0.00147	0.00050	183475	-2.96	0.0031
CDD:hour15:Nest.treatment	-0.00086	0.00030	183475	-2.86	0.0042
CDD:hour16:Nest.treatment	-0.00214	0.00038	183475	-5.61	<0.0001
CDD:hour15:Audit.baseline	-0.00076	0.00038	183475	-1.99	0.0461
CDD:hour16:Audit.baseline	-0.00117	0.00048	183475	-2.44	0.0148
CDD:hour15:Audit.treatment	-0.00119	0.00030	183475	-4.01	0.0001
CDD:hour16:Audit.treatment	-0.00229	0.00038	183475	-6.08	<0.0001
CDD:hour15:control.baseline	-0.00073	0.00035	183475	-2.10	0.0354
CDD:hour16:control.baseline	-0.00144	0.00044	183475	-3.27	0.0011
CDD:hour15:control.treatment	-0.00124	0.00029	183475	-4.31	<0.0001
CDD:hour16:control.treatment	-0.00211	0.00036	183475	-5.78	<0.0001

TABLE 28. MODEL COEFFICIENTS, PEAK MODEL

Variable	Coefficient	Std.Error	DF	t-value	p-value
CDH	0.038939	0.00150	183475	26.02	<0.0001
CDD	0.005628	0.00035	91023	15.87	<0.0001
hour17	1.301354	0.10151	183475	12.82	<0.0001
hour18	1.329982	0.10158	183475	13.09	<0.0001
hour19	1.311609	0.10157	183475	12.91	<0.0001
YDT.treatment	-0.328523	0.04484	91023	-7.33	<0.0001
IHD.baseline	0.060842	0.14244	91023	0.43	0.6693
IHD.treatment	-0.277460	0.13792	91023	-2.01	0.0443
Nest.baseline	-0.039470	0.15015	91023	-0.26	0.7926
Nest.treatment	-0.081445	0.14492	91023	-0.56	0.5741
Audit.baseline	-0.056224	0.14475	91023	-0.39	0.6977
Audit.treatment	-0.246591	0.14007	91023	-1.76	0.0783
control.baseline	-0.179320	0.13278	91023	-1.35	0.1768
control.treatment	-0.287103	0.12923	91023	-2.22	0.0263
CDD:hour18	0.000090	0.00028	183475	0.32	0.7484
CDD:hour19	-0.001160	0.00036	183475	-3.24	0.0012
CDD:YDT.treatment	0.000241	0.00036	91023	0.67	0.5010
CDD:IHD.baseline	-0.001340	0.00045	91023	-2.97	0.0030
CDD:IHD.treatment	-0.000050	0.00036	91023	-0.14	0.8893
CDD:Nest.baseline	-0.000450	0.00048	91023	-0.94	0.3452
CDD:Nest.treatment	-0.000305	0.00036	91023	-0.84	0.4025
CDD:Audit.baseline	0.000205	0.00046	91023	0.45	0.6561
CDD:Audit.treatment	0.000068	0.00036	91023	0.19	0.8499
CDD:control.baseline	-0.001287	0.00042	91023		0.0022
CDD:control.treatment	-0.000351	0.00035	91023	-1.01	0.3135
hour18:YDT.treatment	0.025483	0.03922	183475	0.65	0.5158
hour19:YDT.treatment	0.004386	0.04987	183475	0.09	0.9299
hour18:IHD.baseline	0.023082	0.04997	183475	0.46	0.6441
hour19:IHD.baseline	-0.049018	0.06353	183475	-0.77	0.4404
hour18:IHD.treatment	0.018323	0.03912	183475	0.47	0.6395
hour19:IHD.treatment	-0.003668	0.04974	183475	-0.07	0.9412
hour18:Nest.baseline	0.125801	0.05263	183475	2.39	0.0168
hour19:Nest.baseline	0.138060	0.06692	183475	2.06	0.0391
hour18:Nest.treatment	0.002646	0.03990	183475	0.07	0.9471
hour19:Nest.treatment	-0.072720	0.05073	183475	-1.43	0.1518

hour18:Audit.baseline	0.031630	0.05065	183475	0.62	0.5323
hour19:Audit.baseline	0.030130	0.06440	183475	0.47	0.6399
hour18:Audit.treatment	0.024807	0.03935	183475	0.63	0.5284
hour19:Audit.treatment	-0.000410	0.05003	183475	-0.01	0.9935
hour18:control.baseline	-0.021313	0.04655	183475	-0.46	0.6471
hour19:control.baseline	-0.093052	0.05919	183475	-1.57	0.1159
hour18:control.treatment	0.015101	0.03819	183475	0.40	0.6925
hour19:control.treatment	-0.012973	0.04856	183475	-0.27	0.7893
CDD:hour18:YDT.treatment	0.000016	0.00031	183475	0.05	0.9606
CDD:hour19:YDT.treatment	0.001107	0.00040	183475	2.77	0.0055
CDD:hour18:IHD.baseline	0.000208	0.00039	183475	0.53	0.5978
CDD:hour19:IHD.baseline	0.001262	0.00050	183475	2.51	0.0119
CDD:hour18:IHD.treatment	-0.000092	0.00031	183475	-0.29	0.7691
CDD:hour19:IHD.treatment	0.001026	0.00040	183475	2.58	0.0098
CDD:hour18:Nest.baseline	-0.000456	0.00042	183475	-1.10	0.2731
CDD:hour19:Nest.baseline	0.000351	0.00053	183475	0.66	0.5068
CDD:hour18:Nest.treatment	0.000315	0.00032	183475	0.99	0.3224
CDD:hour19:Nest.treatment	0.001451	0.00041	183475	3.58	0.0003
CDD:hour18:Audit.baseline	-0.000010	0.00040	183475	-0.02	0.9807
CDD:hour19:Audit.baseline	0.000281	0.00051	183475	0.55	0.5826
CDD:hour18:Audit.treatment	-0.000035	0.00031	183475	-0.11	0.9121
CDD:hour19:Audit.treatment	0.001018	0.00040	183475	2.55	0.0109
CDD:hour18:control.baseline	0.000043	0.00037	183475	0.12	0.9068
CDD:hour19:control.baseline	0.000705	0.00047	183475	1.51	0.1317
CDD:hour18:control.treatment	-0.000148	0.00030	183475	-0.49	0.6270
CDD:hour19:control.treatment	0.000919	0.00039	183475	2.38	0.0175

Table 29. Model Coefficients, POST peak model

Variable	Coefficient	Std.Error	DF	t-value	p-value
CDH	0.00866	0.0009685	183470	8.95	<0.0001
CDD	0.00630	0.0003092	91023	20.36	<0.0001
hour20	1.39534	0.0838358	183470	16.64	<0.0001
hour21	1.28745	0.0837886	183470	15.37	<0.0001
hour22	1.25715	0.0838086	183470	15.00	<0.0001
YDT.treatment	-0.32658	0.0404161	91023	-8.08	<0.0001
IHD.baseline	0.00876	0.1177245	91023	0.07	0.9407
IHD.treatment	-0.30463	0.1132690	91023	-2.69	0.0072
Nest.baseline	0.01773	0.1240900	91023	0.14	0.8864
Nest.treatment	-0.19217	0.1189283	91023	-1.62	0.1061
Audit.baseline	-0.08684	0.1196215	91023	-0.73	0.4679
Audit.treatment	-0.28105	0.1150025	91023	-2.44	0.0145
control.baseline	-0.28735	0.1097354	91023	-2.62	0.0088
control.treatment	-0.33886	0.1062419	91023	-3.19	0.0014
CDD:hour21	-0.00055	0.0002836	183470	-1.94	0.0524
CDD:hour22	-0.00191	0.0003514	183470	-5.43	<0.0001
CDD:YDT.treatment	0.00167	0.0003235	91023	5.17	<0.0001
CDD:IHD.baseline	-0.00035	0.0004072	91023	-0.86	0.3886
CDD:IHD.treatment	0.00111	0.0003222	91023	3.43	0.0006
CDD:Nest.baseline	0.00027	0.0004295	91023	0.62	0.5327
CDD:Nest.treatment	0.00081	0.0003289	91023	2.45	0.0142
CDD:Audit.baseline	0.00085	0.0004145	91023	2.06	0.0394
CDD:Audit.treatment	0.00113	0.0003246	91023	3.48	0.0005
CDD:control.baseline	-0.00070	0.0003795	91023	-1.85	0.0640
CDD:control.treatment	0.00083	0.0003139	91023	2.64	0.0083
hour21:YDT.treatment	0.15554	0.0395149	183470	3.94	0.0001
hour22:YDT.treatment	0.15470	0.0487337	183470	3.17	0.0015
hour21:IHD.baseline	0.08203	0.0503424	183470	1.63	0.1032
hour22:IHD.baseline	0.02384	0.0620925	183470	0.38	0.7010
hour21:IHD.treatment	0.10761	0.0394144	183470	2.73	0.0063
hour22:IHD.treatment	0.14405	0.0486082	183470	2.96	0.0030
hour21:Nest.baseline	0.03726	0.0530269	183470	0.70	0.4822
hour22:Nest.baseline	0.00944	0.0654041	183470	0.14	0.8852
hour21:Nest.treatment	0.04942	0.0402035	183470	1.23	0.2190
hour22:Nest.treatment	0.01470	0.0495819	183470	0.30	0.7668

hour21:Audit.baseline	0.11606	0.0510359	183470	2.27	0.0230
hour22:Audit.baseline	0.12593	0.0629467	183470	2.00	0.0454
hour21:Audit.treatment	0.11724	0.0396452	183470	2.96	0.0031
hour22:Audit.treatment	0.14000	0.0488938	183470	2.86	0.0042
hour21:control.baseline	0.09697	0.0469002	183470	2.07	0.0387
hour22:control.baseline	0.10829	0.0578466	183470	1.87	0.0612
hour21:control.treatment	0.09919	0.0384807	183470	2.58	0.0099
hour22:control.treatment	0.10003	0.0474562	183470	2.11	0.0350
CDD:hour21:YDT.treatment	-0.00117	0.0003162	183470	-3.69	0.0002
CDD:hour22:YDT.treatment	-0.00076	0.0003902	183470	-1.95	0.0512
CDD:hour21:IHD.baseline	-0.00037	0.0003976	183470	-0.92	0.3585
CDD:hour22:IHD.baseline	0.00022	0.0004904	183470	0.45	0.6531
CDD:hour21:IHD.treatment	-0.00110	0.0003146	183470	-3.51	0.0004
CDD:hour22:IHD.treatment	-0.00075	0.0003883	183470	-1.94	0.0528
CDD:hour21:Nest.baseline	-0.00036	0.0004193	183470	-0.87	0.3841
CDD:hour22:Nest.baseline	-0.00039	0.0005172	183470	-0.76	0.4467
CDD:hour21:Nest.treatment	-0.00062	0.0003211	183470	-1.94	0.0521
CDD:hour22:Nest.treatment	0.00020	0.0003963	183470	0.49	0.6222
CDD:hour21:Audit.baseline	-0.00079	0.0004047	183470	-1.96	0.0497
CDD:hour22:Audit.baseline	-0.00078	0.0004992	183470	-1.56	0.1189
CDD:hour21:Audit.treatment	-0.00099	0.0003169	183470	-3.14	0.0017
CDD:hour22:Audit.treatment	-0.00060	0.0003911	183470	-1.54	0.1240
CDD:hour21:control.baseline	-0.00039	0.0003705	183470	-1.04	0.2974
CDD:hour22:control.baseline	0.00002	0.0004570	183470	0.05	0.9606
CDD:hour21:control.treatment	-0.00070	0.0003064	183470	-2.29	0.0221
CDD:hour22:control.treatment	-0.00029	0.0003782	183470	-0.75	0.4511

Correlations

There is a high correlation between CDH and CDD variables (peak cor=0.95) because CDD is constructed from CDH (see model description for how CDH and CDD are calculated). Both are needed in the model as one captures temperature at the hourly level while the other captures temperatures at the day level. Potential multicollinearity does not have any effect on interpretation of model coefficients in our case because CDH and CDD values that enter model for predictions always vary together, i.e. if we look at a 106°F day, then both CDH and CDD are calculated from 106°F day temperatures. In other words, we don't make predictions with different temp profiles for CDH and CDD and we will never wish to keep one constant letting the other one take on values from a different temperature profile.

Another possible consequence of multicollinearity is large standard errors for corresponding explanatory variables, which is not the case.

Table 30 through Table 32 provide variance covariance matrices for 3 hour models.

Table 30. Variance covariance matrix, PRE peak model

	Variance	StdDev
Customer (Intercept)	0.9546522	0.97706306
Day (Intercept)	3.578911e-07	0.00059824
Residual	1.382815	1.17593173

Table 31. Variance covariance matrix, PEAK model

	Variance	StdDev
Customer (Intercept)	1.17096734	1.0821124
Day (Intercept)	0.02246246	0.1498748
Residual	1.53699274	1.2397551

Table 32. Variance covariance matrix, POST peak model

	Variance	StdDev
Customer (Intercept)	0.8029259	0.8960613430
Day (Intercept)	2.406600e-07	0.0004905711
Residual	1.293431	1.1372911393

Corrections

AR(1) error structure was the only correction applied. See diagnostic plots.

Model Results

Table 33. Summer weekday impacts for Audit, relative to survey control group

Treatment Group	N	Time Period (hour)	Savings (kWh/h)	Standard Error	95% Confidence Interval		Reference Load (2011)	% Savings
Audit	132	14-16	-0.10*	0.0211	-0.1575	-0.0519	1.80	-5.8%
Audit	132	17-19	-0.22*	0.0224	-0.2751	-0.1629	2.37	-9.2%
Audit	132	20-22	-0.24*	0.0192	-0.2902	-0.1940	2.06	-12%
Audit-gas	102	14-16	-0.11*	0.0233	-0.1552	-0.0640	1.71	-6.4%
Audit-gas	102	17-19	-0.26*	0.0250	-0.3054	-0.2074	2.28	-11%
Audit-gas	102	20-21	-0.22*	0.0208	-0.2634	-0.1820	1.90	-12%
Audit-elec	30	14-16	-0.012	0.0542	-0.1179	0.0946	2.02	-0.6%
Audit-elec	30	17-19	-0.014	0.0562	-0.1238	0.0966	2.63	-0.5%
Audit-elec	30	20-21	-0.35*	0.0530	-0.4548	-0.2472	2.68	-13%

* Statistically significant, α=0.05

Table 34. Summer weekday impacts for Treatments, relative to the Audit only group

Treatment Group	N	Time Period (hour)	Savings (kWh/h)	Standard Error	95% Confidence Interval		Reference Load (2011)	% Savings
IHD	141	hour 14-16	+0.006	0.0226	-0.0481	0.0595	1.64	+0.3%
IHD	141	hour 17-19	-0.020	0.0240	-0.0770	0.0374	2.13	-0.9%
IHD	141	hour 20-21	-0.013	0.0206	-0.0624	0.0356	1.80	-0.7%
Nest	115	hour 14-16	+0.15*	0.0238	0.0886	0.2018	1.66	+8.8%
Nest	115	hour 17-19	+0.12*	0.0253	0.0567	0.1771	2.16	+5.4%
Nest	115	hour 20-21	+0.023	0.0217	-0.0282	0.0750	1.83	+1.3%
YDT	137	hour 14-16	-0.041	0.0227	-0.0949	0.0133	1.68	-2.4%
YDT	137	hour 17-19	-0.064	0.0242	-0.1212	-0.0063	2.16	-3.0%
YDT	137	hour 20-21	+0.043	0.0207	-0.0064	0.0921	1.79	+2.4%

* Statistically significant, α=0.05

TABLE 35.SUMMER WEEKDAY IMPACTS, BETWEEN-TREATMENT COMPARISONS

Treatment Group	Time Period (hour)	Savings (kWh/h)	Standard Error	95% Confidence Intervals	
YDT vs Audit	14-16	-0.041	0.0227	-0.1021	0.0201
IHD vs Audit	14-16	+0.006	0.0226	-0.0551	0.0665
Nest vs Audit	14-16	**+0.15***	0.0238	0.0860	0.2140
YDT vs IHD	14-16	-0.046	0.0224	-0.1063	0.0143
YDT vs Nest	14-16	**-0.19***	0.0236	-0.2535	-0.1265
IHD vs Nest	14-16	**-0.14***	0.0235	-0.2032	-0.0768
YDT vs Audit	17-19	-0.064	0.0242	-0.1291	0.0011
IHD vs Audit	17-19	-0.020	0.0240	-0.0846	0.0446
Nest vs Audit	17-19	**+0.12***	0.0253	0.0519	0.1881
YDT vs IHD	17-19	-0.044	0.0238	-0.1080	0.0200
YDT vs Nest	17-19	**-0.18***	0.0251	-0.2475	-0.1125
IHD vs Nest	17-19	**-0.14***	0.0250	-0.2072	-0.0728
YDT vs Audit	20-22	+0.043	0.0207	-0.0127	0.0987
IHD vs Audit	20-22	-0.013	0.0206	-0.0684	0.0424
Nest vs Audit	20-22	+0.023	0.0217	-0.0354	0.0814
YDT vs IHD	20-22	**+0.056***	0.0204	0.0011	0.1109
YDT vs Nest	20-22	+0.019	0.0215	-0.0388	0.0768
IHD vs Nest	20-22	-0.037	0.0214	-0.0946	0.0206

* Statistically significant, α=0.05

Appendix B. Seasonal Load Model

All days including weekends and holidays were included in the analysis

- Baseline = August 1, 2011 – January 31, 2012
- Treatment = June 1, 2013 – January 31, 2014

Model Equation

$$kw_{ij} = \beta 0 + \beta 1 Season + \beta 2 HDH_{ij} + \beta 3 CDD_{ij} + \beta 4_{m-1} Treatment\_Period_m + \beta 5_{m-1}(Season * Treament\_Period_m) + r_i + \varepsilon_{ij}$$

kw_{ij}: kilowatt load for customer i on day j

CDD_{ij}: cooling degree day for customer i on day j

HDD_{ij}: heating degree day = Sum of 24 HDH values for customer i on day j, where If Temperature < 65 for customer i on day j at hour k, then HDH for customer i on day j at hour [illegible] is 65 - Temperature; otherwise, HDH for customer i on day j at hour k is 0

$Treatment\_Period_m$: indicator variables for treatment and treatment period (YDT.baseline=reference level, YDT.treatment, IHD.baseline, IHD.treatment, Nest.baseline, Nest.treatment, Audit.baseline, Audit.treatment, control.baseline, control.treatment)

$Season$: indicator variable for season (Winter = October, November, December, January, February, March, April, May; Summer = June, July, August, September = reference level)

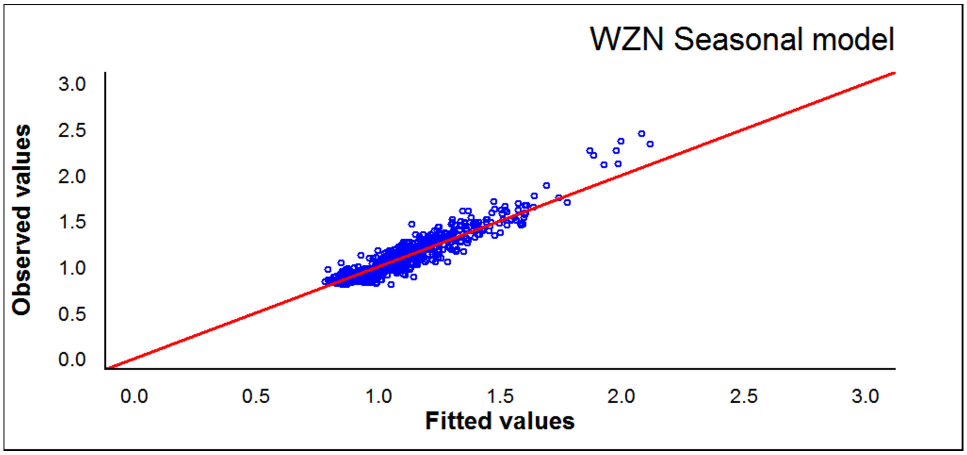
r_i: random effects for customer $\sim N(0, \varphi)$, assumed to be independent for different i

ε_{ij}: error terms $\sim N(0, \delta^2)$**,** assumed to be independent for different i or j and independent of random effects

Model Fit

Figure 45 shows that the modeled loads are nearly identical to the average of the actual loads.

Figure 45. Actual and modeled loads, seasonal model



Model Diagnostics

Figure 46 provides scatter plot of normalized residuals versus fitted values for seasonal model.

Figure 46.Scatter plot of normalized residuals versus fitted values for seasonal model

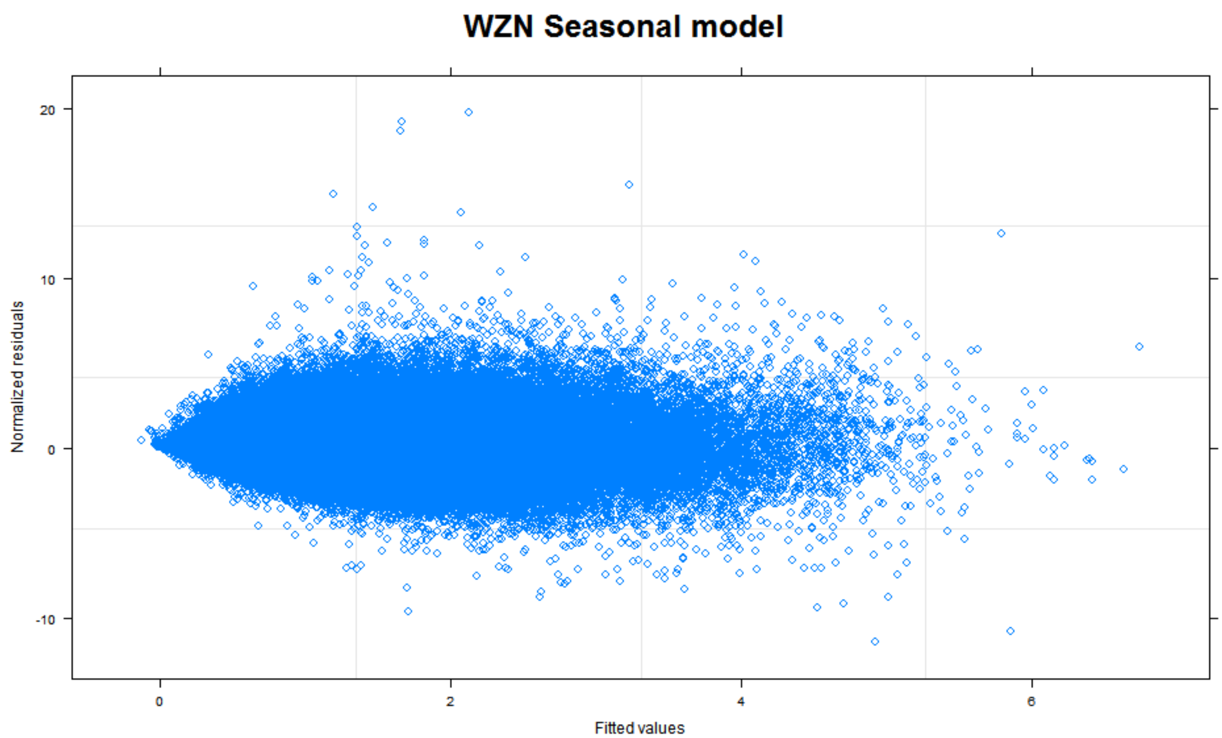


Figure 47 provides normal plots of estimated random effects for seasonal model.

Figure 47.Normal plots of estimated random effects, seasonal model

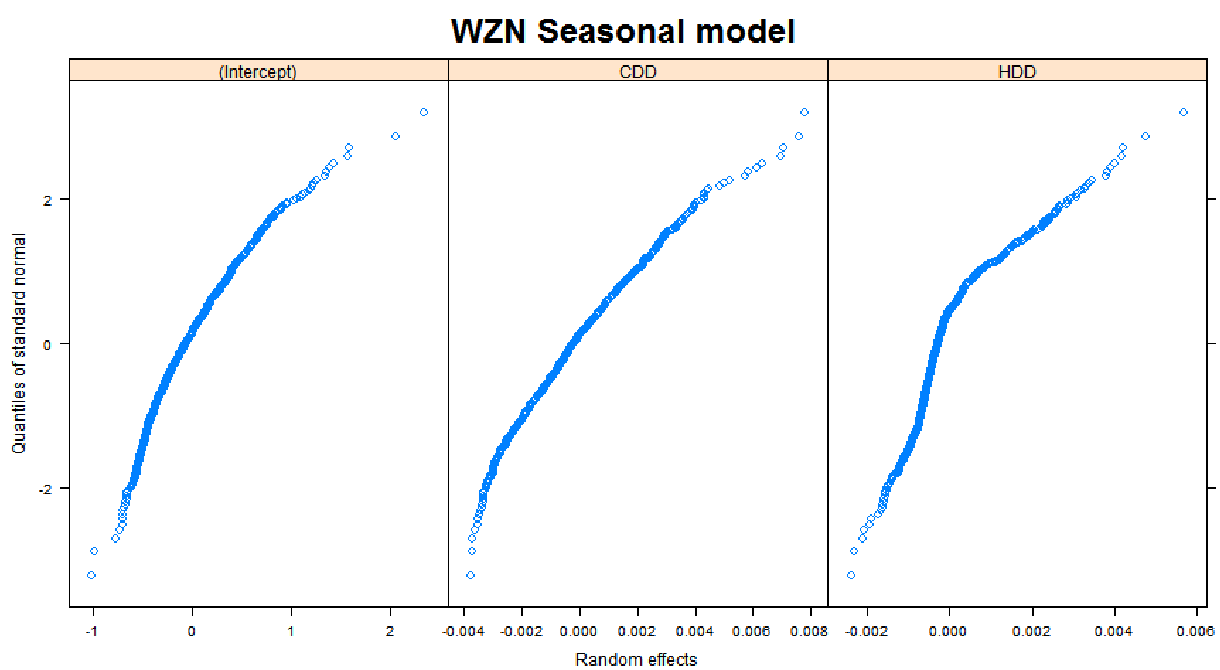


Figure 48 provides scatter plot matrix of random effects for seasonal model.

FIGURE 48.SCATTER PLOT MATRIX OF RANDOM EFFECTS, SEASONAL MODEL

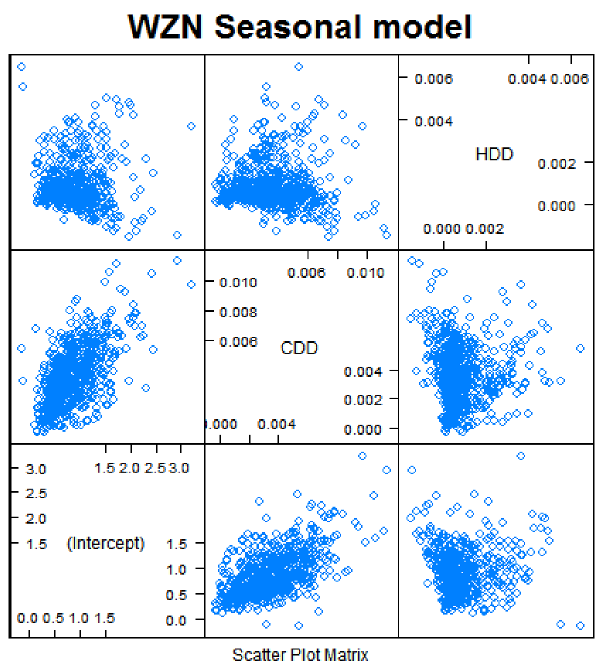


Figure 49 provides normal plot of residuals for seasonal model.

FIGURE 49.NORMAL PLOT OF RESIDUALS, SEASONAL MODEL

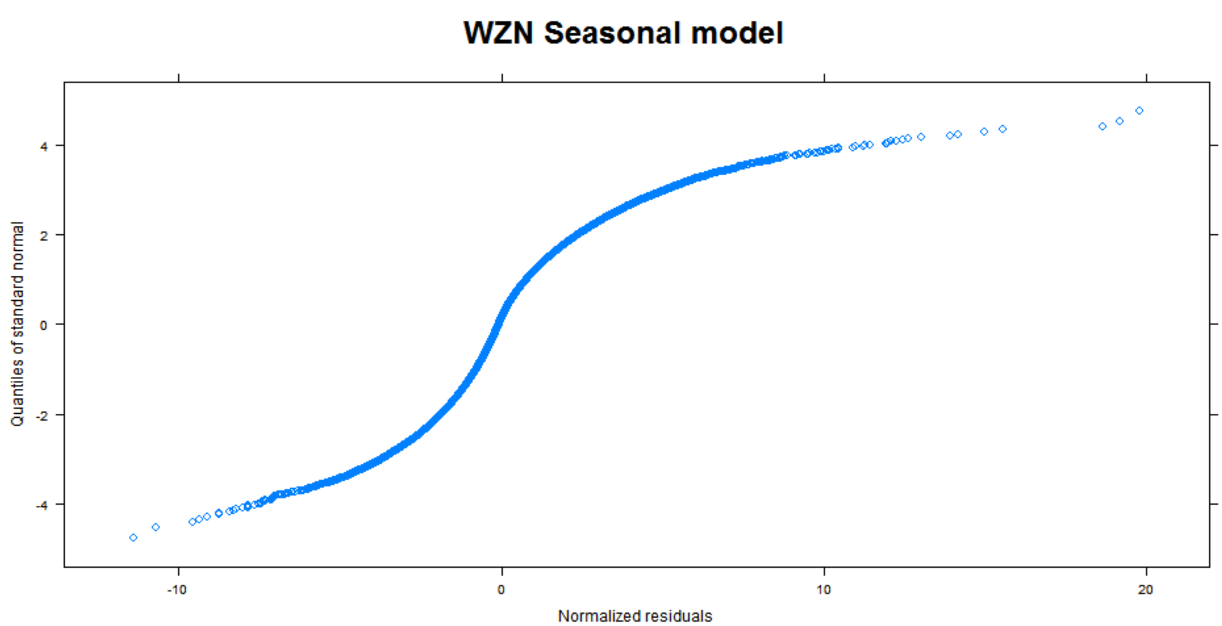


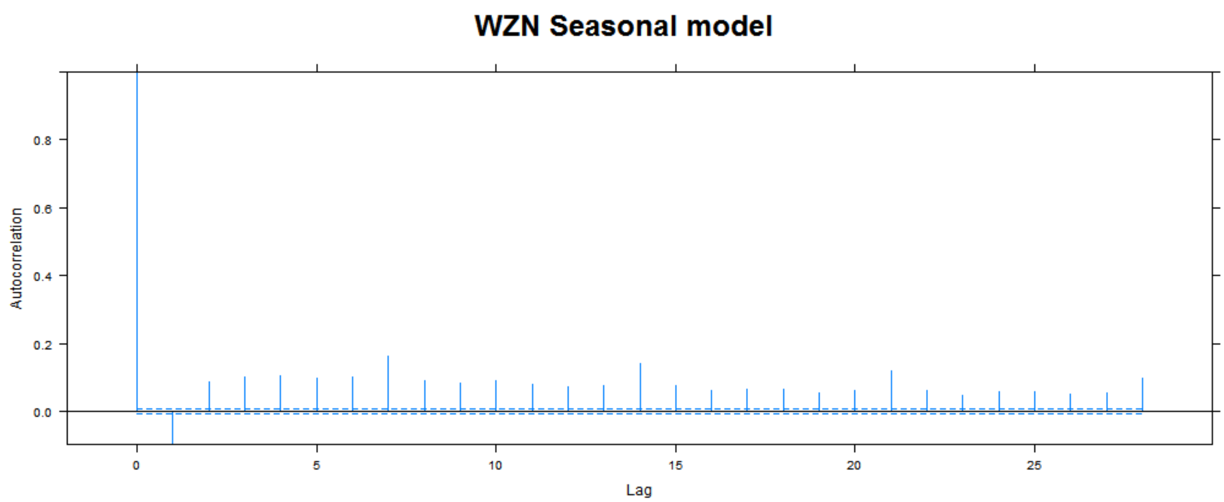
Table 36 provides summary of residuals for seasonal model.

TABLE 36.SUMMARY OF RESIDUALS, SEASONAL MODEL

Min	1st Qu.	Median	Mean	3rd Qu.	Max
-11.4000	-0.5254	-0.0811	-0.0001	0.4240	19.80

Figure 50 provides a plot of the empirical autocorrelation function.

FIGURE 50.EMPIRICAL AUTOCORRELATION FUNCTION CORRESPONDING TO NORMALIZED RESIDUALS, SEASONAL MODEL



MODEL DETAILS

CONTRASTS

1. *Treatment loads are not different from baseline loads (adjusted for weather and exogenous effects)*

$H_0: L = 0$

$H_a: L \neq 0$

$L = \sum_{i=1}^{4} c_i \mu_i \ where \ \sum_{i=1}^{4} c_i = 0, If \ |t^* = \frac{L}{\sigma^2\{L\}}| \leq t(n-p-q), then \ H_0; otherwise, H_a$[4]

For peak model, $c_1 through \ c_4 = 1, -1, -1, 1$

[4] n=number of observations, p = number of model parameters associated with fixed effects, q = number of covariance parameters with random effects or correlations

2. *Treatment type has no effect on impacts (adjusted for weather and exogenous effects)*

Same as in 1 above but different set of means.

Contrasts Examples

YDT summer impact relative to baseline (adjusted for weather and exogenous effects), and comparing YDT and IHD treatments (adjusted for weather and pretreatment differences)

1. *Treatment loads are not different from baseline loads (adjusted for weather and exogenous effects)*

$$\hat{L} = (\hat{\mu}_{YDT.treat.at.summer} - \hat{\mu}_{YDT.base.at.summer}) - (\hat{\mu}_{Control.treat.at.summer} - \hat{\mu}_{Control.base.at.summer})$$

2. *Treatment type has no effect on impacts (adjusted for weather and exogenous effects)*

$$\hat{L} = (\hat{\mu}_{YDT.treat.at.summer} - \hat{\mu}_{YDT.base.at.summer}) - (\hat{\mu}_{IHD.treat.at.summer} - \hat{\mu}_{IHD.base.at.summer})$$

Notes:

$\mu's$ are estimated using regression coefficients with the temperature profile of interest – average temp summer 2013.

Model Comparison

Table 37. Model Comparison, Seasonal model

	Model Name	Model	DF	AIC	BIC	logLik	Test	L.Ratio	p-value
	Seasonal Model **Random Customer (Intercept)**	1	24	583047.0	583312.9	-291499.5			
	Seasonal Model **Random Customer (Slope & Intercept)**	2	29	420651.6	420972.8	-210296.8	1 vs 2	162405.44	<0.0001
	Seasonal Model **Random Customer (Slope & Intercept Diagonal matrix)**	3	26	420898.1	421186.1	-210423.1	2 vs 3	252.56	<0.0001
	Seasonal Model **Random Customer (Slope & Intercept Blocked-diagonal matrix)**	4	27	420666.6	420965.7	-210306.3	3 vs 4	233.51	<0.0001
Final Model	Seasonal Model **Random Customer (Slope & Intercept) AR(1)**	5	30	294683.7	295016.0	-147311.8	4 vs 5	125988.94	<0.0001

Tests for fixed effects

Table 38. F-tests for variables in the model, Seasonal model

Variable	Numerator DF	Denominator DF	F-value	p-value
(Intercept)	1	477456	717.56059	<0.0001
CDD	1	477456	2620.04934	<0.0001
HDD	1	477456	295.66869	<0.0001
season	1	477456	3272.02292	<0.0001
Treatment_Period	9	477456	106.03405	<0.0001
season:Treatment_Period	9	477456	16.56321	<0.0001

MODEL COEFFICIENTS

Conditional R^2 = 0.6197

YDT.baseline is the reference level.

TABLE 39.MODEL COEFFICIENTS, SEASONAL MODEL

Variable	Coefficient	Std.Error	DF	t-value	p-value
(Intercept)	0.86954	0.0280	477456	31.02	<0.0001
CDD	0.00352	0.0001	477456	47.04	<0.0001
HDD	0.00082	0.0000	477456	20.71	<0.0001
winter	-0.16727	0.0060	477456	-27.97	<0.0001
YDT.treatment	0.02827	0.0413	477456	0.68	0.4934
IHD.treatment	0.00339	0.0409	477456	0.08	0.9339
Nest.treatment	0.09284	0.0435	477456	2.13	0.0329
Audit.treatment	0.02382	0.0417	477456	0.57	0.5680
control.baseline	-0.02815	0.0071	477456	-3.94	0.0001
YDT.baseline	0.09633	0.0415	477456	2.32	0.0204
IHD.baseline	0.07438	0.0412	477456	1.81	0.0709
Nest.baseline	0.09667	0.0438	477456	2.21	0.0274
Audit.baseline	0.10259	0.0420	477456	2.44	0.0146
winter:YDT.treatment	0.02245	0.0093	477456	2.43	0.0152
winter:IHD.treatment	0.00125	0.0092	477456	0.14	0.8917
winter:Nest.treatment	-0.02522	0.0098	477456	-2.58	0.0098
winter:Audit.treatment	0.00090	0.0094	477456	0.10	0.9231
winter:control.baseline	0.08238	0.0083	477456	9.97	<0.0001
winter:YDT.baseline	0.00990	0.0105	477456	0.94	0.3450
winter:IHD.baseline	0.00828	0.0104	477456	0.80	0.4258
winter:Nest.baseline	-0.02301	0.0112	477456	-2.06	0.0390
winter:Auidt.baseline	0.00585	0.0106	477456	0.55	0.5821

Correlations

(a) Correlation between CDD and HDD is -0.62.

(b) Variance covariance matrix

Table 40. Variance covariance matrix, Seasonal model

	Variance	StdDev	Corr	
Customer (Intercept)	1.858402e-01	0.431091871	(Intr)	CDD
CDD (slope)	3.869998e-06	0.001967231	0.573	
HDD (Slope)	1.091386e-06	0.001044694	0.014	-0.017
Residual	1.405296e-01	0.374872809		

Corrections

AR(1) error structure was the only correction applied. See diagnostic plots.

Model Results

Table 41. Energy impacts for Audit, relative to the surveyed control group

Treatment Group	N	Time Period	Savings (kWh/h)	Standard Error	95% Confidence Interval		Reference Load (2011)	% Savings
Audit	132	summer	**-0.107***	0.0112	-0.1349	-0.0789	1.42	-7.6%
Audit	132	winter	**-0.029***	0.0066	-0.0460	-0.0130	1.04	-2.8%
Audit	132	summer+winter	**-0.055***	0.0058	-0.0698	-0.0408	1.17	-4.8%
Audit – gas	102	summer	**-0.114***	0.011	-0.1357	-0.0927	1.34	-8.5%
Audit – gas	102	winter	-0.012	0.0064	-0.0244	0.0000	0.90	-1.3%
Audit – gas	102	summer+winter	**-0.046***	0.0057	-0.057	-0.0348	1.05	-4.4%
Audit - elec	30	summer	-0.050	0.0383	-0.1255	0.0247	1.61	-3.1%
Audit - elec	30	winter	**-0.072***	0.0226	-0.1159	-0.0271	1.63	-4.4%
Audit - elec	30	summer+winter	**-0.064***	0.0199	-0.1034	-0.0255	1.62	-4.0%

* Statistically significant, α=0.05

Table 42. Energy impacts for treatments, relative to Audit

Treatment Group	N	Time Period	Savings (kWh/h)	Standard Error	95% Confidence Interval		Reference Load (2011)	% Savings
YDT	137	summer	+0.011	0.0121	-0.0180	0.0394	1.30	+0.8%
IHD	141	summer	+0.0078	0.0120	-0.0207	0.0363	1.28	+0.6%
Nest	115	summer	**+0.075***	0.0126	0.0449	0.1050	1.30	+5.8%
YDT	137	winter	**+0.028***	0.0071	0.0113	0.0451	1.01	+2.8%
IHD	141	winter	+0.0057	0.0071	-0.0111	0.0225	0.98	+0.6%
Nest	115	winter	**+0.078***	0.0074	0.0600	0.0954	0.98	+8.0%
YDT	137	summer+winter	**+0.022***	0.0062	0.0076	0.0371	1.11	+2.0%
IHD	141	summer+winter	+0.0064	0.0062	-0.0082	0.0210	1.08	+0.6%
Nest	115	summer+winter	**+0.077***	0.0065	0.0614	0.0922	1.08	+7.1%

* Statistically significant, α=0.05

TABLE 43. ENERGY IMPACTS, BETWEEN-TREATMENT COMPARISONS

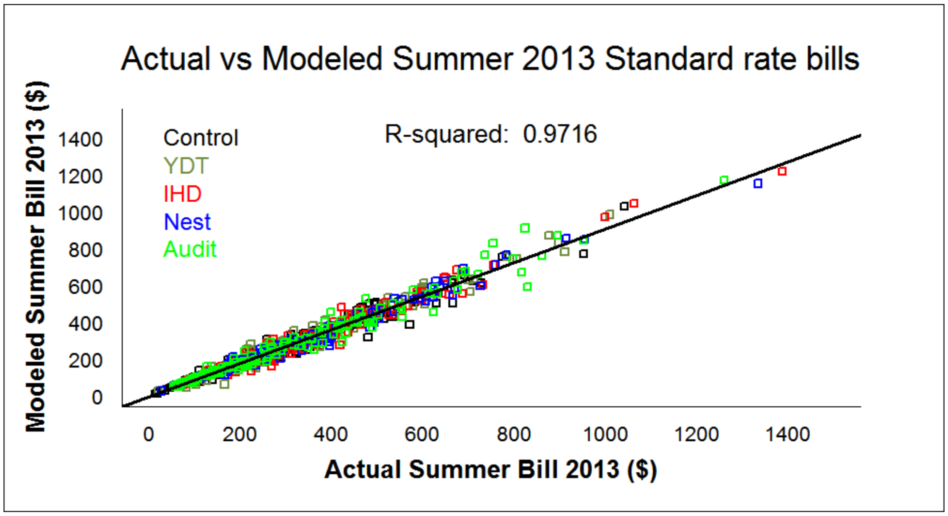
Treatment Group	Time Period	Savings (kWh/h)	Standard Error	95% Confidence Interval	
YDT vs IHD	summer	+0.0029	0.0119	-0.0291	0.0349
YDT vs Nest	summer	**-0.064***	0.0125	-0.0976	-0.0304
YDT vs Audit	summer	+0.011	0.0121	-0.0215	0.0435
IHD vs Nest	summer	**-0.067***	0.0124	-0.1004	-0.0336
IHD vs Audit	summer	+0.0078	0.0120	-0.0245	0.0401
Nest vs Audit	summer	**+0.075***	0.0126	0.0411	0.1089
YDT vs IHD	winter	**+0.023***	0.0070	0.0042	0.0418
YDT vs Nest	winter	**-0.049***	0.0074	-0.0689	-0.0291
YDT vs Audit	winter	**+0.028***	0.0071	0.0089	0.0471
IHD vs Nest	winter	**-0.072***	0.0073	-0.0916	-0.0524
IHD vs Audit	winter	+0.0057	0.0071	-0.0134	0.0248
Nest vs Audit	winter	**+0.078***	0.0074	0.0581	0.0979
YDT vs IHD	summer+winter	+0.016	0.0061	-0.0004	0.0324
YDT vs Nest	summer+winter	**-0.054***	0.0065	-0.0715	-0.0365
YDT vs Audit	summer+winter	**0.022***	0.0062	0.0053	0.0387
IHD vs Nest	summer+winter	**-0.070***	0.0064	-0.0872	-0.0528
IHD vs Audit	summer+winter	+0.0064	0.0062	-0.0103	0.0231
Nest vs Audit	summer+winter	**0.077***	0.0065	0.0595	0.0945

* Statistically significant, α=0.05

Appendix C. Bill model fit

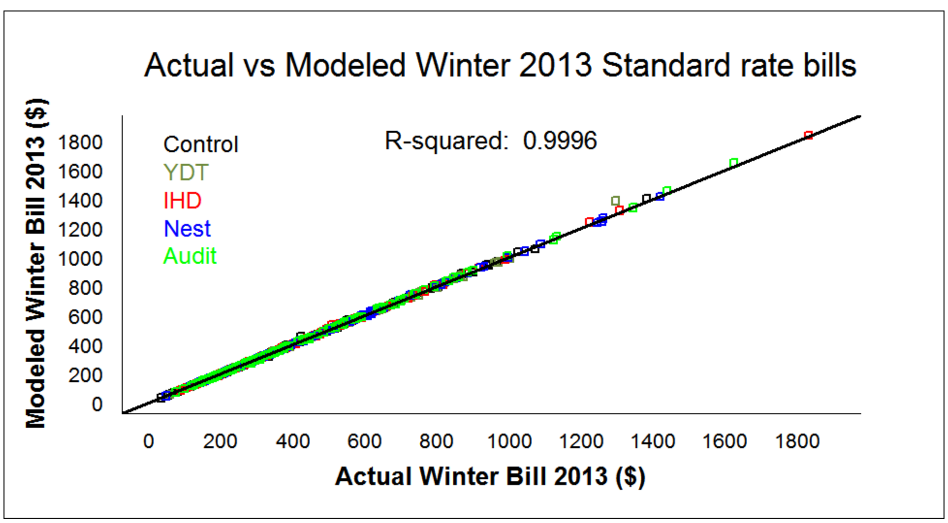
Because the June and July 2011 loads were unavailable for the participants in this pilot, summer bills for all four months are estimated using the available months of August and September. Evidence of the accuracy of this assumption is provided through comparison of actual summer bills calculated from June to September 2013 loads and modeled bills estimated from the modeled August and September 2013 loads corrected for weather. Figure 51 plots these two sets of values showing a reasonable match.

Figure 51. Actual vs. modeled standard low-income rate bills, summer 2013



Similarly, the accuracy of modeled winter bills was considered by comparing actual winter bills from February through May 2013 to October 2013 through January 2014. Figure 52 plots the actual bills against the modeled bills for the same time periods, showing a nearly perfect match.

Figure 52. Actual vs. modeled standard rate bills, winter 2013



Appendix D. Demographic Data Summary

Correlations with Load Impacts

Figure 53 through Figure 56 plot correlations between energy impacts and demographic variables for each treatment.

Figure 53. Correlation matrix: Annual energy impact and demographics, YDT

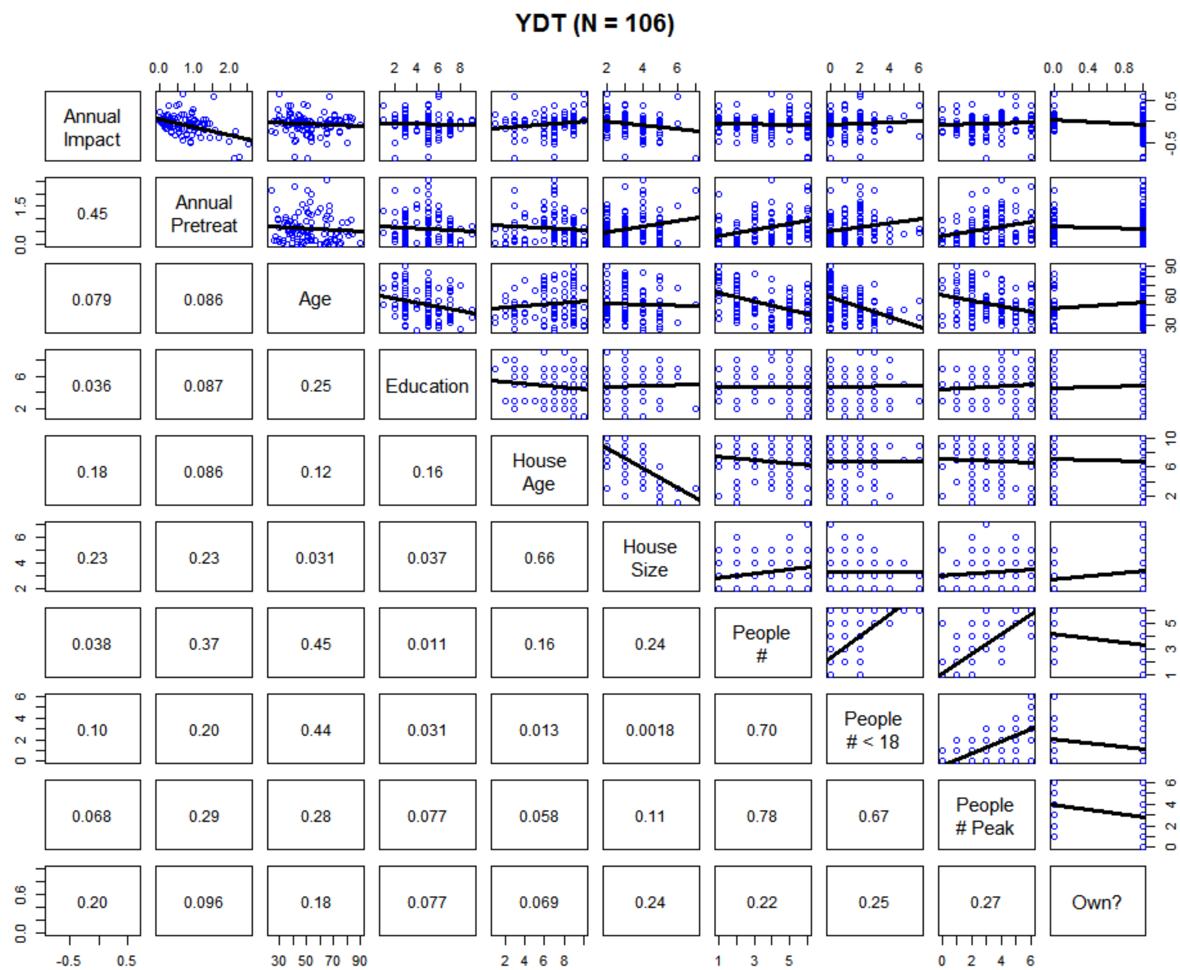


Figure 54. Correlation matrix: Annual energy impact and demographics, IHD

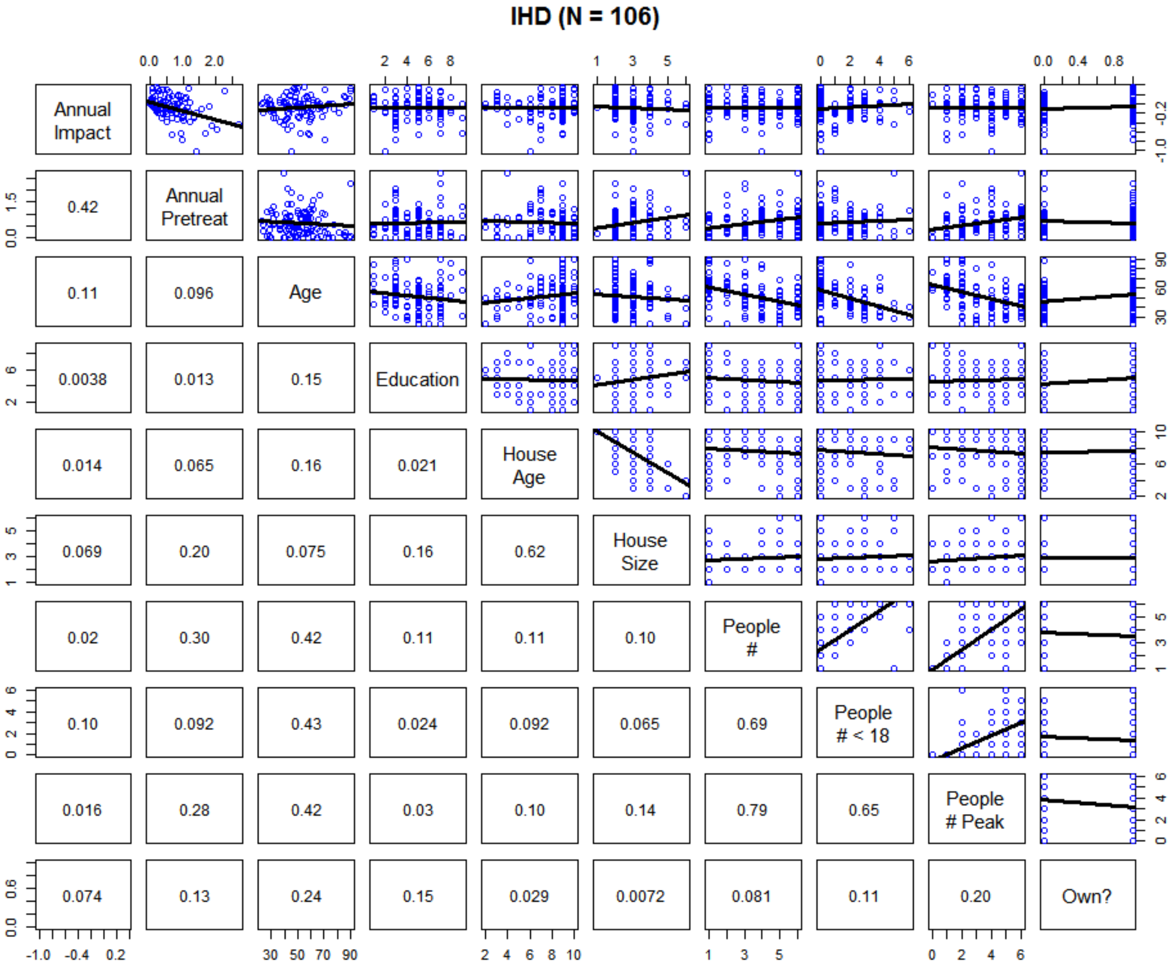


FIGURE 55. CORRELATION MATRIX: ANNUAL ENERGY IMPACT AND DEMOGRAPHICS, NEST

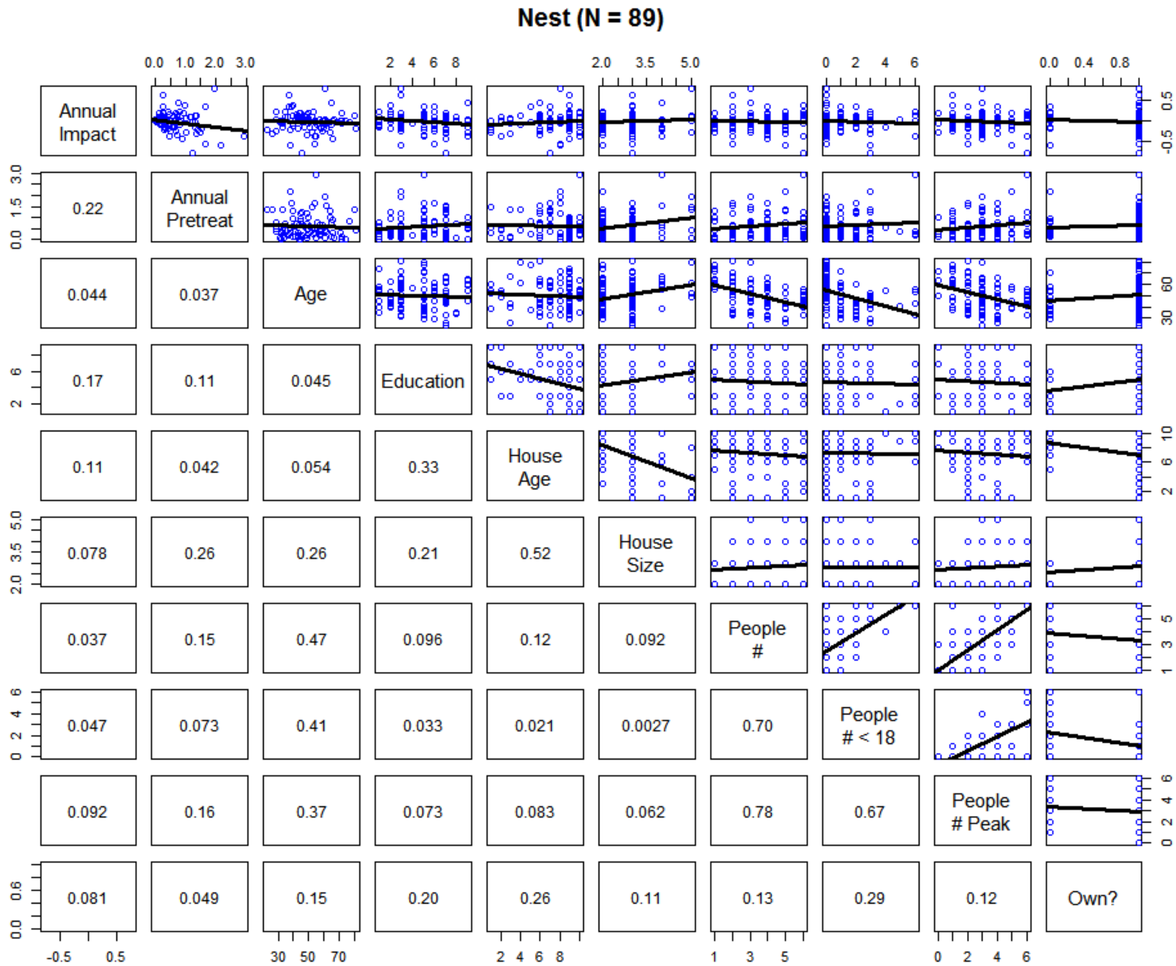
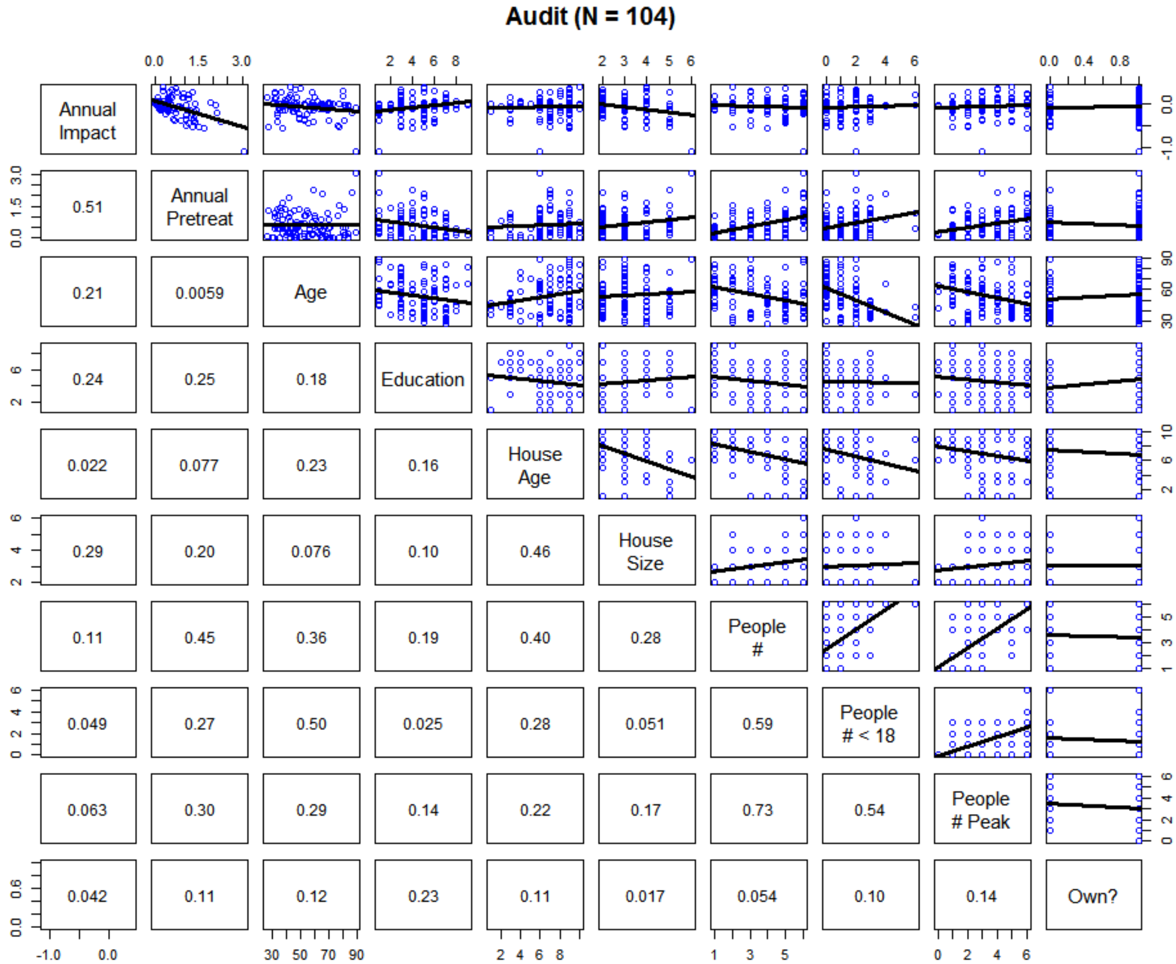


Figure 56. Correlation matrix: Annual energy impact and demographics, Audit



Survey Data Summary

QD1-Do you pay your household's electricity bill, or does someone else typically pay it?

Participant responses recoded to match control group responses:

1 = I pay the bill

2 = My spouse or other family member typically pays the bill

3 = The landlord pays the bill/it's included in the rent

4 = Depends

5 = Prefer not to answer

Table 44 shows the summary of responses for who pays the electricity bill. No statistically significant differences found between any of the treatments.

TABLE 44.SUMMARY OF RESPONSES, WHO PAYS THE ELECTRICITY BILL

Do you pay your household's electricity bill, or does someone else typically pay it?	Control	YDT	IHD	Nest	Audit
I pay the bill	92%	94%	90%	87%	90%
My spouse or other family member typically pays the bill	5.7%	3.6%	7.4%	6.8%	5.8%
The landlord pays the bill/its included in the rent	0%	0.72%	0%	0%	0%
Depends	1.9%	0%	0.68%	0.85%	2.2%
Prefer not to answer	0%	2.2%	2%	5.1%	2.2%

QD2 – IN WHAT YEAR WHERE YOU BORN?

67 zero's in the data, set to NA (most likely zeros = Prefer not to answer).

Excluded one participant with "year born" = 76 (wasn't sure if 76 = age, or 76 = year 1976).

Table 45 provides p-values for mean differences analysis for participant age. No statistically significant differences were found in the participant age in different treatments.

TABLE 45.MEAN DIFFERENCES ANALYSIS FOR PARTICIPANT AGE

Age	N	Mean	YDT	IHD	Nest	Audit
Control	199	55.27	0.5444	0.7336	0.1156	0.9314
YDT	125	52.42				
IHD	128	53.00	0.9986			
Nest	108	50.58	0.9113	0.7867		
Audit	125	53.78	0.9648	0.9954	0.5661	

Table 46 shows the summary of responses when participant age is treated as a categorical variable. Lower proportion of "55 to 64" in Control relative to other treatments.

TABLE 46.SUMMARY OF RESPONSES, PARTICIPANT AGE

Age	Control	YDT	IHD	Nest	Audit
18 to 24	0%	0.72%	2%	1.7%	0%
25 to 34	14%	11%	10%	13%	11%
35 to 44	18%	21%	18%	20%	20%
45 to 54	14%	24%	19%	21%	18%
55 to 64	19%*	**6.5%**	18%*	19%	16%
65 and over	30%	27%	20%	17%	25%
NA	5.2%	10%	13%	8.5%	10%

*= different from **YDT** *=different from **IHD**

*=different from **Nest** *=different from **Audit**

QD3 – What is your gender?

Participant responses recoded to match control group responses:

1 = Male, 2 = Female, 3 = Prefer not to answer

Table 47 shows the summary of responses for gender. Lower proportion of females in Nest treatment.

Table 47. Summary of responses, gender

Gender	Control	YDT	IHD	Nest	Audit
Male	33%	35%	34%	43%	35%
Female	67%*	62%	64%	**50%**	63%
Prefer not to answer	0%	2.9%	2%	6.8%	2.2%
NA	0%	0%	0%	0%	0%

*= different from **YDT** *=different from **IHD**

*=different from **Nest** *=different from **Audit**

QD4 – Including yourself, how many people live in your household?

Table 48 provides p-values for mean differences analysis for the number of household occupants. No statistically significant differences found in the number of household occupants.

Table 48. Summary of responses, household occupants

People	Control	YDT	IHD	Nest	Audit
One	24%	15%	20%	14%	18%
Two	21%	19%	16%	25%	15%
Three	15%	16%	16%	15%	17%
Four	16%	15%	18%	18%	15%
Five	12%	17%	11%	10%	20%
Six or more	10%	17%	17%	14%	14%
Prefer not to answer	1.9%	1.4%	2%	4.2%	1.4%
NA	0%	0%	0%	0%	0%

QD5 – How many people living in your household are under the age of 18?

Zeros in the control group recoded as “None” to match participants.

Table 49 provides p-values for mean differences analysis for the number of household occupants under the age of 18. No statistically significant differences found in the number of household occupants under the age of 18.

Table 49. Summary of responses, household occupants under the age of 18

People	Control	YDT	IHD	Nest	Audit
None	48%	37%	43%	47%	39%
One	19%	19%	15%	16%	22%
Two	16%	19%	14%	15%	21%
Three	9%	13%	15%	10%	12%
Four	3.8%	3.6%	6.1%	1.7%	2.9%
Five	0.95%	1.4%	2.7%	1.7%	0.72%
Six or more	1.9%	3.6%	2%	3.4%	1.4%
Prefer not to answer	1.4%	2.2%	2.7%	5.1%	1.4%
NA	0%	0%	0%	0%	0%

QD6 – On a typical weekday, how many people are at your home between 4PM and 7PM?

23 participants’ responses recoded from "No one is typically home at THIS time" to "No one is typically home at THAT time" to match the control group response.

Table 50 provides p-values for mean differences analysis for the number of household occupants during the 4-7 pm peak. No statistically significant differences found in the number of household occupants during the 4-7 pm peak.

Table 50. Summary of responses, household occupants during the 4-7 pm peak

People	Control	YDT	IHD	Nest	Audit
No one is typically home at that time	5.2%	5.8%	3.4%	3.4%	4.3%
One	20%	14%	15%	15%	19%
Two	24%	22%	22%	20%	17%
Three	18%	14%	14%	23%	19%
Four	13%	19%	18%	16%	17%
Five	9%	7.9%	12%	9.3%	13%
Six or more	7.6%	14%	14%	8.5%	8.6%
Prefer not to answer	3.3%	2.9%	2.7%	4.2%	1.4%
NA	0%	0%	0%	0%	0%

QD7 – Do you own or rent your home?

Table 51 shows the summary of responses for whether participants own or rent their homes. Lower proportion of owners in Control group relative to Nest treatment. Higher proportion of renters in Control group relative to YDT and Nest treatments. Higher proportion of renters in IHD relative to Nest treatment.

Table 51.Summary of responses, own/rent

Own/Rent	Control	YDT	IHD	Nest	Audit
Own	61%*	75%	65%	**81%**	70%
Rent	37%**	**22%**	33%*	**16%**	27%
Prefer not to answer	1.9%	3.6%	2%	3.4%	2.9%
NA	0%	0%	0%	0%	0%

*= different from **YDT** *=different from **IHD**

*=different from **Nest** *=different from **Audit**

QD8 – What ethnic group do you consider yourself a part of or feel closest to?

1 “No opinion/Not Sure” response in the participants group was changed to “Not sure” to match control group.

5 “Other heritage” responses in the participants group were changed to “Other” to match control group.

13 "Asian – Korean, Japanese, Chinese, Vietnamese, Filipino…” responses were changed to “Asian-Korean, Japanese, Chinese, Vietnamese, Filipino, or ot”.

4 “Mixed Heritage” responses were change to “Mixed heritage” responses.

Table 52 shows the summary of responses for ethnic group. Higher proportion of “Caucasian/White” and lower proportion of “Asian” and “Pacific Islander” in Control group relative to YDT.

Table 52.Summary of responses, ethnic group

Ethnic group	Control	YDT	IHD	Nest	Audit
Caucasian/White	45%*	**27%**	34%	42%	33%
Latino/Hispanic/Mexican	14%	13%	17%	19%	18%
African-American/Black	16%	19%	18%	9.3%	12%
Native American Indian or Alaskan Native	1.4%	2.2%	0.68%	0.85%	3.6%
Asian-Korean, Japanese, Chinese, Vietnamese, Filipino, or other Asian	6.7%*	**19%**	14%	12%	14%
Pacific Islander	0.48%*	**7.2%**	5.4%	1.7%	5%
Mixed heritage	1.9%	3.6%	4.7%	5.1%	3.6%

Other	4.3%	1.4%	0.68%	0%	1.4%
Not sure	0.48%	0.72%	0%	0.85%	0.72%
Prefer not to answer	9.5%	5.8%	5.4%	10%	7.9%

*= different from **YDT** *=different from **IHD**

*=different from **Nest** *=different from **Audit**

QD9 – What is the primary language spoken in your home?

In parts group

1 = English, 2 = Spanish, 4 = Prefer not to answer, 3 – 10 (but 4) = Other

Table 53 shows the summary of responses for ethnic group. Higher proportion of English speakers in Control group relative to YDT, Nest, and Audit. Higher proportion of Spanish speakers in Nest relative to control. Lower proportion of "Other" in Control group relative to Audit treatment. No between treatment differences.

Table 53.Summary of responses, primary language spoken at home

language	Control	YDT	IHD	Nest	Audit
English	90%***	**76%**	80%	**68%**	**74%**
Spanish	2.4%*	5.8%	6.8%	**11%**	5.8%
Other	5.7%*	14%	8.1%	14%	**17%**
Prefer not to answer	1.9%	3.6%	4.7%	7.6%	3.6%

*= different from **YDT** *=different from **IHD**

*=different from **Nest** *=different from **Audit**

QD10 – What is the last grade or level you completed in school?

6 "Graduate, professional, doctorate degree (DDS, DVM, JD...)"
were changed to "Graduate, professional, doctorate degree".

Table 54 shows the summary of responses when participant education is treated as a categorical variable. No significant differences found.

Table 54. Summary of responses, participant education

What is the last grade or level you completed in school?	Control	YDT	IHD	Nest	Audit
Elementary (8 or fewer years)	2.4%	2.2%	4.1%	5.9%	7.2%
Some high school (9 to 11 years)	6.2%	7.2%	4.7%	7.6%	5%
High school graduate (12 years)	31%	27%	22%	23%	22%
Technical / Vocational school	1.9%	3.6%	8.1%	0.85%	7.2%
Some college	25%	27%	24%	18%	21%
College graduate (2 year degree)	13%	9.4%	9.5%	10%	12%
College graduate (4 year degree)	13%	13%	14%	17%	14%
Some graduate school	0%	2.2%	2%	1.7%	3.6%
Graduate, professional, doctorate degree	2.9%	1.4%	2.7%	5.9%	2.9%
Prefer not to answer	3.8%	7.9%	8.8%	10%	6.5%
NA	0%	0%	0%	0%	0%

Ranked education level from 1 to 9. Prefer not to answer = NA

Table 55 provides p-values for mean differences analysis for participant education. No statistically significant differences were found in the participant education in different treatments.

Table 55. Mean differences analysis for participant education

Education	N	Mean	YDT	IHD	Nest	Audit
Control	202	4.58	0.99999	0.9689	0.9183	0.9980
YDT	128	4.57				
IHD	134	4.72	0.9732			
Nest	106	4.77	0.9301	0.9994		
Audit	130	4.65	0.9979	0.9983	0.9869	

Q15 – At what temperature is your thermostat normally set at during daylight hours in the summer months (June-September)?

Table 56 shows the number of participants in each treatment that were excluded due to no response to this question. In addition, five survey respondents with setpoint < 65 degrees were excluded from the analysis.

Table 56. Number of participants with no response, daylight summer hours thermostat settings

treat	# of customers with no response
YDT	10
IHD	21
Nest	15
Audit	11

Table 57 provides p-values for mean differences analysis for summer daylight hours thermostat setting. No significant differences found.

Table 57. Mean differences analysis for summer daylight hours thermostat settings

Setpoint – daylight – summer	N	Mean	YDT	IHD	Nest	Audit
Control	NA	NA	NA	NA	NA	NA
YDT	127	75.25				
IHD	126	74.91	0.9098			
Nest	102	75.25	1	0.921		
Audit	127	75.58	0.9154	0.5537	0.9294	

Q16 – At what temperature is your thermostat normally set at during night time hours in the summer months (June-September)?

Table 58 shows the number of participants in each treatment that were excluded due to no response to this question. In addition, 12 customers with setpoint < 65 and 2 customers with setpoint = 787, 773 were excluded from the analysis.

Table 58. Number of participants with no response, summer night time hours thermostat settings

Treat	# of customers with no response
YDT	35
IHD	43
Nest	31
Audit	41

Table 59 provides p-values for mean differences analysis for summer night time hours thermostat setting. No significant differences found.

Table 59. Mean differences analysis for summer night time hours thermostat settings

Setpoint – night – summer	N	Mean	YDT	IHD	Nest	Audit
Control	NA	NA	NA	NA	NA	NA
YDT	102	75.25				
IHD	99	75.03	0.9837			
Nest	83	74.37	0.4987	0.7203		
Audit	96	75.33	0.9989	0.9583	0.4247	

Q17 – At what temperature is your thermostat normally set during daylight hours in the winter months (December – February)?

Table 60 shows the number of participants in each treatment that were excluded due to no response to this question.

Table 60. Number of participants with no response, winter daylight hours thermostat settings

treat	# of customers with no response
YDT	16
IHD	21
Nest	13
Audit	23

Table 61 provides p-values for mean differences analysis for winter daylight hours thermostat setting. No significant differences found.

Table 61. Mean differences analysis for winter daylight hours thermostat settings

Setpoint – daylight – winter	N	Mean	YDT	IHD	Nest	Audit
Control	NA	NA	NA	NA	NA	NA
YDT	123	71.44				
IHD	127	71.76	0.9547			
Nest	105	71.76	0.9584	1		
Audit	116	71.77	0.9531	1	1	

Q18 – At what temperature is your thermostat normally set during night time hours in the winter months (December – February)?

Table 62 shows the number of participants in each treatment that were excluded due to no response to this question. In addition, excluded one customer with setpoint = 693.

Table 62. Number of participants with no response, winter night time hours thermostat settings

treat	# of customers with no response
YDT	26
IHD	36
Nest	21
Audit	34

Table 63 provides p-values for mean differences analysis for winter night time hours thermostat setting. No significant differences found.

Table 63. Mean differences analysis for winter night time hours thermostat settings

Setpoint – night – winter	N	Mean	YDT	IHD	Nest	Audit
Control	NA	NA	NA	NA	NA	NA
YDT	113	70.57				
IHD	112	71.24	0.8069			
Nest	97	71.12	0.8919	0.9988		
Audit	104	70.88	0.9759	0.9669	0.9906	

Dwelling type

Table 64 shows the summary of responses for the dwelling type. Majority of customers were in single-family homes.

Table 64. Summary of responses, dwelling type

Dwelling type	# of customers
No answer	12
Mobile home	16
Residential	1
Single-family	525

Renter

Table 65 shows the number of owners and renters.

Table 65. Summary of responses, own/rent

Renter	# of customers
No	401
Yes	153

Rate

Table 66 shows the number of participants in each rate category.

Table 66. Summary of responses, rate

rate	# of customers
RSCH -> Closed Electric-heated	1
RSCH_E -> Closed Electric-heated & Low Income	15
RSEH -> Open Electric-heated	2
RSEH_E -> Open Electric-heated & Low Income	67
RSGH -> Open Gas-heated	20
RSGH_E -> Open Gas-heated & Low Income	435
RWCH_E -> Closed Electric-heated & Well & Low Income	1
RWEH_E -> Open Electric-heated & Well & Low Income	8
RWGH_E -> Open Gas-heated Well & Low Income	4

Who pays bills

Table 67 shows how many participants pay their own bills.

Table 67. Summary of responses, who pays bills

Who pays the bills	# of customers
Depends	9
I pay the bill	685
My spouse or other family member typically pays the bill	44
Prefer not to answer	15
The landlord pays the bill/its included in the rent	1