Herter Energy
RESEARCH SOLUTIONS

SMUD's Residential Summer Solutions Study 2011-2012

A 2-year investigation of the effects of dynamic pricing, customer-programmed thermostat automation, utility-controlled thermostat automation, and real-time energy and cost information, on residential conservation, peak reduction, and demand response

ANALYSIS ADDENDUM

1. Bill Impacts and Demographics (by rate)
2. Bill Impacts and Behavior (by rate)
3. Extrapolation of Savings Estimates to Population
4. Baseline Calculation for Load Impact Evaluation (method comparison)

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1. Bill impacts and demographics (by rate)

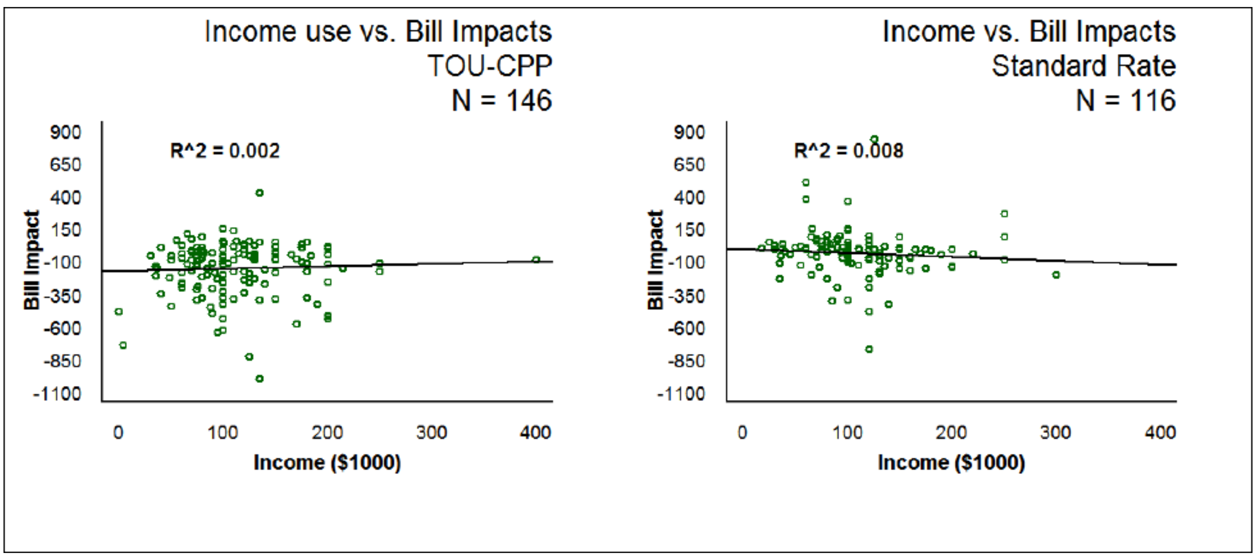
The 2011-2012 Residential Summer Solutions study bill impact evaluation found that summer bill savings for participants on the tiered TOU-CPP rate averaged $145, while bill savings for participants on the standard tiered rate averaged $40. This section considers whether the following pre-existing household conditions are correlated with customer-specific bill impacts:

- Income
- Pretreatment energy use
- Certain electrical end-uses (e.g. pool pumps, spas, electric water heating)
- Certain motivations for participating (e.g. money, environment, community)

Income

Correlations between the self-reported household income values collected in the pre-treatment survey and bill impacts were insignificant for both the 147 participants on the TOU-CPP rate (r=0.063, p=0.45) and for the 117 participants on the standard rate (r=-0.005, p=0.95).

Figure 1. Correlations between bill impacts and income



PRETREATMENT ENERGY USE AND PEAK DEMAND

Correlation analysis shows that pretreatment energy use (Figure 2).is a stronger predictor of TOU-CPP bill impacts than is pretreatment peak demand (Figure 3). Correlations between pretreatment summer energy use values and customer bill impacts were significant for both rates (Figure 2). The correlation was stronger for customers on the TOU-CPP rate (R = -0.77, p < 0.0001) than for those on the standard rate (r = -0.26, p = 0.03). Correlations between pretreatment summer peak demand and customer bill impacts were also significant for both rates (Figure 3).

FIGURE 2. CORRELATIONS BETWEEN BILL IMPACTS AND PRETREATMENT ENERGY USE, BY RATE

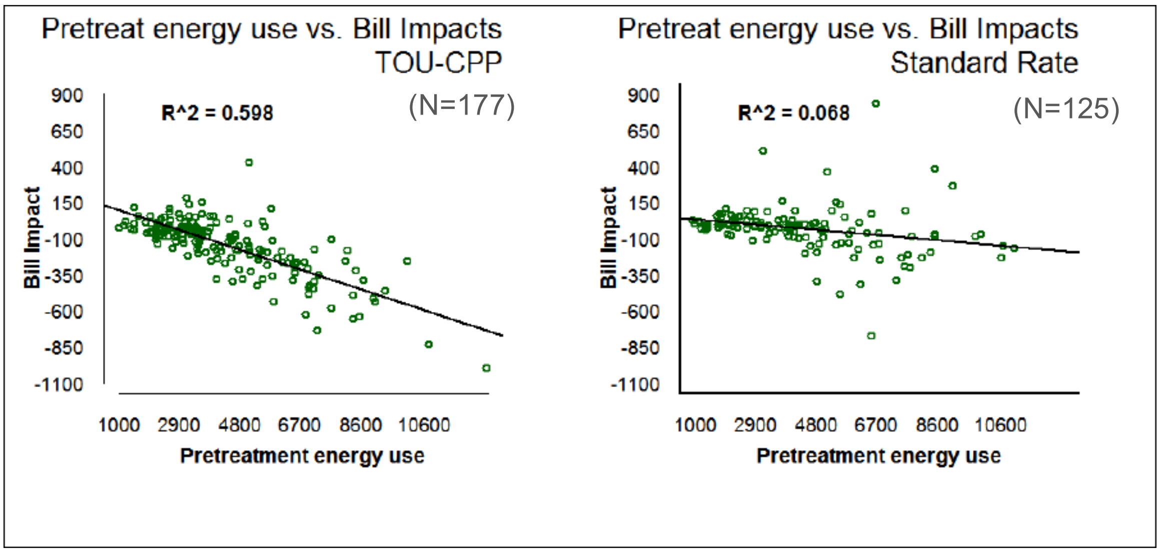
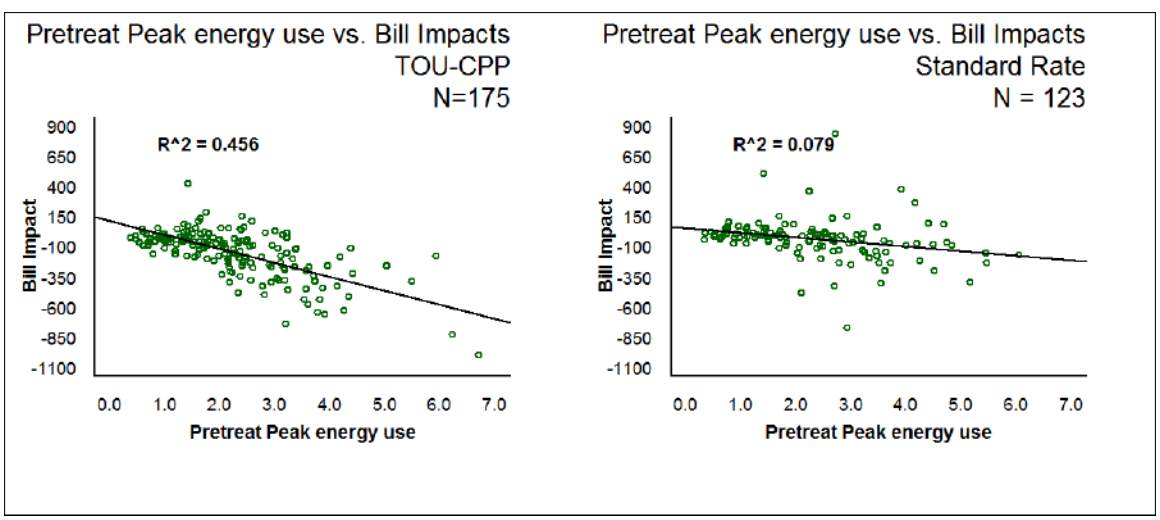


FIGURE 3. CORRELATIONS BETWEEN BILL IMPACTS AND PRETREATMENT PEAK DEMAND, BY RATE



CERTAIN ELECTRICAL END-USES

Table 1 shows that the number of electrical end uses in TOU-CPP participant home were significantly correlated with bill impacts in seven cases – swimming pool pumps, hot tubs, passive solar pool heaters, televisions, electric ovens, central AC units, and computers – such that customers having these end-uses saved more money on their TOU-CPP bills.

For participants on the standard rate, only the number of passive solar pool heaters was significantly correlated with bill impacts.

TABLE 1. CORRELATIONS BETWEEN BILL IMPACTS AND CERTAIN ELECTRICAL END-USES

Survey Question	Electrical end use	TOU-CPP Rate (N=174)	Standard Rate (N=122)
Pre8.10	Swimming pool pumps	**-0.49***	-0.17
Pre8.12	Hot tub or spa	**-0.23***	0.10
Pre8.11	Passive solar pool heater	**-0.20***	**-0.21***
Pre8.8	Televisions	**-0.19***	0.12
Pre8.4	Electric ovens	**-0.18***	-0.14
Pre8.14	Central AC units	**-0.18***	-0.11
Pre8.9	Computers	**-0.17***	0.03
Pre8.5	Refrigerator/freezer in the house	**-0.14***	0.05
Pre8.16	Thermostats	-0.10	-0.15
Pre8.6	Refrigerator/freezer in the garage	-0.08	-0.12
Pre8.1	Electric water heaters	-0.07	0.01
Pre8.13	Whole-house attic fan	-0.04	0.02
Pre8.7	Dishwashers	-0.03	-0.01
Pre8.15	Room AC units	0.02	0.07
Pre8.2	Electric clothes dryers	0.03	0.02
Pre8.3	Electric cooktops	0.06	-0.10

CERTAIN MOTIVATIONS FOR PARTICIPATING

The pre-treatment survey asked each of the participating customers their reasons for signing up for the Summer Solutions study. None of the stated motivations were significantly correlated with bill impacts.

TABLE 2. CORRELATIONS BETWEEN BILL IMPACTS AND MOTIVATION FOR PARTICIPATING

		TOU-CPP Rate (N=171)	Standard Rate (N=121)
Pre14.1	Opportunity to save money	-0.05	-0.10
Pre14.2	Free equipment/technology	0.12	0.05
Pre14.3	Free home energy assessment	0.08	0.07
Pre14.4	Opportunity to contribute to the community	-0.01	0.13
Pre14.5	Benefit the environment	0.07	0.16

2. Bill impacts and behavior (by rate)

This section considers whether the following self-reported behavior changes are correlated with bill impacts:

- Precooling and other load shifting behaviors
- Efficiency and peak conservation behaviors

Only those who changed their behavior from "no" in the pretreatment survey to "yes" in the post-treatment survey are included in the analysis. Participants that responded "yes" in both the pre-treatment and post-treatment surveys were excluded from this correlation analysis, under the assumption that there was no change in behavior related to the study.

Table 3. Precooling and other load shifting behaviors

Change in behavior relative to pretreatment	TOU-CPP Rate	Standard Rate
I pre-cooled my home several hours before the peak period	0.09	0.13
I increased the thermostat setpoint to a higher-than-normal temperature during the peak period	-0.17	-0.02
I made sure the pool pump or hot tub ran off-peak	-0.31	-0.40
I avoided taking hot showers during the peak	0.10	-0.08

TABLE 4. EFFICIENCY AND PEAK CONSERVATION BEHAVIORS

Change in behavior relative to pretreatment	TOU-CPP Rate	Standard Rate
I removed a refrigerator from the garage (or unplugged it)	**-0.51***	0.18
I replaced an old AC unit with a newer, more efficient one	**-0.30***	-0.02
I changed into lighter clothing	-0.30	0.09
I set my thermostat at 68 degrees or lower for the winter	-0.24	0.35
I increased the thermostat setpoint to a higher-than-normal temperature during the peak period	-0.17	-0.02
I lowered the temperature setting on my water heater	-0.11	0.19
I set my thermostat at 78 degrees or higher for the summer	-0.11	-0.44
I installed more efficient light bulbs	-0.09	-0.01
I installed a whole house fan, attic fan, or attic vents	-0.09	-0.23
I sealed leaky heating and air-conditioning ducts	-0.07	**-0.39***
I insulated the hot water pipes at the water heater	-0.05	-0.03
I left my home and went somewhere cool	-0.01	-0.11
I increased the insulation in my attic	0.01	0.12
I cooled the house at night and in the early morning hours by opening windows and/or running the whole house fan	0.02	0.30
I put my office equipment or entertainment center on a power strip and turn it off when not in use	0.07	0.07
I caulked around old windows or installed new efficient ones	0.23	--
I avoided using electricity to cook during the peak	**0.30***	0.02
I replaced an old refrigerator in my kitchen with a newer, more efficient one	0.37	0.02
I used shades or awnings to keep sunlight out	**0.59***	0.41

3. Extrapolation of Load Impacts to SMUD's Population

This section describes the development of an ex-ante model that can be used to estimate the expected event and nonevent peak impacts of a voluntary program with offerings similar to those of the Summer Solutions study. The model assumes that the program is offered to all of SMUD's residential single-family households.

Impacts for multi-family households are assumed to be zero because this subgroup was excluded from the Summer Solutions analysis.

Continuous Variables

This section examines the relationship between customer-specific impacts and continuous demographic variables.

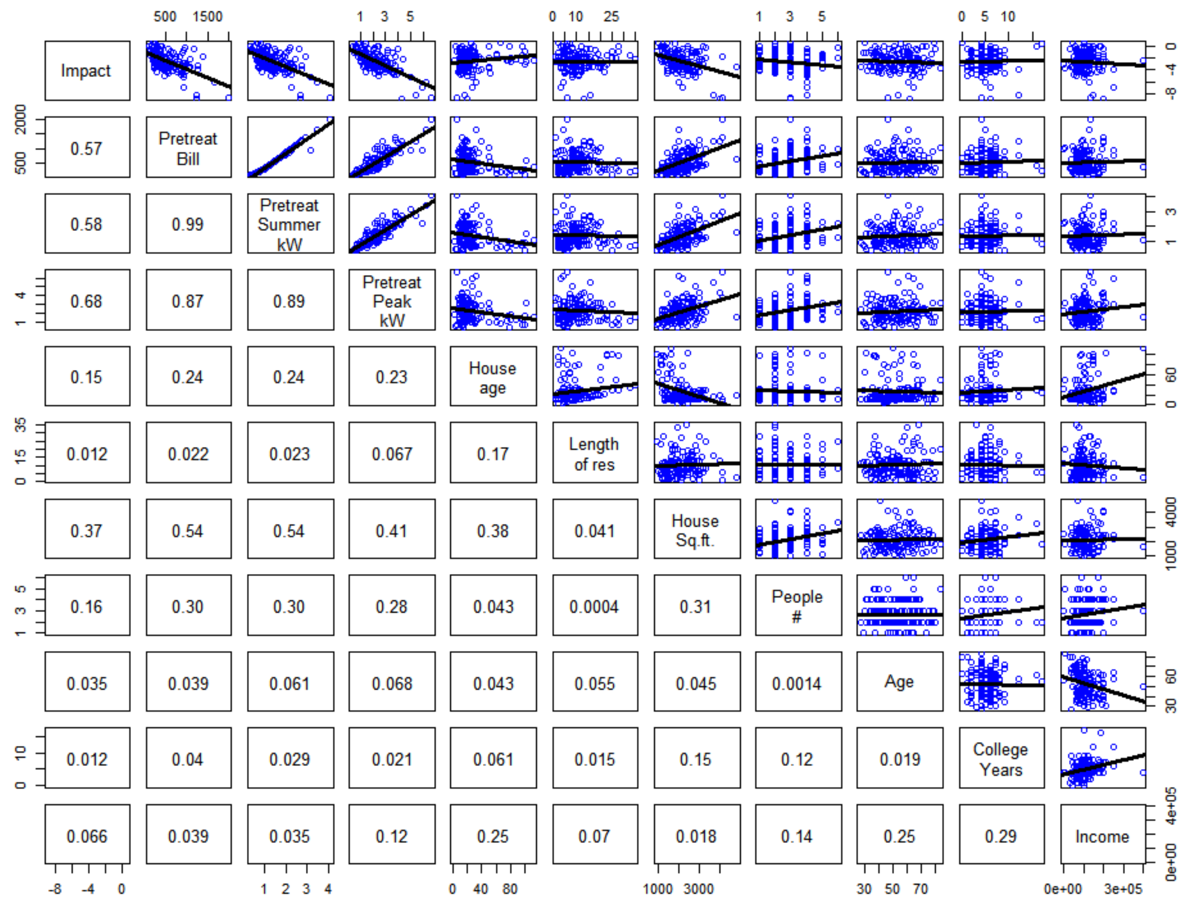
Following are the continuous variables available for both the Summer Solutions participants and also available for SMUD's general population of customers

- **Impact**. Customer-specific event impacts, calculated as the difference between average actual hot event-day loads (> 99°F) and average actual hot pretreatment weekday loads.
- **Pretreat.Bill**. 2010 energy bill based on the standard 2-tier residential rate
- **Pretreat.Summer.kW**. Calculated as averages of 24 hourly kW values across all days in summer 2010.
- **Pretreat.Peak.kW**. Calculated as averages of 3 hourly kW values (hour 17- 19) across all weekdays in summer 2010.
- **House.Age**. Age of the home.
- **Length.of.Res**. The number of years the participants has lived in the home.
- **House.Sq.ft**. Size of the home in square feet.
- **People.#**. Number of people occupying the home during peak summer hours[1]
- **Age**. Age of the participant.
- **College.Years**. Years of college education for the participant.
- **Income**. Household income.

The first row of Figure 2 provides scatter plots of the response variable (Impact) against predictor variables (demographics, pretreatment variables) in each column to aid in determining the relationship between impacts and possible predictor variables. Scatter plots between predictor variables show correlation among predictors. Impacts are correlated strongly with pretreatment bill (r=0.57), pretreatment summer kW (r=0.58), and pretreatment summer peak kW (r=0.68). House size has a weaker, yet visible correlation with impacts (r = 0.37).

[1] Assumed to be highly correlated with the number of people in the household

FIGURE 4. LOAD AND DEMOGRAPHICS SCATTER PLOT MATRIX



All pretreatment variables (Bill, Summer kW and Peak kW) are highly correlated among themselves. Of the three, Pretreat Peak kW has the strongest relationship with Impact, so is used as a covariate in the final mixed effects model.

Of the remaining non-load variables, only House.Sq.ft shows a relatively strong correlation; however, inclusion of House.Sq.ft in a regression of Impact on Pretreat.Peak.kW improves the explanatory efficacy of the model by less than 1% compared to a model with just Pretreat.Peak.kW. Furthermore, house size in the larger model is not statistically significant (α=0.05). As a result, the variable for house size is excluded from the final model (Table 5).

TABLE 5. COMPARISON OF MODEL COEFFICIENTS

	Model 1	Model 2
(Intercept)	-0.333	0.097
Pretreat.Peak.kW coefficient	-0.980	-0.920
House.Sq.ft coefficient	--------	0.000
Adjusted R-squared	0.4429	0.4498

Categorical Variables

To test the possibility that demographic variables affect impacts in a non-linear way, a mixed-effects model was designed to compare different levels of the following categorical variables.

- Income
- Age of participant
- Age of home
- Length of residency

Impacts were normalized using pretreatment peak average energy usage, which was shown above to be an excellent predictor of event impacts.

Equation 1. Load impacts model to test effects of categorical demographic variables

$$kw_{ijk} = \beta_{(hour)ijk} hour_{ijk} + \beta_{(CDH)ijk} CDH_{ijk} + \beta_{(MaxTemp)ij} MaxTemp_{ij} + \beta_{(hour*Avg\_Peak*DemVar*DayType)ijk} hour_{ijk} * Avg\_Peak * Dem\_Var * DayType + r_i + r_{ij} + \varepsilon_{ijk}$$

kw_{ijk}: kilowatt load for customer i on day j at hour k
$hour_{ijk}$: categorical variables (17-19) indicating the hour of the day
CDH_{ijk}: cooling degree hour on day j at hour k
$MaxTemp_{ij}$: maximum temperature on day j
$DayType$: categorical variables for day type (event, pretreatment)
Dem_Var: categorical demographic variable
Avg_Peak : Average pretreatment peak load for customer i (calculated as average of 3*122 hourly kW values, summer 2010)
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

After normalizing event impacts by pretreatment peak kW, load impacts are not significantly different for any of the demographic variable categories considered: income (Figure 5), age of participant (Figure 6), age of home (Figure 7), length of residency (Figure 8).

Figure 5. Effect of income on event impacts

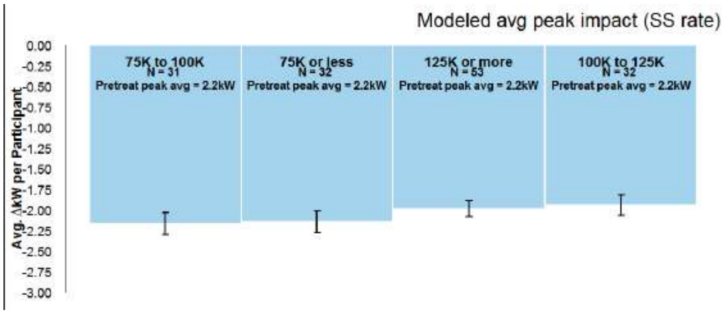


Figure 6. Effect of participant age on event impacts

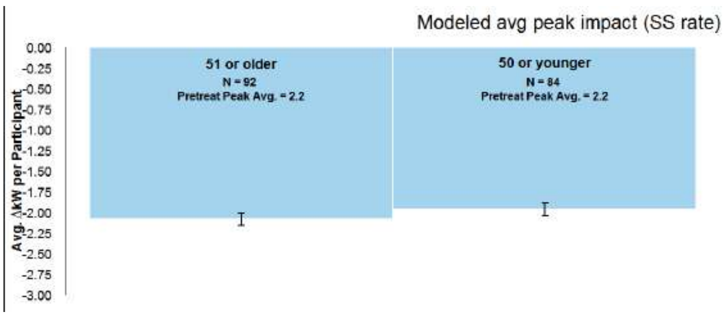


Figure 7. Effect of house age on event impacts

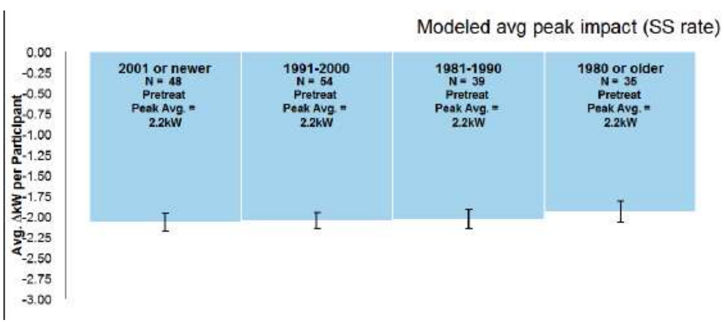
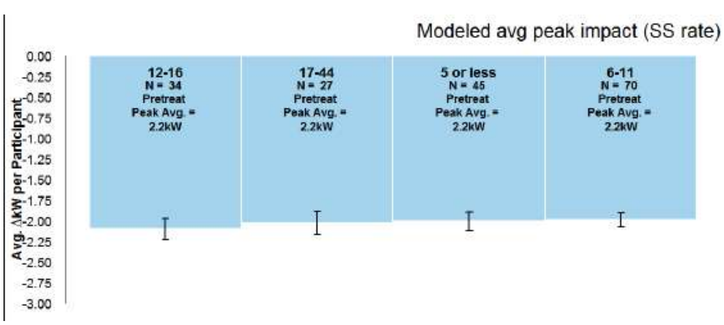


Figure 8. Effect of length of residency on event impacts



Mixed Effects Model

The mixed effects model employed in this section is similar to the model used for the load impacts estimates provided in the main report, shown in Equation 3. The only difference between Equation 2 and Equation 3 is the inclusion of pretreatment peak kW (Avg_Peak) interaction with MaxTemp, hour and program_day type to capture the effect of pretreatment peak energy use and outdoor temperatures on the load impacts for different program options and day types. All days except weekends and holidays were included in the analysis: June 1through September 30, 2010 and June 1 through September 30, 2012.

Equation 2. Load impact model used for extrapolation to SMUD's population

$$kw_{ijk} = \beta_{(CDH)ijk} CDH_{ijk} + \beta_{(MaxTemp*hour*Program\_DayType)ijk} MaxTemp * hour_{ijk} * Avg\_Peak * Program\_DayType \ + r_i + r_{ij} + \varepsilon_{ijk}$$

kw_{ijk}: kilowatt load for customer i on day j at hour k
$hour_{ijk}$: categorical variables (17-19) indicating the hour of the day
CDH_{ijk}: cooling degree hour on day j at hour k
$MaxTemp_{ij}$: maximum temperature on day j
Avg_Peak : Average pretreatment peak load for customer i (calculated as average of 3*122 hourly kW values, summer 2010)
$Program\_DayType$: categorical variables for program option and day type (Neither_Event_2012, Neither_Nonevent_2012, Neither_Pretreatment_2010, ATC_Event_2012, ATC_Nonevent_2012, ATC_Weekday_2010, SS_Rate_Event_2012, SS_Rate _Nonevent_2012, SS_Rate _Weekday_2010, SS_Rate_and_ATC_Event_2012, SS_Rate_and_ATC_Nonevent_2012, SS_Rate_and_ATC_Weekday_2010, Control_Weekday_2012, Control_Weekday_2010)
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

Results

Figure 9 shows the results of the model under the assumptions that 80% of SMUD's residential population is invited, and that 15% of those invited become participants. Note that 15% is on the lower end of what SMUD realized for their similarly designed voluntary Smart Pricing Options program. Results indicate that peak impacts on a 105°F *non-event* weekday would be about 8 MW for the load control program and 80 MW for the TOU-CPP rate.

Figure 9. Extrapolation to residential sector loads: a 105°F non-event weekday

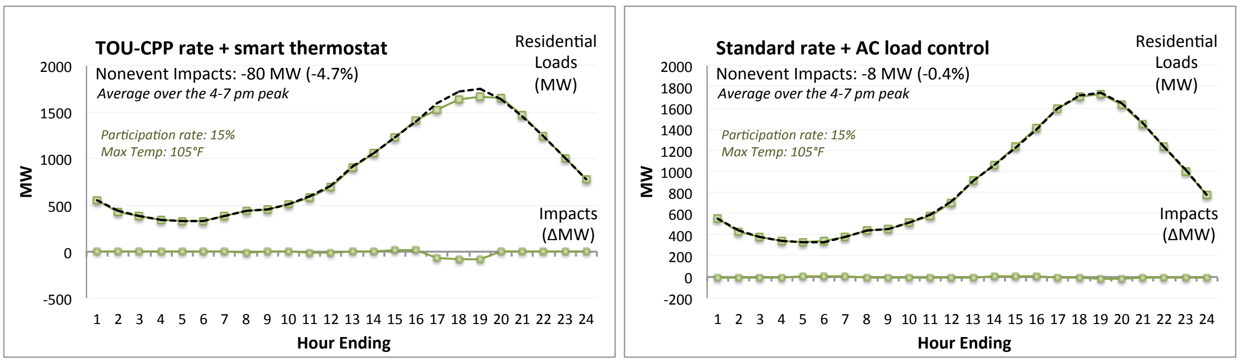
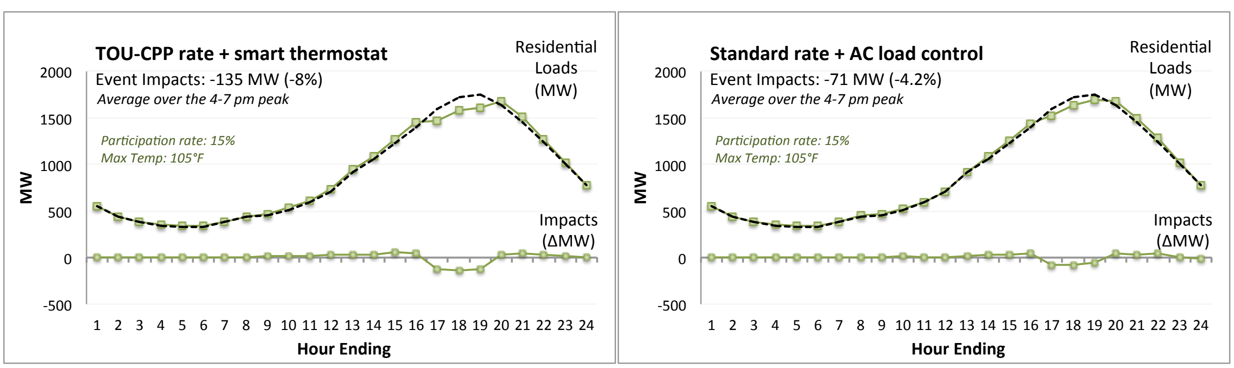


Figure 10 shows the residential impacts on an *event* weekday. Here, the TOU-CPP rate effects an average 135 MW peak load shed, while the load control program achieves just 71 MW load shed.

Figure 10. Extrapolation to residential sector loads: a 105°F event weekday



See also the calculator: "2014 Herter - SMUD Residential Summer Solutions – Addendum.xlsx"

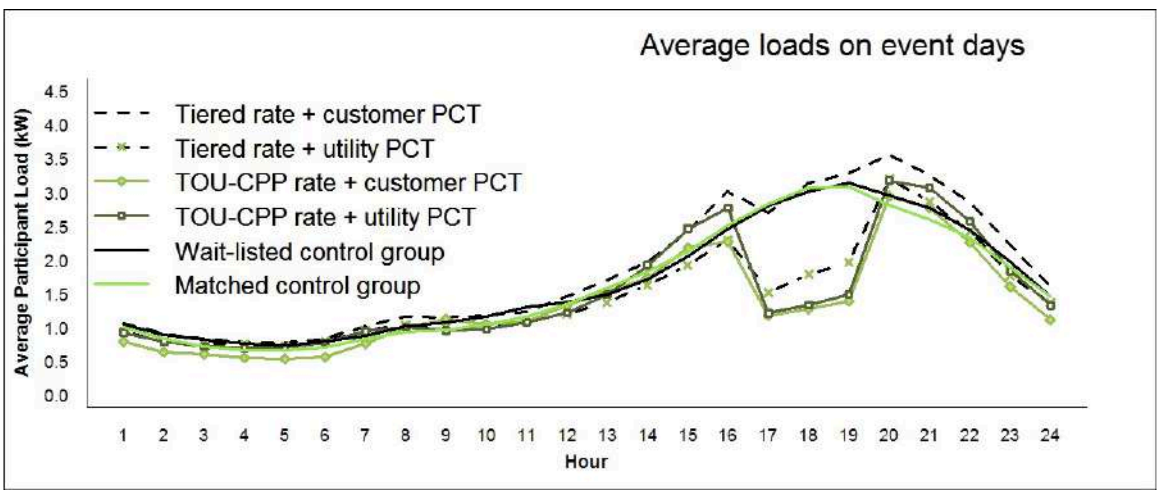
4. Baseline Calculation for Load Impact Evaluation

Participation in the first year of the Summer Solutions study was limited to 270 customers, leaving 173 customers on a wait list that could be used as a recruited control group, thus eliminating the potential for self-selection bias. In the second year of the study, these customers were installed with the Summer Solutions equipment and enrolled as participants. As a result, they could no longer be used as a control group in the load impact analysis, and a matched control group was used instead.

This section considers whether there are substantial differences between the baselines and load impact estimates derived from the hourly loads of (a) the recruited, waitlisted control group, (a) an uninvited, geographically matched control group, and (c) a baseline modeled through difference-in-differences (DID) mixed-effects regression.

Figure 11 shows the average event day loads for the participant and control groups in summer 2011. The participant groups include the 267 customers who completed the study in 2011. The recruited control group consists of the 137 wait-listed customers who submitted applications for participation after the participation limit was reached. The matched control group consists of 250 customers chosen by location from a larger randomly selected control group of 4,000 to match the neighborhoods of the existing participants. Figure 11 shows that the recruited and matched control group loads are very similar.

Figure 11. Actual loads for participant and control groups



Modeled Baseline

Baseline loads were modeling using a multilevel mixed effects regression model that incorporated 2010 and 2011 treatment and matched control group loads. The model was designed with three levels, one for hourly data, one for daily data, and one for participant data, with random effects for Day and Participant as shown in Equation 3.

Equation 3. Original model used to estimate hourly load impacts in the main report

$$kw_{ijk} =$$

$$\beta_{(hour)ijk} hour_{ijk} + \beta_{(CDH)ijk} CDH_{ijk} + \beta_{(MaxTemp)ijk} MaxTemp_{ijk} +$$

$$\beta_{(hour*program\_event)ijk} hour_{ijk} * program\_event + r_i + r_{ij} + \varepsilon_{ijk}$$

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

$hour_{ijk}$: categorical variables (1-24) indicating the hour of the day, where hour 1 spans the period from midnight to 1:00 a.m. and hour 24 spans the period from 11:00 p.m. to midnight

CDH_{ijk}: cooling degree hour on day j at hour k

$MaxTemp_{ijk}$: maximum temperature on day j

$program\_event$: categorical variable for program and event (Control_2010, Control_2011, Neither_2010, Neither_Event, Neither_Nonevent, ATC_2010, ATC_Event, ATC_Nonevent, SS_rate_2010, SS_rate_Event, SS_rate_Nonevent, SS_rate_and_ATC_2010, SS_rate_and_ATC_Event, SS_rate_and_ATC_Nonevent)

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

Baseline Comparison

Figure 12 and Figure 13 show the average hourly baseline loads for event days and non-event days, respectively. The control group baselines are calculated as hourly averages of the actual data on those days, while the modeled baseline was created using Equation 3.

Figure 12. Baseline loads on 2011 event days

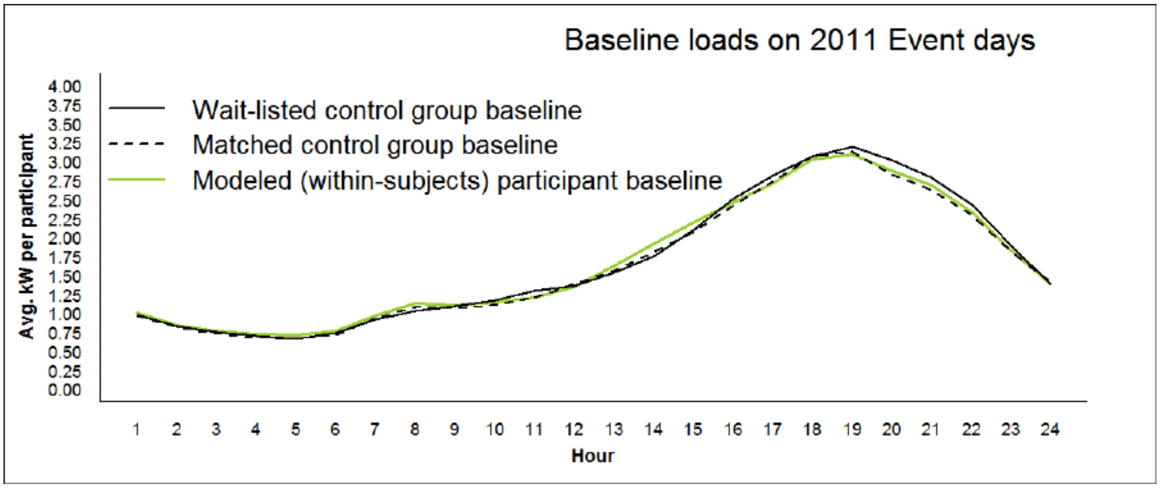
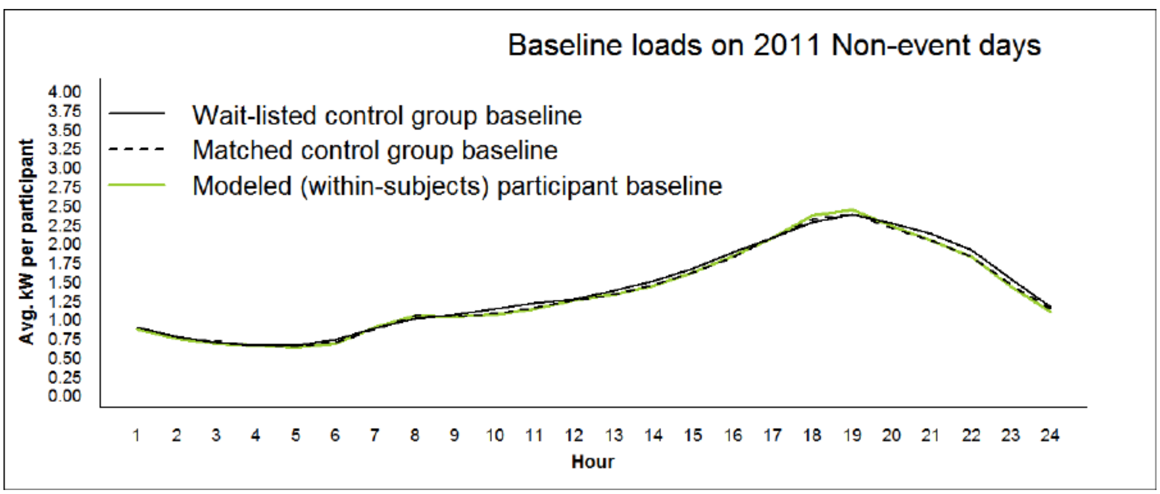


Figure 13. Baseline loads on 2011 non-event weekdays



Impacts Comparison

Figure 14 and Figure 15 show the average hourly load impacts for event days and non-event days, respectively. In each case, impacts are calculated as the difference between the baselines, shown in Figure 12 and Figure 13, and the actual average loads on event or non-event days.

Figure 14. Impacts on 2011 event days

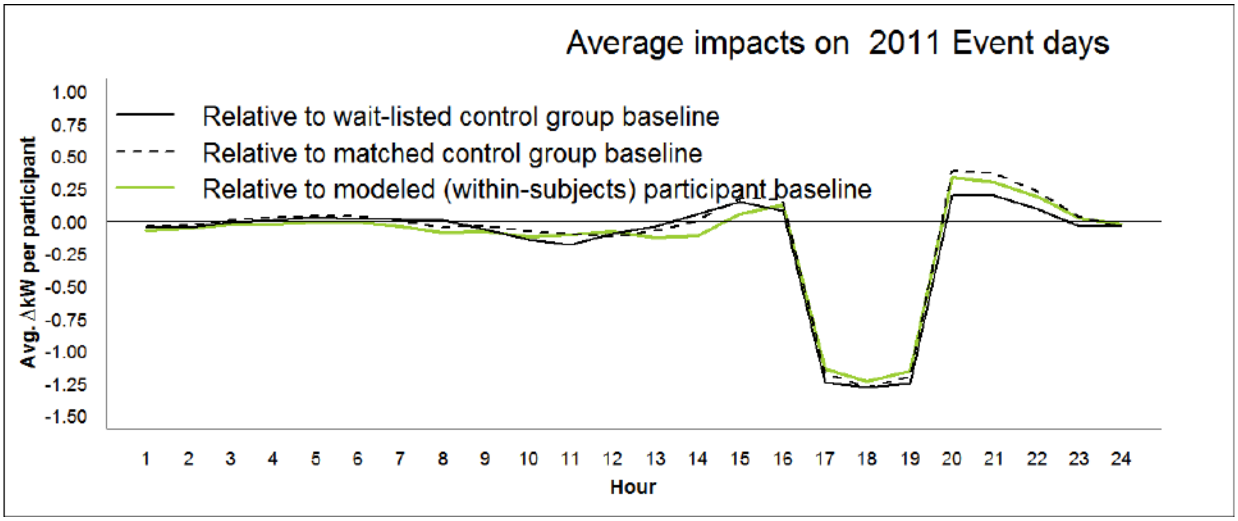


Figure 15. Impacts on 2011 non-event weekdays