REPORT

SoCalGas® 2016-2017 Winter Demand Response Load Impact Evaluation

September 1, 2017

Prepared for
Southern California Gas Company

Prepared by
Josh Schellenberg
Vice President

Aimee Savage
Consultant

Adriana Ciccone
Consultant

Nexant, Inc.

1 Executive Summary

California Public Utilities Commission Resolution G-3522 approved SoCalGas' proposed winter demand response programs (AL 5035-G) with modifications and directed SoCalGas to undertake evaluation efforts of the ex post load reductions provided. These pilot programs were implemented during the 2016-2017 winter. All three programs utilized the messaging "SoCalGas Advisory – A Call to Conserve Natural Gas" to execute and communicate natural gas demand response events called Advisory days. The pilots were:

- **SoCalGas Advisory Pilot Rebate Program:** An offering that includes incentives for gas usage below a customer-specific 10/10 baseline on Advisory days;
- **Core Notification Campaign:** Mass media campaign promoting customer reduction in gas usage on SoCalGas Advisory days; and
- **Noncore Notification Campaign:** Similar to the Core Notification Campaign, but specifically for large noncore customers.

During the SoCalGas Advisory program, SoCalGas called two Advisories, the first from December 18 through 20, 2016 and the second from January 23 through 26, 2017, totaling seven days.

1.1 Load Impact Evaluation Results

Gas impacts on Advisory days were estimated by applying the best practices that have been developed for electric Demand Response (DR) program measurement and evaluation in California. As in the annual electric DR evaluations, the SoCalGas Advisory load impact estimates leverage the wide availability of interval data from advanced meters to estimate the usage reductions. Applying these best practices, Nexant estimated the load impact results, as summarized in this report. **The key finding is that the three SoCalGas Advisory programs generally did not produce statistically significant reductions in gas usage. The one exception is that the My Account customer segment of the Pilot Rebate Program delivered a 3.7% reduction in total gas usage during three days of the second Advisory (January 23 through 25, 2017).** The total amount of gas usage reduced was 792 therms.

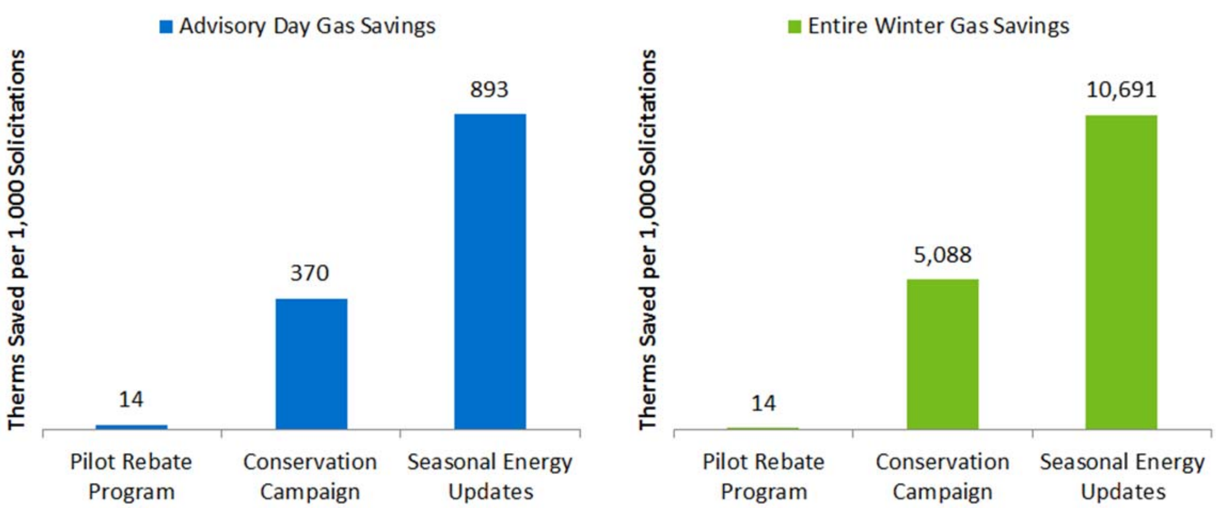
These load impact results are consistent with those outlined in Nexant's memo "2016-2017 SoCalGas Winter Demand Response Programs Preliminary Load Impact Results" sent to CPUC staff by SoCalGas on June 23, 2017.

1.2 Comparison to SoCalGas Advanced Meter Conservation Campaign Treatments

In accordance with the criteria outlined in SoCalGas' AL 5035, the solicitation lists of nearly 55,000 residential My Account and Non-My Account SoCalGas Advisory Pilot Rebate Program customers were randomly selected from the control groups of the SoCalGas Advanced Meter 2016-2017 Conservation Campaign, which launched at the same time as the winter gas demand response programs. Therefore, the Pilot Rebate Program results can be directly compared to those of several behavioral program interventions from the Conservation Campaign that involved over 245,000 solicited residential customers. While the behavioral treatments from the Conservation Campaign did not ask customers to conserve on any particular day, the gas savings for Conservation Campaign pilot programs were estimated for the Advisory days as well as for the entire winter from December 2016 through March 2017.

For My Account and Non-My Account customers, Figure 1-1 scales the total therms saved by the number of customers solicited for the Pilot Rebate Program, Conservation Campaign overall and the Seasonal Energy Update (SEU) monthly energy reports treatment, which was the highest performing of the Conservation Campaign. In total, the Conservation Campaign treatments produced nearly 91,000 therms saved across the two Advisories, which equates to 370 therms saved per 1,000 solicited customers. Even though reducing usage on specific days was not a focus of the Advanced Meter Conservation Campaign, these treatments produced nearly *26 times* more gas savings per solicited customer than the Pilot Rebate Program. The most effective Conservation Campaign treatment, “Seasonal Energy Update” monthly energy reports, produced more gas savings per 1,000 solicited customers on Advisory days than the entire Pilot Rebate Program produced with nearly 55,000 total solicited customers. Importantly, these Conservation Campaign treatments have the significant additional benefit of producing gas savings on non-Advisory days, which brings in an additional 1.16 million therms saved throughout the winter (around 4,700 therms saved per 1,000 solicited customers).

Table 3-4: Comparison of Pilot Rebate Program and Conservation Campaign



1.3 Nexant Observations and Recommendations

The SoCalGas Advisory had a variety of significant challenges, some of which were likely due to the short lead time for designing and launching the pilots. If a similar need for conservation arises in the future, SoCalGas may be able to address some of these challenges to improve the impacts for these types of pilots, but many of the issues are likely to persist, including:

- Long, multi-day events lead to relatively low impacts (or no impacts)

- Typical, relatively low enrollment rates in the opt-in Pilot Rebate Program for most segments (4.5% overall enrollment rate, ranging from 0.5% for the CTA-served customer segment to 8.6% for the My Account segment)[1]
- Settlement baseline error for the Pilot Rebate Program, as summarized in Section 6
- As in the most recent CPUC-filed Statewide Flex Alert evaluation of electricity impacts,[2] mass market calls for energy conservation do not produce measurable impacts

Therefore, if a similar need for conservation arises in the future, Nexant recommends scaling up the many successful behavioral interventions from the Advanced Meter Conservation Campaign, most notably Seasonal Energy Update energy reports. These interventions have the dual benefit of providing significant gas savings on both Advisory days and non-Advisory days throughout the winter.

1.4 Baseline Accuracy Assessment

Nexant evaluated 22 different potential baseline methodologies as alternate methods for the SoCalGas winter demand response programs. These included the 10/10 baseline methodology specified in CPUC Resolution G-3522, as well as regression-based approaches, such as that proposed in the draft CPUC resolution. The key finding of this analysis was that "day matching" baseline methods performed best, especially those with short look-back periods such as the top 3/5 and top 4/4. While "weather matching" results performed well, their results were never best overall.

---

1 As SoCalGas stated in its response to the Energy Division "Data Request for Estimated therms savings for Winter Demand Response Proposed Programs in Advice Letter No. 5035-G," requested on September 30, 2016, submitted on October 7, 2016, "Best case and worst case scenario [therms savings] assumptions are derived from several studies and analyses performed over the last five years of electric "Peak Time Rebate" and "Critical Peak Pricing" pilots and programs offered across the country. Upper bounds on "opt-in" rates for the most successful programs appear to be roughly 20 to 25%. The lower end on "opt-in" rates in these same studies is around 5%, however average response rates for direct response solicitations across all industries and marketing solicitation types more broadly can be as low as 1 to 2%."

2 Christensen Associates. "2013 Impact Evaluation of California's Flex Alert Demand Response Program." February 28, 2014. CALMAC Study ID: SCE0343.01.

2 Introduction

California Public Utilities Commission Resolution G-3522 approved SoCalGas' proposed winter demand response programs (AL 5035-G) with modifications and directed SoCalGas to undertake evaluation efforts of the ex post load reductions provided.[3] Pursuant to this directive, SoCalGas worked with Nexant to conduct a load impact analysis to estimate the therm reductions for all three "Natural Gas Conservation" pilot programs included in the Resolution.

These pilot programs were implemented during the 2016-2017 winter, from December 1, 2016 through March 31, 2017. All three programs utilized the messaging "SoCalGas Advisory – A Call to Conserve Natural Gas" to execute and communicate natural gas demand response events called Advisory days. The pilots were:

- **SoCalGas Advisory Pilot Rebate Program:** An offering that includes incentives for gas usage below a customer-specific 10/10[4] baseline on Advisory days;
- **Core Notification Campaign:** Mass media campaign promoting customer reduction in gas usage on SoCalGas Advisory days; and
- **Noncore Notification Campaign:** Similar to the Core Notification Campaign, but specifically for large noncore customers.

In addition, as another element of the Pilot Rebate Program, SoCalGas implemented a Smart Thermostat direct control demand response pilot, called the "SoCalGas Advisory Thermostat Program." Appendix D provides an overview of this pilot.

During the SoCalGas Advisory program, SoCalGas called two Advisories, the first from December 18 through 20, 2016 and the second from January 23 through 26, 2017, totaling seven days. Pilot Rebate Program participants were eligible to receive rebates if they reduced usage below their customer-specific 10/10 baseline on those days. This report summarizes the impact estimates and impact estimation methodology for each pilot. For the Pilot Rebate Program specifically, this report also provides a summary of enrollment and rebates by customer segment and a baseline accuracy assessment.

Gas impacts on Advisory days were estimated by applying the best practices that have been developed for electric Demand Response (DR) program measurement and evaluation in California. In 2008, the California Public Utilities Commission (CPUC) and joint electric Investor-Owned Utilities (IOUs) developed California's Load Impact Protocols, which required the electric utilities to conduct annual evaluations of all DR programs in the state. As in the annual electric DR evaluations, the SoCalGas Advisory load impact estimates leverage the wide availability of

---

3 Paragraph 7 of the Resolution "Findings" directed SoCalGas as follows: "It is reasonable to authorize SoCalGas an additional $800,000 to undertake evaluation efforts of the ex post load reductions provided by all three proposed programs, including the modifications to the Natural Gas Conservation Rebate Pilot adopted in this resolution. The evaluations should also include an analysis of the accuracy of the baseline method for the Natural Gas Conservation Rebate Pilot and those that were proposed in the draft resolution."

4 Also referred to as a "10-10 baseline." Paragraph 4 on page 2 of the Resolution directed SoCalGas as follows: "SoCalGas shall use a 10-10 baseline methodology to calculate the load drops for purposes of determining the incentive payment for all participants in the program." On page 13, the methodology is further defined as: "using the participant's gas load profile for the past 10 days, a simple daily use average is calculated to determine the customer's gas load for the day in which the DR event occurred. Weekends, holidays and days when a DR event occurred are all removed from the 10 day calculation and replaced with the next available day in the calendar."

interval data from advanced meters to estimate the usage reductions. The Pilot Rebate Program methodology that uses a matched control group is similar to how most electric DR programs have been evaluated for several years, including Southern California Edison's Save Power Days Program,[5] which is also a peak-time rebate program. In addition, the core and noncore Notification Campaign methodologies draw from the most recent CPUC-filed Statewide Flex Alert evaluation,[6] which also used a regression approach to model aggregate load and estimate load impacts.

The remainder of this report proceeds as follows:

- **Section 3:** Pilot Rebate Program background, impact evaluation methodology and daily impact estimates, including comparisons to experimental design results and to the gas savings from the SoCalGas Advanced Meter 2016-2017 Conservation Campaign treatments.
- **Section 4:** Core Notification Campaign background, impact evaluation methodology and daily impact estimates.
- **Section 5:** Noncore Notification Campaign background, impact evaluation methodology and daily impact estimates.
- **Section 6:** Pilot Rebate Program baseline accuracy assessment, including alternative baselines tested and Nexant recommendations.

In addition, the appendices provide various supporting tables for the Pilot Rebate Program impact analysis and baseline accuracy assessment.

[5] Nexant. "2016 Load Impact Evaluation of Southern California Edison's Save Power Days Program." April 1, 2017. CALMAC Study ID: SCE0409.

[6] Christensen Associates. "2013 Impact Evaluation of California's Flex Alert Demand Response Program." February 28, 2014. CALMAC Study ID: SCE0343.01.

3 Pilot Rebate Program

This section summarizes the Pilot Rebate Program background, impact evaluation methodology and daily impact estimates. It also provides comparisons to experimental design results and to the gas savings from the SoCalGas Advanced Meter 2016-2017 Conservation Campaign treatments for residential My Account and Non-My Account customers.

3.1 Background

Figure 3-1 shows the cumulative enrollments in the Pilot Rebate Program by day from December 2016 through March 2017. The two SoCalGas Advisories are highlighted by the gray bars. Customers were eligible to receive rebates on a given Advisory day if it was on or after their enrollment date. About 48% of customers were enrolled in the program by the first Advisory day, and 76% were enrolled by the last. Ultimately, 3,408 customers enrolled in the program, but about 24% enrolled too late to be eligible to receive rebates on an Advisory day.

Figure 3-1: Cumulative Enrollment in the SoCalGas Advisory Pilot Rebate Program by Date (December 1, 2016 through March 31, 2017)

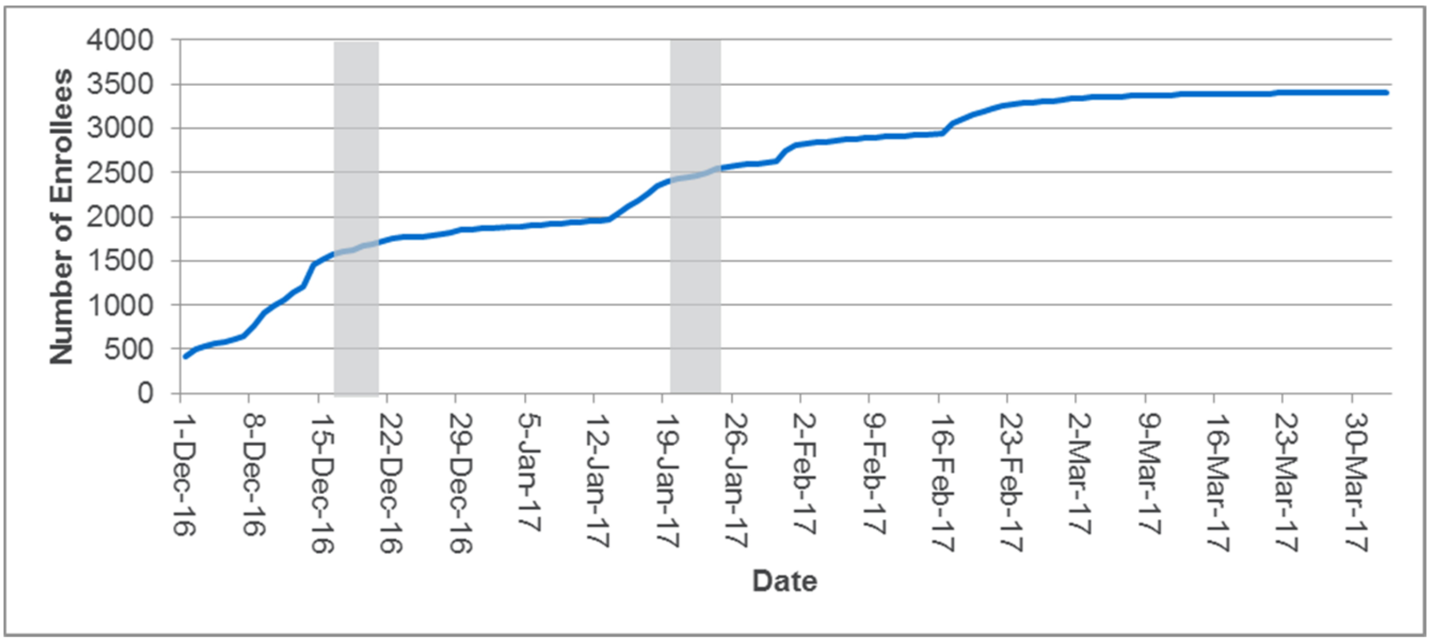


Table 3-1 presents the total customers solicited/eligible and enrolled in the Pilot Rebate Program in each segment, including Core Transport Agent (CTA)-served customers, Highest Winter Load (HWL), My Account and Non-My Account customers. The table also shows the number of customers eligible to receive rebates, the number of customers who earned rebates, and the average rebates they earned. Using the 10/10 baseline methodology as described in Resolution G-3522, Nexant calculated rebates for the 2,556 customers who were enrolled during at least one Advisory day. Rebates were calculated for each customer by adding up the therms the customer reduced below their baseline on each Advisory day and multiplying that total by $2.50 per therm. The final two columns show the total rebates that were paid to each customer segment and total usage below the baseline.

Table 3-1: Summary of Enrollment and Rebates by Customer Segment

Customer Segment	Total Solicited/ Eligible	Enrolled as of March 31, 2017	Percent Enrolled	Eligible to Receive Rebate*	Earned Rebate (saved 1 therm or more)	Average Rebate (for those who earned a rebate)**	Total Rebates	Total Usage (therms) below Baseline
CTA	10,439	54	0.5%	37	12	$7.50	$90.00	36
HWL	10,465	189	1.8%	141	65	$235.96	$15,337.50	6,135
My Account	27,499	2,353	8.6%	1,768	417	$6.26	$2,610.00	1,044
Non-My Account	27,388	812	3.0%	610	116	$7.00	$812.50	325
Total	**75,791**	**3,408**	**4.5%**	**2,556**	**610**	**$30.90**	**$18,850**	**7,540**

* Enrolled during at least one Advisory day and met eligibility criteria. Note: As of June 23, calculation of potential rebates earned was still underway for 19 enrolled customers across the four customer segments, due to exceptions in the data for these accounts that required further assessment. These customer accounts are not reflected above. Three of the accounts were determined to be ineligible for the program, four did not earn a rebate, one earned a rebate, and an alternative calculation method was used to determine rebate amounts for eleven residential accounts with some missing advanced meter usage data.

** Does not include additional $5 participation credit provided to Non-My Account customers

Importantly, while many customers received rebates, they may not have actually reduced usage on the Advisory days. The 10/10 baseline can be biased upward for individual customers on individual days, leading to rebates even if the customer did not respond. Nexant's load impact evaluation summarized below provides a much more reliable estimate of program-level usage reductions for the Pilot Rebate Program participants by leveraging data throughout the winter, including hourly usage data for a control group of non-participants that was developed. In addition, Section 6 provides a detailed assessment of baseline accuracy.

3.2 Impact Evaluation Methodology

Nexant developed several control groups of carefully selected non-participants in order to estimate reductions in gas consumption on Advisory days. The methods used to assemble the control groups are designed to ensure that the control group load on Advisory days is an accurate estimate of what load would have been among Pilot Rebate Program participants on Advisory days if they had not participated. The fundamental idea behind the matching process is to find customers who did not participate in the pilot with similar characteristics to those who did.

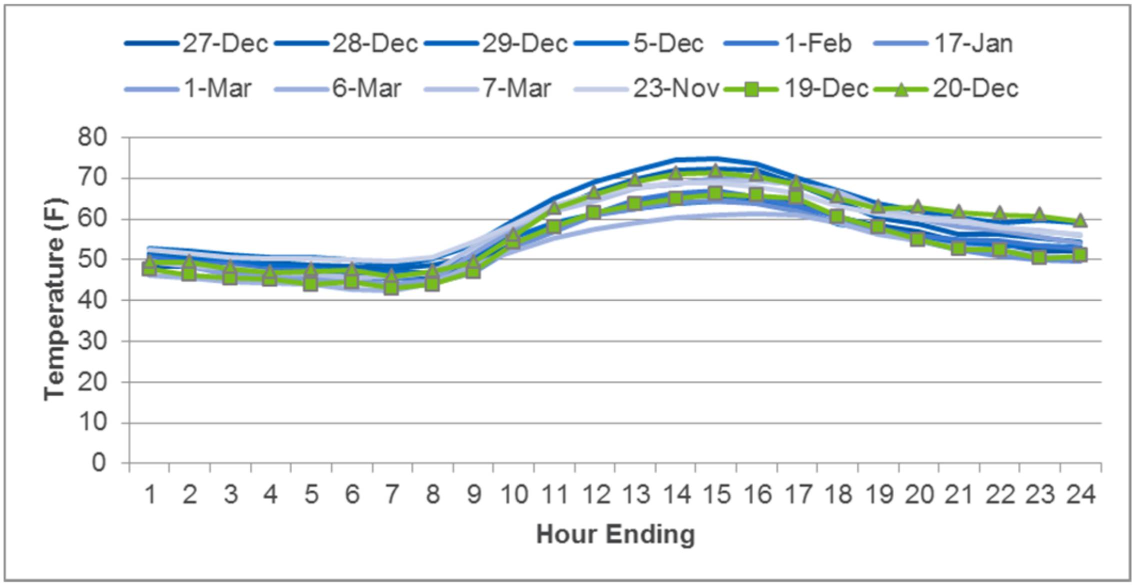
The control groups were selected using a propensity score match to find customers who, on non-Advisory days, had hourly gas usage most similar to pilot participants. In this procedure, a probit model is used to estimate a propensity score for each customer based on a set of observable variables. A probit model is a regression model designed to estimate the propensity score and each customer in the control group is matched to a pilot participant with a similar estimate score given the observed variables.

The first step in the matching process was to select non-Advisory days on which participants and non-participants will be matched; these are called *proxy days*.[7] A separate set of proxy days

[7] Depending on the available data and objectives for each analysis and customer group, the number and mix of proxy days varies between each analysis described in this report.

was selected for each customer segment and three groups of Advisory days: December 18 (a Sunday), December 19 and 20, and January 23 through 26. The weather on the proxy days was similar to the weather on the corresponding Advisory days. Figure 3-2 shows hourly temperature profiles for the December 19 and 20 advisory days and their corresponding proxy days.

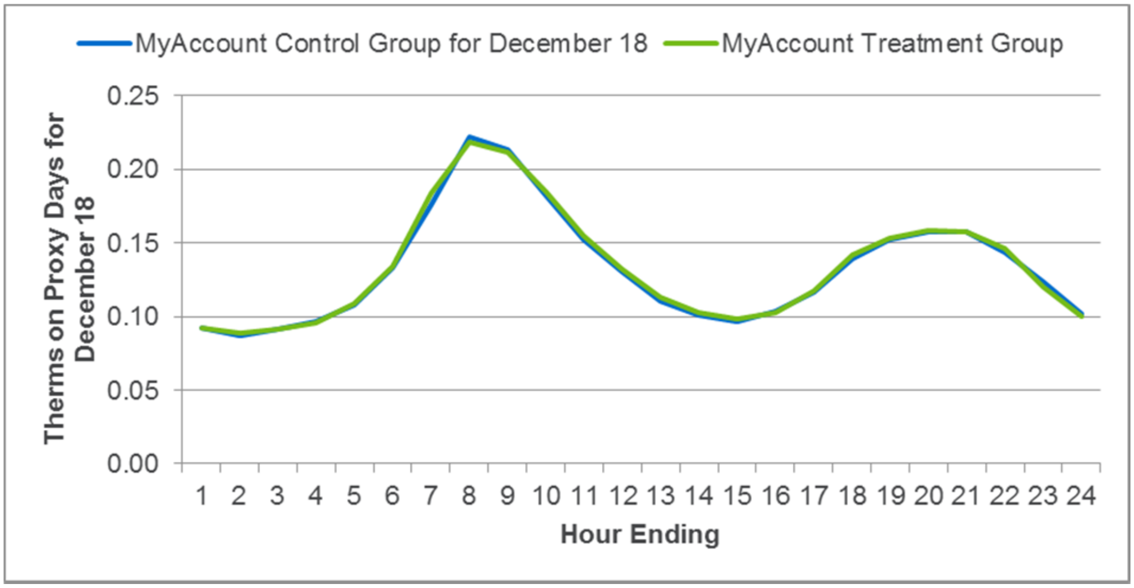
Figure 3-2: Proxy Day Weather Profiles



Next, the propensity score model was used to match each participant to a non-participant with similar hourly gas usage on proxy days. A participant could have up to three different matches (one for each set of Advisory days) or they could be matched to the same non-participant multiple times. Customers were guaranteed to be matched to customers within their geographic location and customer segment (for CTA and HWL customers, matched control group customers also had to be on the initial eligibility lists). Each control group customer is only matched to one participant per set of Advisory days.

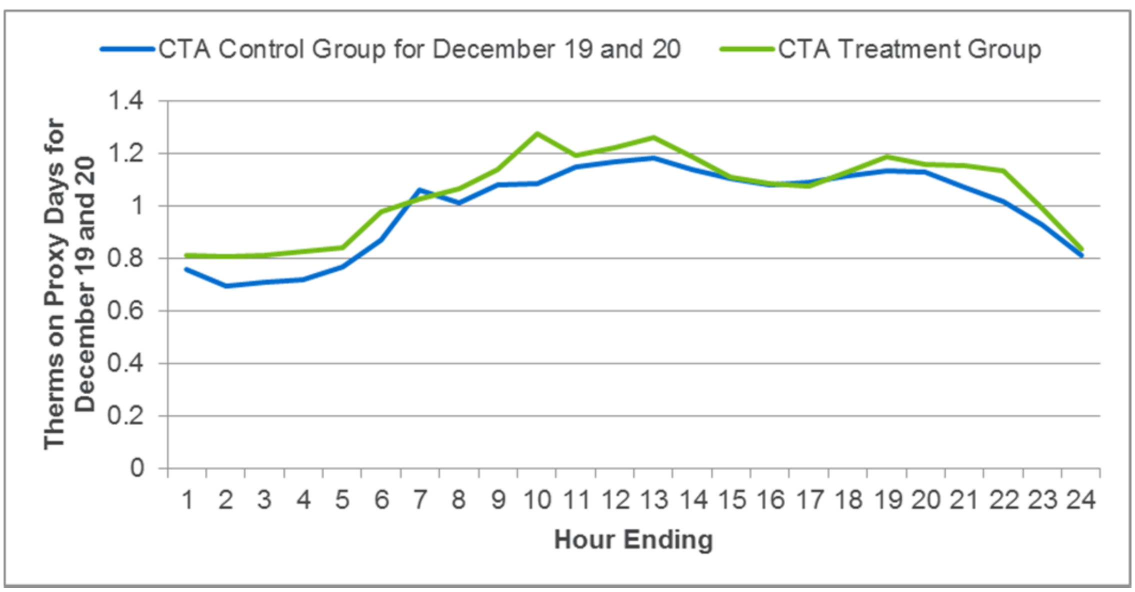
To summarize, any particular participant has a corresponding control customer for December 18 (a Sunday), another for December 19 and 20, and another for the January Advisory days, given that load patterns on these three sets of days are different. The control customer for December 18 has similar hourly gas consumption during corresponding proxy days, and so on. Figure 3-3 presents the average hourly gas usage on proxy days corresponding to the December 18 Advisory day. The customers presented in this figure are all My Account customers. This figure shows that the treatment group and their corresponding control group have very similar usage patterns on non-Advisory days. It is reasonable to assume that these two groups would have similar usage patterns on Advisory days if not for the effect of the Pilot Rebate Program that is estimated.

Figure 3-3: My Account Control and Treatment Groups on December 18 Proxy Days



Unfortunately, when enrollment is lower than 100 customers as in the CTA customer segment, it is often difficult to find control groups as well-matched as the one above. Average gas usage for this group is rather noisy, as shown in Figure 3-4 below. Because of this, there are small differences between the control group and treatment group on proxy days.

Figure 3-4: CTA Control and Treatment Groups on December 19 and 20 Proxy Days



While this may be concerning, the method used to estimate load impacts accounts for differences between treatment and control groups on non-Advisory days. The analysis method used is referred to as difference-in-differences (DiD) analysis. This method estimates impacts by subtracting non-Advisory day differences between treatment and control groups from Advisory day differences between the two groups. Table 3-2 presents an example in which the non-Advisory day difference in consumption between the two groups is 1.0 therm. The difference on the Advisory day is 3.0. Therefore, the estimated gas consumption impact is 3.0 minus 1.0, or 2.0 therms.

Table 3-2: Difference-in-Differences Example

Group	Non-Advisory Day Usage (Therms)	Advisory Day Usage (Therms)	Total Impact (Therms)
Control	3.0	6.0	3.0 - 1.0 =
Treatment	2.0	3.0	
Difference	**1.0**	**3.0**	**2.0**

The DiD analysis can be done with simple calculations using averages, as in Table 3-2, but regression analysis is required to produce accurate standard errors for assessing statistical significance. Customer fixed effects regression analysis allows each customer's mean usage to be modeled separately, which reduces the standard error of the impact estimates without changing their magnitude. Additionally, standard regression software allows for the calculation of standard errors, confidence intervals, and significance tests for load impact estimates that correctly account for the correlation in customer loads over time. A typical regression specification for estimating impacts is shown in this equation:

$$therms_{i,t} = \alpha_i + \gamma \text{advisory}_t + \beta(\text{treatmentXadvisory})_{i,t} + \ v_i + \ \varepsilon_{i,t}$$

In this equation, the variable $therms_{i,t}$ equals gas usage during the time period of interest, which in this case is the Advisory day. The index *i* refers to customers and the index *t* refers to the Advisory day of interest. The analysis dataset contains gas usage data during both the non-Advisory proxy days and Advisory days for both treatment and matched control group customers. The variable *advisory* is equal to 1 during a specific advisory day and 0 on proxy days. The *treatmentXadvisory* term is the interaction of *treatment* and *advisory* and its coefficient β is a difference-in-differences estimator of the treatment effect that makes use of the proxy day data. The primary parameter of interest is β, which provides the estimated gas usage impact of the pilot during the relevant period. The parameter $\mathrm{a_i}$ is equal to mean usage for each customer for the relevant time period (e.g., daily). The $\mathrm{v_i}$ term is the customer fixed effects variable that controls for unobserved factors that are time-invariant and unique to each customer. This model is estimated separately for each customer segment and Advisory day.

3.3 Daily Impact Estimates

Table 3-3 presents gas usage impacts for each customer segment and each Advisory day. The number of customers for each day is based on the number of customers who were enrolled on a particular Advisory day. The Reference Therms column presents what we expect pilot participants would have used if not for the Advisory day. The Observed Therms column presents the average gas consumption for that group of customers on the Advisory day. The estimated impact is the difference between Reference Therms and Observed Therms. A positive value indicates that customers reduced their consumption, while a negative value indicates that they have increased it. The three rows with gas usage reductions that are statistically significant (p-value less than 0.05) are highlighted in light blue.

My Account customers showed statistically significant gas consumption reductions on January 23, 24, and 25. Across the three days, each customer saved 0.45 therms on average (3.7% of total gas usage), which totals nearly 800 therms in aggregate. CTA, HWL, and Non-My Account customers did not provide statistically significant gas usage reductions. In some cases, these customers show negative gas impacts, but these estimated increases in usage were also not statistically significant.

Table 3-3: Pilot Rebate Program Gas Consumption Daily Impacts by Customer Segment

Pilot Rebate Program - Customer Segment	Number of Customers	Date	Reference (Therms)	Observed (Therms)	Impact (Therms)	Impact (%)	95% Confidence Interval		P-Value
CTA	5	December 18, 2016	17.6	16.8	0.78	4.5%	-28%	37%	0.79
	5	December 19, 2016	15.6	15.9	-0.30	-1.9%	-14%	10%	0.75
	5	December 20, 2016	14.5	15.2	-0.73	-5.1%	-17%	7%	0.39
	10	January 23, 2017	31.1	33.1	-1.99	-6.4%	-18%	5%	0.27
	24	January 24, 2017	25.3	25.3	-0.04	-0.2%	-7%	7%	0.97
	33	January 25, 2017	25.1	26.2	-1.14	-4.6%	-11%	2%	0.16
	33	January 26, 2017	25.6	25.9	-0.25	-1.0%	-7%	5%	0.76
HWL	59	December 18, 2016	87.4	86.4	1.01	1.2%	-20%	22%	0.91
	58	December 19, 2016	101.8	117.3	-15.52	-15.2%	-42%	12%	0.27
	61	December 20, 2016	94.3	105.9	-11.56	-12.3%	-39%	14%	0.36
	135	January 23, 2017	116.1	112.4	3.75	3.2%	-6%	12%	0.49
	138	January 24, 2017	117.6	118.7	-1.10	-0.9%	-10%	8%	0.84
	140	January 25, 2017	121.3	118.6	2.70	2.2%	-8%	13%	0.67
	141	January 26, 2017	120.4	118.8	1.55	1.3%	-6%	8%	0.73
My Account	1,307	December 18, 2016	4.1	4.0	0.09	2.1%	-1%	6%	0.23
	1,335	December 19, 2016	3.1	3.2	-0.11	-3.5%	-7%	0%	0.05
	1,348	December 20, 2016	2.5	2.6	-0.05	-1.9%	-5%	1%	0.27
	1,748	January 23, 2017	3.9	3.6	0.24	6.1%	4%	8%	0.00
	1,764	January 24, 2017	4.3	4.2	0.09	2.1%	0%	4%	0.04
	1,769	January 25, 2017	4.0	3.9	0.13	3.2%	1%	5%	0.00
	1,775	January 26, 2017	3.8	3.8	0.07	1.8%	0%	4%	0.08
Non-My Account	248	December 18, 2016	3.9	3.9	0.04	0.9%	-6%	8%	0.79
	259	December 19, 2016	3.2	3.2	0.07	2.1%	-4%	9%	0.52
	269	December 20, 2016	2.5	2.6	-0.09	-3.4%	-11%	4%	0.39
	585	January 23, 2017	3.9	3.8	0.11	2.9%	-1%	6%	0.10
	595	January 24, 2017	4.4	4.4	0.02	0.6%	-3%	4%	0.75
	605	January 25, 2017	4.1	4.1	0.03	0.7%	-3%	4%	0.69
	612	January 26, 2017	4.0	4.0	-0.04	-1.1%	-5%	3%	0.55

3.4 Comparison to Experimental Design Results

In accordance with the criteria outlined in SoCalGas' AL 5035, the solicitation lists for residential My Account and Non-My Account SoCalGas Advisory Pilot Rebate Program customers were randomly selected from the control groups of the SoCalGas Advanced Meter 2016-2017 Conservation Campaign. Therefore, for comparison purposes, Nexant leveraged these randomized groups to estimate the impacts using an experimental design, which is the CPUC's preferred method for evaluating energy savings, especially for behavioral interventions. Given that not all solicited customers enrolled in the Pilot Rebate Program, Nexant estimated the impacts using a Randomized Encouragement Design (RED). If the RED results showed that there were statistically significant impacts among customers in the *encouraged* group (solicited My Account and Non-My Account customers), the impacts for enrolled customers could then be deduced. However, if the RED results were not statistically significant, the impacts for enrolled customers would not be measurable, given the effect size and percent of customers enrolled on each Advisory day (around 1% to 7%, depending on date and customer segment).

Figure 3-5 and Figure 3-6 provide the results of the Pilot Rebate Program impacts based on the experimental design. The figures show the daily impacts for each encouraged group relative to its respective control group for My Account and Non-My Account customers. Advisory days and non-Advisory days are included to check that the randomization is valid and determine whether there is a change in the pattern when SoCalGas called the Advisories. From December 1, 2016 through February 1, 2017, the estimated change in daily usage for the encouraged groups relative to their respective control groups is not statistically significant. The estimated impacts on both Advisory and non-Advisory days fall within a remarkably narrow range of -1% to 1% of daily usage throughout the winter, even as Pilot Rebate Program enrollment increases. These results confirm that the randomization was valid and corroborate the finding that the Pilot Rebate Program generally did not produce statistically significant reductions in gas usage.

Figure 3-5: Pilot Rebate Program Experimental Design Results for My Account (Impacts for Encouraged Group Relative to Control Group)

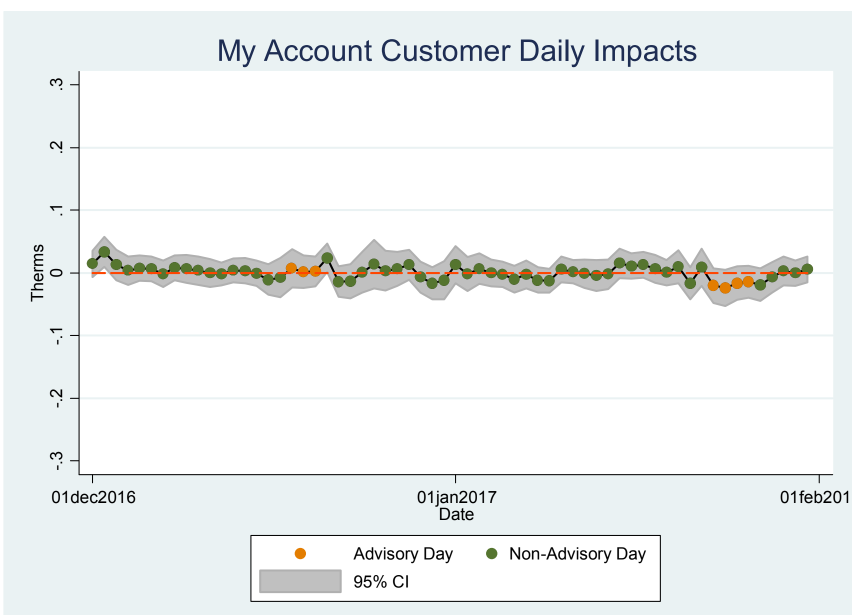
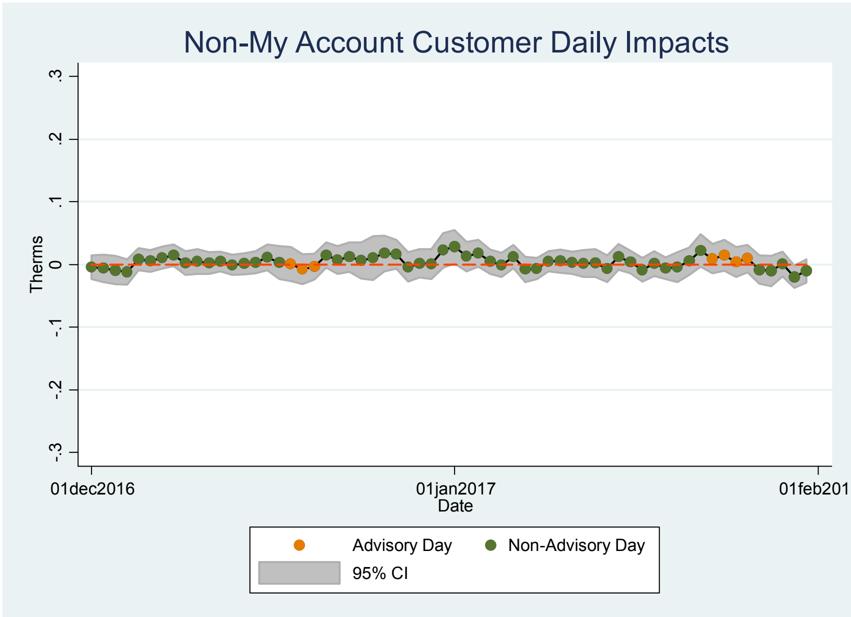


Figure 3-6: Pilot Rebate Program Experimental Results for Non-My Account (Impacts for Encouraged Group Relative to Control Group)



3.5 Comparison to SoCalGas Conservation Campaign Treatments

Given that the solicitation lists for My Account and Non-My Account customers were randomly selected from the control groups of the SoCalGas Advanced Meter Conservation Campaign, the results of several behavioral interventions that SoCalGas launched at the same time can be directly compared. While the behavioral treatments from the Conservation Campaign did not ask customers to conserve on any particular day, the gas savings can be estimated for the Advisory days as well as for the entire winter from December 2016 through March 2017. Table 3-4 summarizes the results for My Account and Non-My Account treatments as compared to the Pilot Rebate Program. The gas savings on Advisory days were positive and statistically significant for every Conservation Campaign treatment during the January Advisory. In total, these Conservation Campaign treatments produced nearly 91,000 therms saved across the two Advisories. Even though reducing usage on specific days was not a focus of the Advanced Meter (AM) Conservation Campaign, these treatments produced nearly 26 times more gas savings per solicited customer than the Pilot Rebate Program (370 therms saved per 1,000 solicited customers as compared to 14 therms saved). The most effective Conservation Campaign treatment, “Seasonal Energy Update” monthly energy reports (SEU), produced more gas savings per 1,000 solicited customers on Advisory days than the entire Pilot Rebate Program produced with nearly 55,000 total solicited customers. Importantly, these Conservation Campaign treatments have the significant additional benefit of producing gas savings on non-Advisory days, which brings in an additional 1.16 million therms saved throughout the winter (around 4,700 therms saved per 1,000 solicited customers).

Table 3-4: Comparison of SoCalGas Advisory Pilot Rebate Program and 2016-2017 AM Conservation Campaign Gas Savings by Customer Segment

Customer Segment	Treatment	Total Customers Solicited	Advisory Day Gas Savings		Entire Winter Gas Savings	
			Total (Therms)	Per 1,000 Solicited Customers	Total (Therms)	Per 1,000 Solicited Customers
My Account	SoCalGas Advisory Pilot Rebate Program	27,499	792	29	792	29
	Bill Tracker Alert (BTA) w/Tips + Paper Opower HER	40,554	17,722	437	255,322	6,296
	BTA w/o Tips	32,322	5,564	172	70,435	2,179
	BTA w/ Tips	32,022	6,747	211	83,103	2,595
Non-My Account	SoCalGas Advisory Pilot Rebate Program	27,388	0	0	0	0
	Paper Opower HER	53,500	9,032	169	209,944	3,924
	Paper Aclara HER	33,000	12,158	368	143,375	4,345
	Paper In-House HER	13,750	3,338	243	53,596	3,898
	SEU	20,350	18,644	916	211,926	10,414
	SEU (Weatherization version)	20,350	17,687	869	223,203	10,968
Total	**Pilot Rebate Program**	**54,887**	**792**	**14**	**792**	**14**
	AM Conservation Campaign	**245,848**	**90,892**	**370**	**1,250,904**	**5,088**

4 Core Notification Campaign

This section summarizes the Core Notification Campaign background, impact evaluation methodology and daily impact estimates.

4.1 Background

The SoCalGas Advisory Notification Campaign encourages voluntary reduction in gas usage on Advisory days by issuing public notifications through mass media marketing channels. These notifications were provided on the same seven Advisory days as for the Pilot Rebate Program.

Each Advisory included the following level of outreach:

- Traditional radio: 24 stations with an average of 10 spots per day (6.8 million total impressions)
- Digital radio: Pandora delivered 800,000 impressions (first Advisory) and 650,000 impressions (second Advisory)
- SoCalGas e-mail notifications: Approximately 3.2 million per deployment
- SoCalGas SMS notifications: 3,200 text messages deployed (first Advisory) and 14,200 (second Advisory) text messages deployed
- Social media: Over 1.8 million impressions (first Advisory) and 1.6 million impressions (second Advisory)

4.2 Impact Evaluation Methodology

In order to estimate gas consumption impacts, hourly gas consumption data was collected for a sample of SoCalGas core customers. The random sample had approximately 5,000 residential and 5,000 non-residential customers, each with at least 18 months of historical hourly gas consumption data. The sample was designed to contain a representative group among several levels of gas consumption, with oversampling among higher usage customers to maximize precision (following standard load research sampling techniques). Pilot Rebate Program customers were not included in the sample.

The first step in estimating Advisory day impacts is developing reference loads for the customers in the residential and non-residential samples. Reference loads indicate how customers would have behaved in the absence of the Notification Campaign. They are estimated using regression analysis of customer usage on non-Advisory days. Given that any customer could have received the mass media notifications, a matched control group of non-participants could not be used in this case. The observed loads on Advisory days are then subtracted from the predicted reference loads to estimate impacts. Generally speaking, customer gas consumption is a function of weather and day type. Figure 4-1 and Figure 4-2 illustrate this relationship. As temperatures decrease, gas consumption increases. Above a certain temperature, around 75 degrees Fahrenheit, gas consumption is relatively constant. While this figure presents 18 months of daily data, Nexant tested many model specifications and determined that it is best if the final analysis dataset only includes days less than 60 degrees Fahrenheit, given that the Advisory days were all less than that threshold.

Figure 4-1: Residential Core Gas Consumption vs. Temperature

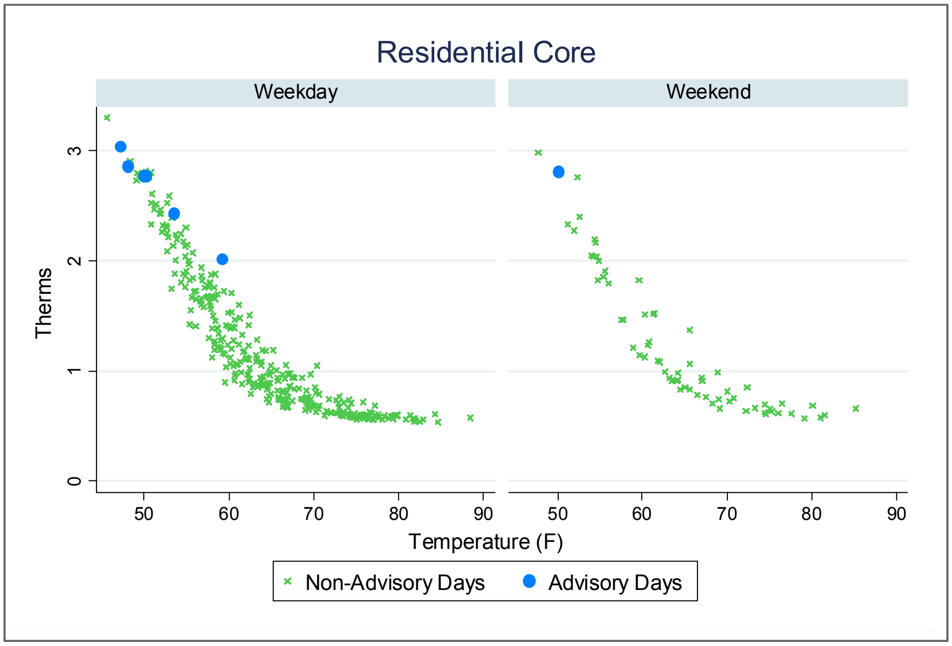
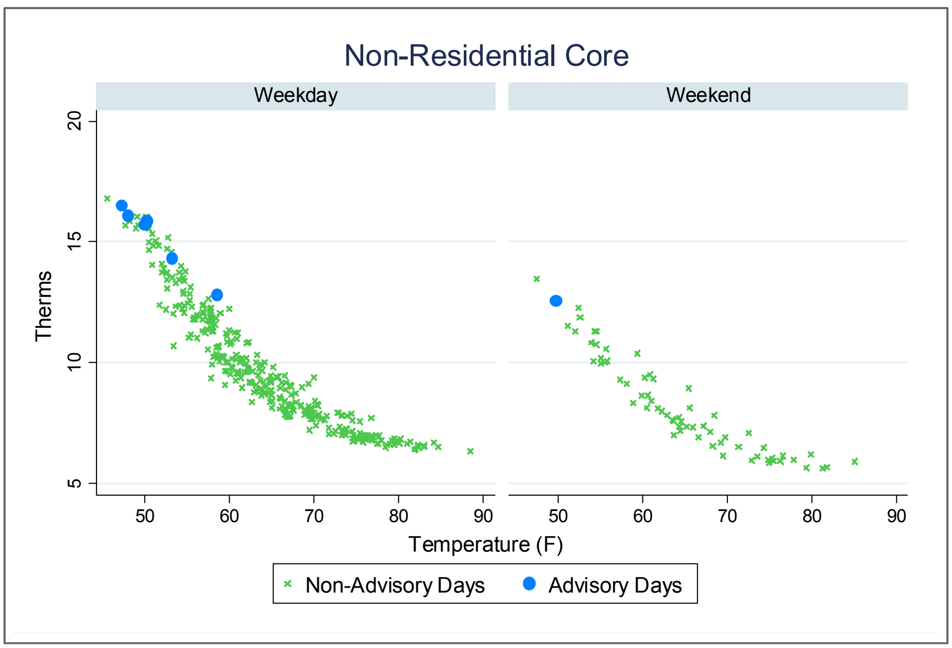


Figure 4-2: Non-Residential Core Gas Consumption vs. Temperature



Below 60 degrees Fahrenheit, the relationship between temperature and gas consumption for residential and non-residential customers is somewhat linear. Therefore, a simple temperature variable was included in the regression model along with day of week and time variables as follows:

$$therms_t = \alpha + \gamma(\text{temperature})_t + \lambda(\text{day\_of\_week})_t + \delta(\text{year\_month})_t + \beta(\text{advisory})_t + \varepsilon_t$$

In this equation, the *day_of_week* variable is a binary variable for each weekday. The variable *year_month* refers to the year and month of a particular day. Essentially, gas consumption for residential customers is a function of average daily temperature, the day of the week, and the year and month of the day. The primary parameter of interest is β, which provides the estimated gas usage impact of the campaign during the relevant period. This regression model was run separately for residential and non-residential customers.

4.3 Daily Impact Estimates

Table 4-1 presents daily impact estimates for core customers on each Advisory day. Values have been scaled up from a per-customer level to a population level. In other words, estimates have been multiplied by the number of customers that met the sampling criteria, most notably that 18 months of advanced meter data was available.

The Reference Therms column presents the predicted load on each day (in other words, the gas consumption estimated if it were not an Advisory day). The Observed Therms column is the average consumption among customers in the sample on those days. The Impact column is the difference between the two, where a positive value indicates a reduction in gas consumption. On nearly every Advisory day, these results suggest that residential and non-residential customers increased their gas consumption.

Table 4-1: Core Gas Consumption Impacts by Customer Segment and Advisory Day

Population	Number of Customers	Date	Reference (Therms)	Observed (Therms)	Impact (Therms)	Impact (%)	95% Confidence Interval		P-Value
Core - Non-Residential	131,635	December 18, 2016	1,646,834	1,654,432	-7,599	0%	-10%	9%	0.93
		December 19, 2016	1,726,845	1,883,828	-156,983	-9%	-18%	0%	0.06
		December 20, 2016	1,458,674	1,685,587	-226,912	-16%	-27%	-5%	0.01
		January 23, 2017	1,945,835	2,086,727	-140,892	-7%	-15%	1%	0.09
		January 24, 2017	2,121,236	2,172,737	-51,501	-2%	-10%	5%	0.54
		January 25, 2017	2,076,012	2,117,467	-41,455	-2%	-10%	6%	0.62
		January 26, 2017	1,956,733	2,066,099	-109,366	-6%	-14%	3%	0.19
Core - Residential	3,212,437	December 18, 2016	8,336,045	9,017,107	-681,062	-8%	-20%	4%	0.19
		December 19, 2016	6,833,277	7,806,352	-973,075	-14%	-29%	0%	0.06
		December 20, 2016	4,486,703	6,464,019	-1,977,315	-44%	-66%	-22%	0.00
		January 23, 2017	8,568,014	8,889,288	-321,274	-4%	-15%	8%	0.53
		January 24, 2017	9,837,362	9,744,646	92,716	1%	-9%	11%	0.86
		January 25, 2017	9,501,260	9,169,643	331,616	3%	-7%	14%	0.52
		January 26, 2017	8,650,882	8,896,350	-245,467	-3%	-14%	9%	0.63

To explore why these negative impacts were estimated, Figure 4-3 and Figure 4-4 add the predicted reference usage on Advisory days to the two figures above. In every case, the predicted usage on Advisory days falls within the range of usage that has been observed at a given temperature, which suggests that the predictions are reasonable. However, the Advisory days exhibit usage that is higher than the average usage that is typically observed at a given temperature in many cases. Most notably, the Advisory day that had average temperatures of nearly 60 degrees – December 20 – had average usage for both residential and non-residential core customers that is similar to the level of usage that is typically observed when it is several degrees colder. As a result, the estimates for this day show large negative impacts, even though the usage prediction seems reasonable. Appendix A includes further information on the accuracy testing of the regression models for the Core Notification Campaign to show that the available variables cannot explain this unusually high usage.

Figure 4-3: Residential Core Gas Consumption and Predicted Usage vs. Temperature

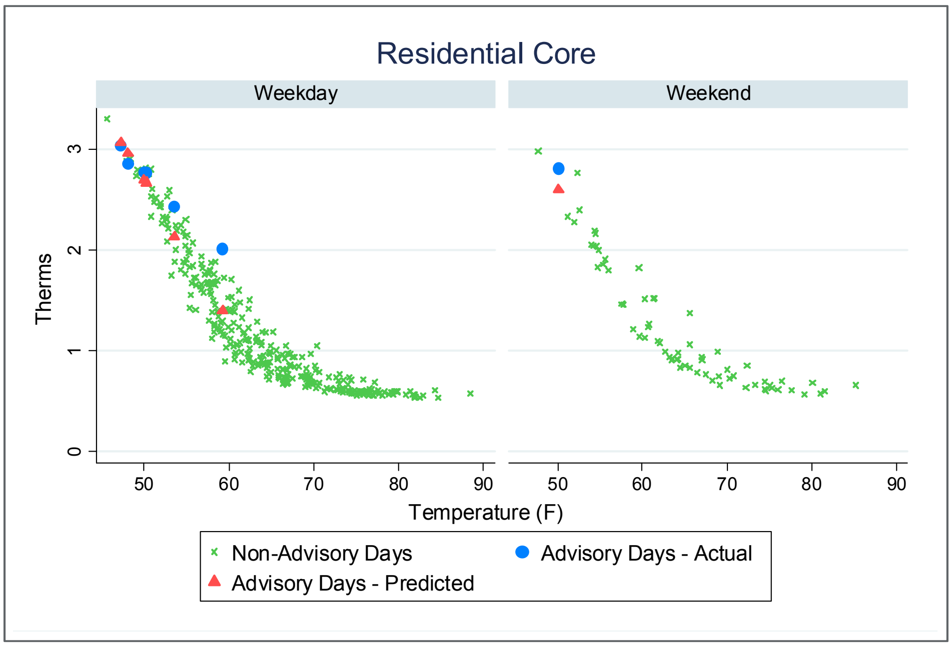
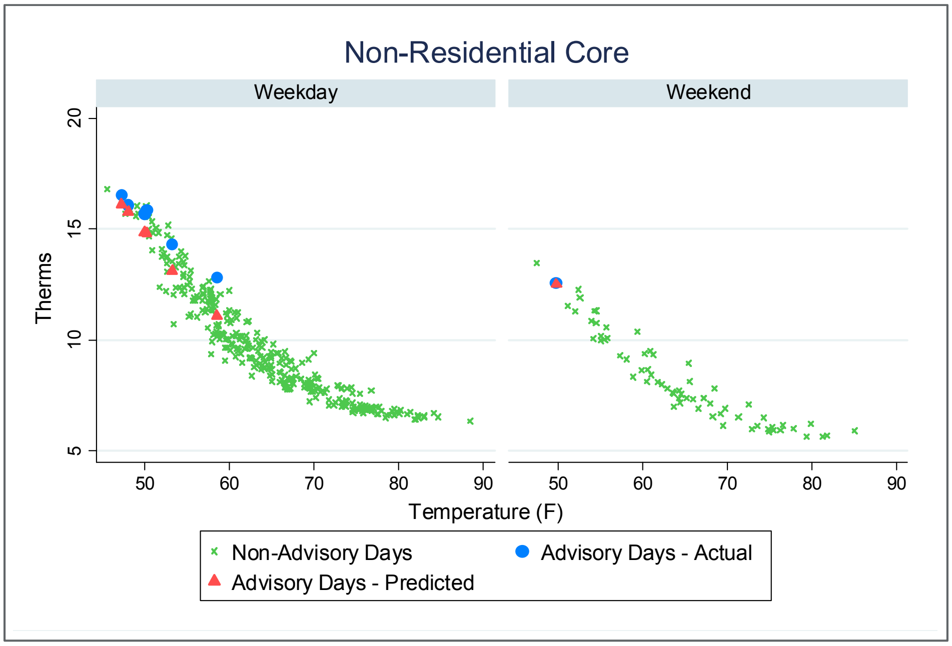


Figure 4-4: Non-Residential Core Gas Consumption and Predicted Usage vs. Temperature



5 Noncore Notification Campaign

This section summarizes the Noncore Notification Campaign background, impact evaluation methodology and daily impact estimates.

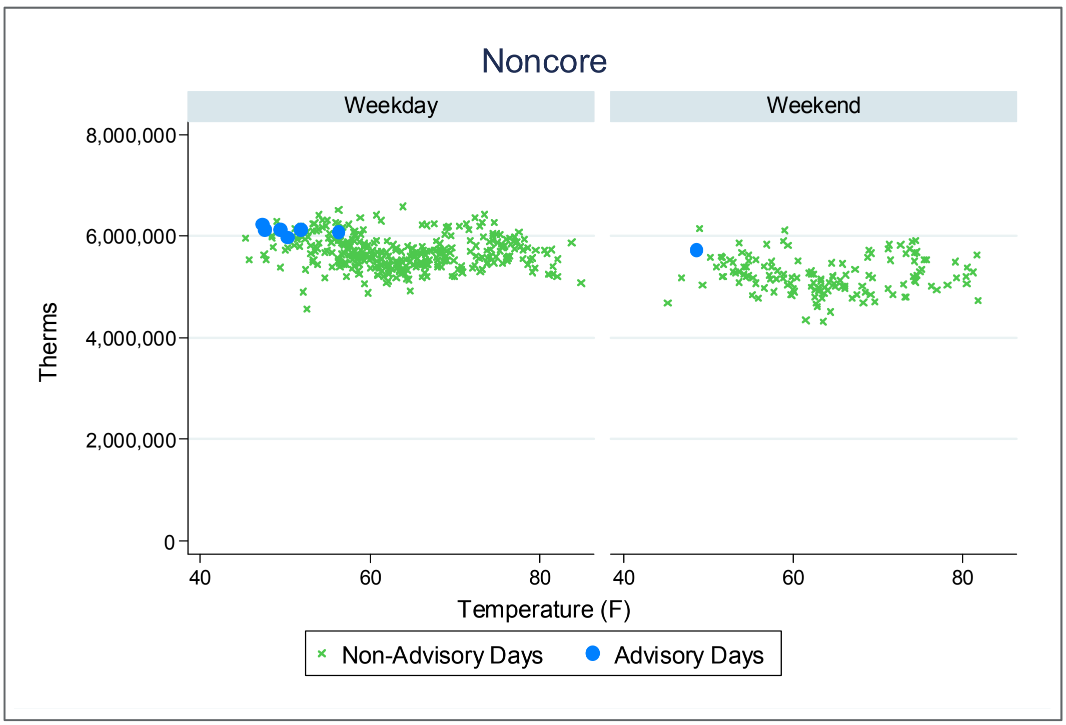
5.1 Background

The Noncore Notification Campaign is similar to the pilot described in the previous section, but it is specific to large, noncore customers and included direct email communications to noncore, non-electric generation customers, in addition to the radio and social media announcements summarized in Section 4.1 for core customers.

5.2 Impact Evaluation Methodology

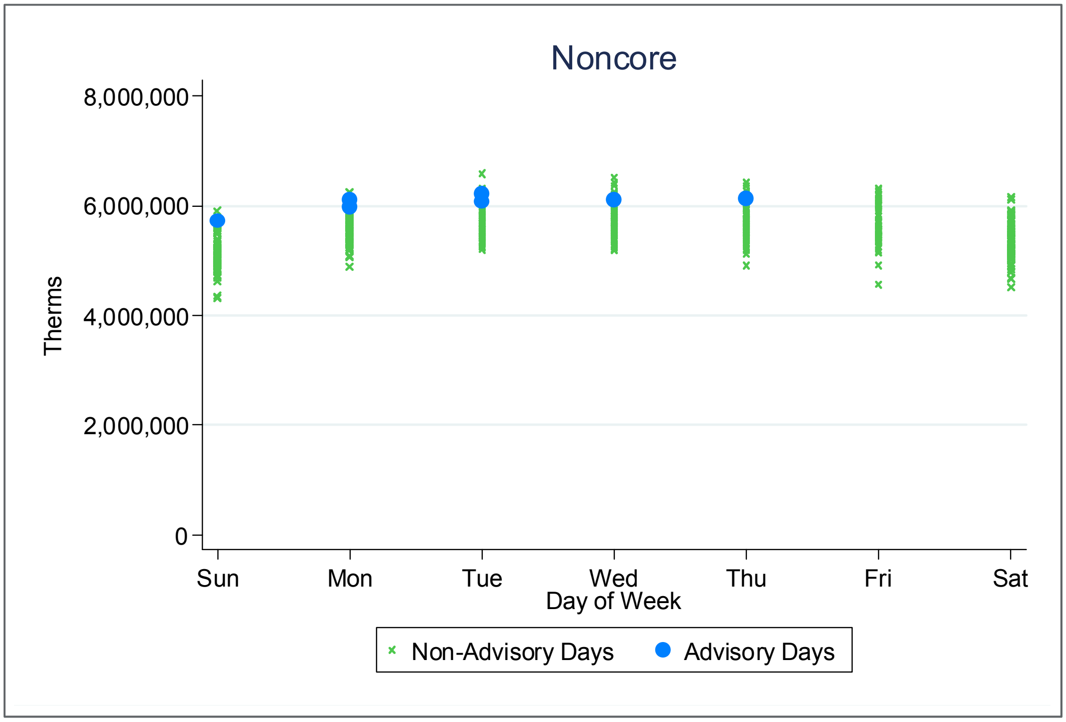
The method for estimating load impacts for the Noncore Notification Campaign is very similar to that used for the core campaign. The analysis dataset was limited to 601 noncore customers with 18 months of hourly gas consumption data. A major difference between core and noncore customers is that noncore customer consumption is not as closely correlated with weather, as shown in Figure 5-1. Note that this figure presents total noncore therms, not therms per customer.

Figure 5-1: Noncore Gas Consumption vs. Temperature



In fact, gas consumption for noncore customers is more closely tied to the day of week. This relationship is shown in Figure 5-2. The time of year plays a large part as well.

Figure 5-2: Noncore Gas Consumption vs. Day of Week



After testing over 30 models with different combinations of weather and day type variables, a final specification was selected, as shown in this equation:

$$therms_t = \alpha + \gamma(\text{HDD\_65})_t + \delta(\text{HDD\_65})\text{\^{}}2_t + \kappa(\text{day\_of\_week})_t + \lambda(\text{year\_month})_t + \beta(\text{advisory})_t + \varepsilon_t$$

The variable *HDD_65* is the heating degree days with a base of 65 degrees Fahrenheit. This is estimated by determining the maximum of 65 minus average daily temperature, and 0. For example, a day with an average temperature of 60 degrees has a *HDD_65* value of 5, while a day with an average temperature of 70 degrees has a *HDD_65* value of 0. The model for noncore customers includes a squared HDD term as well. As before, the coefficient β provides the estimated gas usage impact of the campaign during the relevant period.

5.3 Daily Impact Estimates

Table 5-1 presents the aggregate therm impact estimates for noncore customers for each Advisory day. Impacts were not statistically significant on any day.

Table 5-1: Noncore Gas Consumption Impacts by Customer Segment and Advisory Day

Population	Number of Customers	Date	Reference (Therms)	Observed (Therms)	Impact (Therms)	Impact (%)	95% Confidence Interval		P-Value
Noncore	601	December 18, 2016	5,736,235	5,720,791	15,444	0.3%	-5.8%	6.3%	0.93
		December 19, 2016	6,148,670	6,118,975	29,695	0.5%	-5.1%	6.1%	0.87
		December 20, 2016	6,181,585	6,073,865	107,720	1.7%	-3.8%	7.3%	0.54
		January 23, 2017	5,910,559	5,972,285	-61,726	-1.0%	-6.9%	4.8%	0.72
		January 24, 2017	6,044,072	6,219,816	-175,744	-2.9%	-8.7%	2.9%	0.33
		January 25, 2017	6,085,918	6,118,554	-32,637	-0.5%	-6.3%	5.2%	0.85
		January 26, 2017	6,068,712	6,128,313	-59,602	-1.0%	-6.7%	4.7%	0.73

6 Pilot Rebate Program Baseline Accuracy Assessment

This section summarizes the alternative baseline accuracy assessment for the Pilot Rebate Program. It summarizes the results, reviews the baseline methodology, the advantages and disadvantages of each type of baseline method, and then explores baseline accuracy on proxy days and rebates on Advisory days. The full proxy day and Advisory day results are located in Appendix B and Appendix C.

6.1 Summary of Results

Nexant tested 22 different baselines, including the 10/10 and regression-based approaches. In addition, both day-matching and weather-matching baselines were tested. Nexant found that:

1. The regression-based method performed the worst of all methods tested across all customer segments, including among customers with relatively high weather sensitivity.
2. Both the 10/10 and regression-based models were highly biased when compared to observed proxy day gas consumption. These models were downward biased, which indicates that impacts calculated using these methods were lower than their true values.
3. Day matching methods performed best, especially those with short look-back periods such as the top 3/5 and top 4/4. While weather matching results performed well, their results were never best overall.
4. Baseline choice has some implications for total rebates paid out. The best-performing baselines resulted in higher estimated rebates; however some of this is likely due to the upward bias of that baseline in general, and is not necessarily because customers responded that aggressively to the program.

6.2 Baselines Tested

For this analysis, Nexant leveraged the methodology developed for electricity baselines in the California ISO's Baseline Accuracy Working Group (BAWG), which informed the baselines that would be used for all electric DR programs that are settled in California's wholesale electricity market. The group was tasked with developing alternative baselines compared to the existing 10/10 day matching method on the basis of accuracy (baselines showing little bias) and precision (baseline accuracy not varying over event days and populations). The final BAWG-recommended baselines are shown in Table 6-1. For more information regarding the methods and process used to test, develop, and evaluate these baselines, refer to the 2017 Baseline Accuracy Working Group Proposal that was adopted by the California ISO.[8]

[8] https://www.caiso.com/Documents/2017BaselineAccuracyWorkGroupProposal-Nexant.pdf

Table 6-1: CAISO BAWG Recommended Baselines

Customer Segment	Weekday	Baselines Recommended
Residential	Weekday	Control group
		4 day weather matching using maximum temperature
		Highest 5/10 day matching
	Weekend	Control group
		4 day weather matching using maximum temperature
		Highest 3/5 weighted day matching
Non-residential	Weekday	Control Group
		4 day weather matching using maximum temperature
		10/10 day matching
	Weekend	Control group
		4 day weather matching using maximum temperature
		4 eligible days immediately prior (4/4)

In addition to the recommended BAWG baselines, Nexant incorporated several other baselines evaluated in the BAWG, as well as the current 10/10 day matching baseline for the Pilot Rebate Program and the regression-based approach described in the draft CPUC resolution for the SoCalGas winter demand response programs. The full summary of baselines tested is shown in Table 6-2 and comprise both weather matching and day matching options.

Table 6-2: Tested Baselines for Pilot Rebate Program

Baseline Method	Baseline Type	Notes
Weather Matching	Matching on top X closest weather days based on average temp	Top 3, 4, 5, 10 and 20 days were tested. Method picks the top X days out of last 90
	Matching on top X closest weather days based on HDD(60)	
	Matching on top X closest weather days based on min temp	
Day Matching	Matching the top 4 of the past 4 days	
	Matching the top 3 of the past 5 days	
	Matching the top 3 of the past 5, weighted so that the days closest to the Advisory matter more	
	Matching the top 5 of the past 10 days	
	Matching the top 10 of the past 10 days	
Regression Methods	Regression	
	Regression with Month/DOW	

6.3 Baseline Calculation Process

The baselines shown above were constructed at the individual customer level, and while the baselines developed for modeling electricity consumption also involved a same-day adjustment, Nexant did not include the adjustment as part of this analysis. Same-day adjustments improve accuracy for hourly baselines of relatively short electric demand response events with sufficient pre-event hourly data. This data is used on the day of the event to provide a calibration of the baseline to the observed pre-event unperturbed load. As the SoCalGas Advisory days were multi-day events, there was not a comparable pre-event period that would be able to meaningfully improve accuracy. It is also unlikely that such a pre-event adjustment would perform well for a demand response event that lasts multiple days, as in the Advisories. The next two sections cover the general methods used to construct day and weather matching baselines. While only two specific baselines are shown, the process can easily be generalized to create other baselines.

Day Matching Baselines

Table 6-3 summarizes the methodology for day matching baselines, which are constructed by picking days with high system loads from within eligible days directly preceding the Advisory. Their viability relies on the assumption that customers on days that have similar system-level loads to the Advisory day will perform similarly on Advisory days. Because these baselines often do not have a look-back period longer than 3 weeks, any seasonal effects of customer behavior can effectively be ignored, as loads are not expected to change significantly over that horizon. However, if weather on the Advisory day is significantly different than the days that comprise the baseline, it’s possible that day-matching methods will result in biased baselines for highly weather-sensitive customers.

Table 6-3: Day Matching Baseline Methodology

Step	Top 3/5 Days, Weighted
Baseline calculation process	1. Identify the past 5 eligible baseline days that occurred prior to an Advisory 2. Identify the hourly participant gas consumption on the Advisory day and on each eligible baseline day during the Advisory period hour. Sum to get daily consumption. 3. Identify the top 3 days of the eligible days based on aggregate demand
Eligible baseline days	Weekdays, excluding Advisory days and federal holidays
Baseline day selection criteria	Aggregate load (total population gas consumption)
Number of days selected to develop baseline	Top 3 based on system load
Calculation of temperatures	N/A
Advisory	The Advisory is defined as the entire day that the SoCalGas Advisory notification program is activated
Baseline	The day closest in time to the baseline day is weighted 50%, the second closest is weighted 30% and the third day is weighted 20%. The three days are averaged with weights to construct the baseline.

Weather Matching Baselines

Table 6-4 summarizes the methodology for weather matching baselines, which directly address the question of bias for customers with weather-sensitive loads. These methods involve finding days with similar weather profiles to the Advisory day, based on average temperature, minimum temperature, maximum temperature, or other weather metrics. Because finding a good weather matching day requires more data, considerations of having sufficient data must be balanced against seasonal patterns in gas consumption. For both the BAWG-recommended baselines and the baselines evaluated in this analysis, the look-back period for weather matching baselines was capped at 90 days. While most customers are likely to have 90 days of prior data from which to construct a baseline, customer account changes could impact the number of days available for new customers, reducing the accuracy of the baseline.

Table 6-4: Weather Matching Baseline Methodology

Step	Weekday Baseline 4 Day Matching Using Daily Minimum Temperature
Baseline calculation process	1. Identifying eligible baseline days that occurred prior to an Advisory 2. Identify the hourly participant gas consumption on the Advisory day and on each eligible baseline day during the Advisory period hour. Sum to get daily consumption. 3. Identify the participant-experienced temperatures for each hour of each Advisory day and eligible baseline day
Eligible baseline days	Weekdays, excluding Advisory days and federal holidays, in the 90 days immediately prior to the Advisory.
Baseline day selection criteria	Rank eligible days based on how similar daily minimum temperature is to the Advisory day
Number of days selected to develop baseline	4 days with the closest daily minimum temperature
Calculation of temperatures	Calculate the average temperature, HDD60 or daily minimum temperatures across all 24 hours in both the Advisory day and eligible baseline days.
Advisory	The Advisory is defined as the entire day that the SoCalGas Advisory notification program is activated
Baseline	The daily total average of the customer's gas consumption during baseline days. The baseline includes all 24 hours in day.

Regression-based Baselines

Regression-based baselines were not tested in the BAWG, but were proposed in the draft CPUC resolution for the SoCalGas winter demand response programs as an alternative method to develop baselines. The procedure for regression baselines is to fit a model that will explain daily therm consumption from the Heating Degree Day (HDD) that a customer experiences. HDD is meant to approximate the heating needs of a customer and is calculated by computing the maximum of either the difference between a base temperature, 60°F in this case, and the day's average temperature and zero. So a day with an average daily temperature of 45°F would have an HDD (base 60°F) of 15. A day with an average daily temperature of 70°F would have an HDD of 0.

For this method, all weekend, holiday and Advisory days were excluded before Nexant fit a regression that related daily total load for each customer to their daily HDD values using a full year of pre-Advisory data. This method is intended to work similarly to a weather-matching baseline by making the assumption that weather conditions are the primary driver of gas consumption. However, by imposing the requirement of including a full year of data, this approach is not be able to control for seasonal effects without the inclusion of additional modeling variables. In addition, customer account churn and a lack of Advanced Meter data going back a year limit the availability of a full year of interval data for a subset of customers. This implies that fewer customers will have accurate results because they will not have data available for the prior winter; the period in which most of the information about HDD and load is available.

The draft CPUC resolution also stipulated that this method be used only for customers with a correlation between gas consumption and HDD that is greater than 0.8. Statistical correlation, most commonly calculated using Pearson's correlation coefficient, is a measurement of how two variables move together. It has a range of -1 to 1, where values closer to either -1 or 1 indicate that the variables highly correlated. A correlation coefficient of 0 indicates that there is no measurable correlation between the two variables. By limiting this regression model to be applied to only customers with a correlation coefficient of 0.8 or greater, the modeling is done on customers that experience high degrees of positive correlation between temperature and load. In this case, it can be interpreted that the cooler the conditions (i.e., the higher the HDD value), the higher the customer's gas consumption will be.

Nexant found that approximately 25% of customers enrolled in the Pilot Rebate Program met this correlation threshold requirement. The average customer had a correlation coefficient of 0.65, while the median customer had a correlation coefficient of 0.72. This indicates that, while these customers are generally weather-sensitive, 75% are not sufficiently so such that they would qualify for the proposed regression-based baseline. After factoring in the requirement to also have a full year of available interval data, only 389 out of the 3,408 Pilot Rebate Program participants (11.4%) met both regression-based baseline criteria.

6.4 Recommended Baseline Results on Proxy Days

To identify the best baselines for this analysis, Nexant assessed baseline performance on proxy days. A proxy day is a day with similar characteristics to the Advisory day in terms of weather conditions, but on which an Advisory was not actually called. Using a proxy day is useful for baseline accuracy analysis because, since no Advisory was called, the baseline can be compared to the observed load and any difference between the baseline and the observed load must be attributable to error. Two metrics of interest were used to identify the best baselines:

1. Mean Percent Error is a measure of bias, or how different the average baseline result is to the true value
2. Normalized Root Mean Squared Error, a measure of precision, or how variable individual baseline estimates are from each other.

For more information on how these metrics are calculated, refer back to the 2017 BAWG Proposal. For this analysis, we report the average customer mean percent error a well as the aggregate percent difference. The best baseline is in the top three of absolute mean percent error, meaning that it is not substantially biased upward or downward. Of the top three baseline methods for each program, the best baseline is the one that minimized the normalized root mean squared error. Basically, the best baseline is the one that is the least noisy from day to day and customer to customer.

Best Baselines for Each Segment

Table 6-5 shows the results of the best baseline by customer segment in comparison to the original 10/10 baseline method and the regression-based method. In all cases, day matching methods perform best. The 3/5 baseline, either weighted or unweighted, perform best for three of the four customer groups, in addition to the program overall. The 4/4 baseline performs best for CTA customers. In general, the 3/5 baseline demonstrated a slight upward bias overall, meaning that it tends to overestimate the reference load, causing higher impacts. The regression and 10/10 methods tend to significantly underestimate reference loads, leading to smaller impacts.

Shown in the farthest column on the right is the rank of the baselines' overall bias compared to other baseline methods for that customer segment. This should be interpreted as a value of 1 being the least biased, and a value of 2 being the second-least biased, and so on. There were 22 baselines methods tested for each customer segment, and in each case, the regression-based method performed the worst of all methods tested.

Table 6-5: Best Baseline Performance Compared to Original Baseline Methods

Program (Population)	Baseline Type	Average Daily Use	Average Baseline Predicted Use	Percent Difference	Average Customer Day Bias	Rank of Bias Compared to Other Baselines Tested
All (3,403)	3/5	8.8	9.1	4%	9%	1
	10/10	8.8	7.5	-14%	-18%	17
	Regression	8.8	6.3	-28%	-39%	22
CTA (52)	4/4	26.2	25.5	-3%	-2%	3
	10/10	26.2	24.5	-7%	-5%	19
	Regression	26.2	23.5	-10%	-8%	22
HWL (188)	3/5	104.4	107.9	3%	6%	1
	10/10	104.4	93.0	-11%	-8%	9
	Regression	104.4	82.2	-21%	-19%	22
MA (2,351)	3/5	2.7	2.9	4%	9%	2
	10/10	2.7	2.2	-22%	-18%	18
	Regression	2.7	1.5	-47%	-40%	22
Non-My Account (812)	3/5, Weighted	2.9	3.1	6%	9%	3
	10/10	2.9	2.3	-22%	-19%	18
	Regression	2.9	1.5	-49%	-45%	22

Table 6-6 shows the results for the small subset of 389 highly weather-sensitive customers with a correlation coefficient above 0.8 and a full year of Advanced Meter data from which to fit a regression. Among this select group of customers, the best performing baselines are still day-matching methods. In general, these results are similar to that of the full population. The customers that meet the weather correlation and data criteria are more likely to be part of the CTA or Non-My Account customer segments. For these segments, however, there is still no benefit to the regression models as they continue to exhibit the highest bias in each customer group.

Table 6-6: Best Baseline Performance Compared to Original Baseline Methods for Weather-Sensitive Customers with a Full Year of Data

Program (Population)	Baseline Type	Average Daily Use	Average Baseline Predicted Use	Percent Difference	Average Customer Day Bias	Rank of Bias compared to Other Baselines Tested
All (389)	3/5	7.7	7.3	-6%	1%	1
	10/10	7.7	5.5	-28%	-26%	20
	Regression	7.7	4.4	-43%	-48%	22
CTA (52)	4/4	37.3	36.2	-3%	-3%	1
	10/10	37.3	30.5	-18%	-18%	22
	Regression	37.3	31.6	-15%	-15%	17
HWL (16)	3/5	93.1	82.6	-11%	-12%	1
	10/10	93.1	62.6	-33%	-33%	20
	Regression	93.1	50.8	-45%	-46%	22
My Account (245)	3/5	3.1	3.1	-1%	1%	1
	10/10	3.1	2.3	-26%	-25%	19
	Regression	3.1	1.6	-48%	-48%	22
Non-My Account (118)	3/5, Weighted	3.2	3.1	-4%	-3%	2
	10/10	3.2	2.3	-28%	-28%	19
	Regression	3.2	1.6	-51%	-50%	22

6.5 Recommended Baseline Results on Advisory Days

Nexant then performed the baseline modeling procedure on Advisory days to assess the degree to which modeling choices influence the resulting aggregate rebate values. The results of this exercise are shown in Table 6-7. The method used to calculate rebates in the table below assign a value of $2.50 per therm saved, but did not round to the nearest therm, meaning that the total rebate values may be slightly different than those reported in Section 3.1. For this analysis, the comparative results are of more interest than the exact dollar values.

In general, the methods identified as having the best performance on proxy days tend to result in higher aggregate rebates to customers. This is especially pronounced in the HWL customer segment, where there is a $10,000 difference in total rebates. While this difference is significant, it is important to note that while the recommended baselines were the least biased of the available options, they all demonstrated slight upward bias, while the 10/10 and regression-based methods demonstrated significant downward bias. The 3/5, 4/4 and 3/5 weighted methods are likely to overstate the impacts of the program and increase the amount of rebates, while the 10/10 and regression methods understate the program impacts, leading to lower aggregate rebates. A full set of results can be found in Appendix C.

Table 6-7: Rebates Calculated on Advisory Days for Different Baseline Methods

Customer Segment	Baseline Type	Average Daily Use	Average Baseline Predicted Use	Average Percent Difference	Total Rebate
CTA	4/4	26.2	24.6	-6%	$115
	10/10	26.2	23.9	-8%	$92
	Regression	26.2	22.0	-16%	$91
HWL	3/5	114.8	114.5	0%	$25,796
	10/10	114.8	100.7	-12%	$15,287
	Regression	114.8	81.6	-29%	$15,215
My Account	3/5	3.6	2.9	-20%	$5,250
	10/10	3.6	2.4	-33%	$2,638
	Regression	3.6	1.5	-59%	$1,456
Non-My Account	3/5, Weighted	3.9	3.3	-16%	$1,930
	10/10	3.9	2.6	-32%	$841
	Regression	3.9	1.5	-61%	$367
All	**Best Baseline for Each Segment**				$33,091
	10/10				$18,858
	Regression				$17,129

Appendix A Accuracy Testing of Core Regression Models

This appendix includes further information on the accuracy testing of the regression models for the Core Notification Campaign to show that the available variables cannot explain the unusually high usage on December 19 and 20 that has led to negative estimated impacts. Nexant tested over 60 different models to find the one that best predicted core customer gas consumption on a set of proxy days that were most similar to the Advisory days, as described in Section 3.2. The independent variables tested included weather variables such as average daily temperature and heating degree days, as well as variables such as calendar month and day of the week. A list of the independent variables is presented below in Table A-1.

Table A-1: Core Gas Consumption Modeling – Independent Variables

Variable	Description
dow	day of week
event	binary indicator for Advisory day of interest
HDD_58	heating degree days (base 58)
HDD_65	heating degree days (base 65)
HDD_65_0	heating degree days (base 65), equal to 0 if average temperature is below 58 degrees
HDD65_2	heating degree days (base 65), squared
mean7	average temperature over first 7 hours in the day
month	calendar month
prev_day_temp	average temperature over previous 24 hour day
temp2	average temperature over 24 hour day, squared
temperature	average temperature over 24 hour day
temperatureXym	temperature and ym interaction
weekday	binary weekday indicator
ym	year and month

Table A-2 each combination of independent variables and conditions tested for modeling gas consumption on proxy days. To measure each model's performance, Nexant calculated the sum of the squared errors for each model. Using this metric, Nexant determined that model 51 performed the best in terms of predicting proxy day gas consumption for residential and non-residential customers.

As reported in Section 4-3, model 51 predicted an increase in gas consumption, with the largest increases on December 19 and 20. Each model's prediction of gas consumption on these days is included in the table to show that this is true for every model Nexant tested. Therefore, the available variables cannot explain the unusually high usage on December 19 and 20 that has led to negative estimated impacts.

Table A-2: Core Gas Consumption Models

Model Number	Independent Variables	Conditions	Non-Residential				Residential			
			19-Dec-16		20-Dec-16		19-Dec-16		20-Dec-16	
			% Impact	p-value	% Impact	p-value	% Impact	p-value	% Impact	p-value
1	HDD65_2, HDD_65, dow, event	-	-10.1%	0.138	-16%	0.043	-14%	0.086	-45%	0.000
2	HDD65_2, HDD_65, dow, ym, event	-	-12.5%	0.009	-16%	0.004	-16%	0.004	-38%	0.000
3	HDD65_2, HDD_65, event	-	-11.9%	0.142	-20%	0.039	-13%	0.097	-43%	0.000
4	HDD65_2, HDD_65, weekday, event	-	-8.3%	0.201	-16%	0.040	-14%	0.085	-44%	0.000
5	HDD65_2, HDD_65, weekday, ym, event	-	-11.1%	0.014	-16%	0.003	-17%	0.003	-38%	0.000
6	HDD65_2, HDD_65, ym, event	-	-14.2%	0.033	-19%	0.014	-16%	0.004	-37%	0.000
7	HDD_65, HDD_58, weekday, month, event	-	-8.9%	0.048	-15%	0.006	-12%	0.022	-36%	0.000
8	HDD_65, HDD_58, weekday, ym, event	-	-10.8%	0.018	-16%	0.002	-15%	0.008	-39%	0.000
9	HDD_65, dow, event	-	-10.0%	0.144	-18%	0.027	-14%	0.090	-42%	0.001
10	HDD_65, dow, ym, event	-	-13.2%	0.007	-15%	0.005	-18%	0.005	-37%	0.000
11	HDD_65, event	-	-11.8%	0.150	-22%	0.025	-13%	0.100	-40%	0.001
12	HDD_65, weekday, event	-	-8.2%	0.213	-18%	0.025	-14%	0.088	-41%	0.001
13	HDD_65, weekday, ym, event	-	-11.8%	0.011	-16%	0.004	-19%	0.004	-36%	0.000
14	HDD_65, ym, event	-	-14.9%	0.028	-19%	0.017	-18%	0.005	-36%	0.000
15	HDD_65_0, HDD_58, event	-	-17.5%	0.135	-21%	0.116	-22%	0.128	-48%	0.024
16	HDD_65_0, HDD_58, weekday, ym, event	-	-9.6%	0.078	-14%	0.032	-14%	0.055	-32%	0.002
17	HDD_65_0, HDD_58, ym, event	-	-12.8%	0.083	-17%	0.047	-14%	0.062	-32%	0.002
18	dow, month, event	-	-15.2%	0.110	-3%	0.780	-21%	0.211	-2%	0.889
19	dow, ym, event	-	-22.5%	0.022	-9%	0.342	-38%	0.046	-16%	0.391
20	mean7, dow, event	-	-7.7%	0.310	-3%	0.739	-12%	0.409	-9%	0.610
21	mean7, dow, ym, event	-	-6.8%	0.247	-1%	0.907	-7%	0.476	-2%	0.844
22	mean7, weekday, event	-	-7.8%	0.293	-2%	0.753	-15%	0.302	-9%	0.607
23	mean7, weekday, ym, event	-	-7.1%	0.216	-1%	0.910	-11%	0.297	-2%	0.837
24	temp2, dow, event	-	-17.5%	0.040	-14%	0.120	-31%	0.082	-32%	0.143
25	temp2, dow, ym, event	-	-17.3%	0.011	-12%	0.097	-28%	0.035	-24%	0.119
26	temp2, event	-	-20.8%	0.035	-19%	0.082	-32%	0.069	-31%	0.144
27	temp2, month, event	-	-14.9%	0.063	-10%	0.231	-18%	0.136	-12%	0.404

Model Number	Independent Variables	Conditions	Non-Residential				Residential			
			19-Dec-16		20-Dec-16		19-Dec-16		20-Dec-16	
			% Impact	p-value	% Impact	p-value	% Impact	p-value	% Impact	p-value
28	temp2, temperature, dow, ym, , event	-	-13.4%	0.005	-15%	0.004	-19%	0.004	-36%	0.000
29	temp2, temperature, weekday, ym, event	-	-12.0%	0.008	-15%	0.003	-19%	0.004	-36%	0.000
30	temp2, weekday, event	-	-16.7%	0.043	-15%	0.108	-33%	0.063	-32%	0.134
31	temp2, weekday, ym, event	-	-16.9%	0.011	-12%	0.083	-31%	0.022	-24%	0.111
32	temperature, HDD65_2, HDD_65, ym, event	-	-14.3%	0.029	-19%	0.013	-16%	0.004	-37%	0.000
33	temperature, HDD_58, dow, ym, event	-	-11.2%	0.021	-17%	0.003	-13%	0.038	-38%	0.000
34	temperature, HDD_58, weekday, ym, event	-	-10.1%	0.029	-17%	0.002	-14%	0.031	-38%	0.000
35	temperature, HDD_58, ym, event	-	-13.3%	0.049	-20%	0.012	-13%	0.037	-38%	0.000
36	temperature, HDD_65, dow, ym, event	-	-13.3%	0.005	-15%	0.005	-19%	0.005	-37%	0.000
37	temperature, HDD_65, weekday, ym, event	-	-12.0%	0.007	-15%	0.003	-19%	0.004	-36%	0.000
38	temperature, HDD_65, ym, event	-	-15.1%	0.024	-19%	0.016	-18%	0.005	-35%	0.000
39	temperature, dow, event	-	-15.7%	0.036	-15%	0.079	-27%	0.079	-32%	0.100
40	temperature, dow, ym, event	-	-16.2%	0.009	-13%	0.055	-26%	0.029	-26%	0.064
41	temperature, event	-	-18.7%	0.036	-19%	0.058	-28%	0.067	-31%	0.101
42	temperature, weekday, event	-	-14.8%	0.042	-15%	0.070	-29%	0.061	-32%	0.093
43	temperature, weekday, ym, event	-	-15.6%	0.009	-13%	0.045	-28%	0.018	-27%	0.059
44	temperature, ym, event	-	-18.7%	0.017	-16%	0.060	-27%	0.022	-26%	0.066
45	temperatureXym, event	-	-18.7%	0.019	-16%	0.063	-27%	0.026	-27%	0.066
46	temperatureXym, weekday, event	-	-15.5%	0.012	-13%	0.048	-28%	0.022	-28%	0.059
47	weekday, month, event	-	-15.0%	0.110	-3%	0.755	-24%	0.160	-3%	0.865
48	HDD_65_0, HDD_58, event	temperature<60	-12.5%	0.185	-25%	0.036	-13%	0.168	-43%	0.002
49	HDD_65_0, HDD_58, weekday, ym, event	temperature<60	-9.8%	0.069	-18%	0.007	-15%	0.043	-39%	0.000
50	HDD_65_0, HDD_58, ym, event	temperature<60	-14.2%	0.108	-23%	0.033	-14%	0.046	-39%	0.000
51	**temperature, dow, ym, event**	**temperature<60**	**-9.1%**	**0.058**	**-16%**	**0.006**	**-14%**	**0.058**	**-44%**	**0.000**
52	temperature, prev_day_temp, dow, event	temperature<60	-3.2%	0.604	-7%	0.336	-5%	0.486	-30%	0.007
53	temperature, prev_day_temp, dow, ym, event	temperature<60	-6.4%	0.245	-9%	0.147	-8%	0.170	-32%	0.000
54	temperature, prev_day_temp, ym, event	temperature<60	-10.4%	0.219	-14%	0.165	-9%	0.138	-30%	0.000
55	temperature, weekday, event	temperature<60	-7.3%	0.245	-15%	0.045	-13%	0.147	-49%	0.001

Model Number	Independent Variables	Conditions	Non-Residential				Residential			
			19-Dec-16		20-Dec-16		19-Dec-16		20-Dec-16	
			% Impact	p-value	% Impact	p-value	% Impact	p-value	% Impact	p-value
56	temperature, weekday, ym, event	temperature<60	-9.6%	0.068	-15%	0.013	-15%	0.035	-45%	0.000
57	temperature, ym, event	temperature<60	-14.1%	0.112	-19%	0.066	-15%	0.038	-44%	0.000
58	temperature, dow, ym, event	temperature<=65	-11.0%	0.047	-14%	0.032	-17%	0.034	-37%	0.001
59	temperature, weekday, event	temperature<=65	-8.2%	0.162	-14%	0.037	-14%	0.131	-40%	0.004
60	temperature, weekday, ym, event	temperature<=65	-10.6%	0.040	-15%	0.014	-18%	0.027	-37%	0.001
61	temperature, ym, event	temperature<=65	-14.7%	0.074	-19%	0.049	-17%	0.030	-37%	0.001

Appendix B Pilot Rebate Program Baseline Proxy Day Results

Table B-1: Full Proxy Day Results

Customer Segment	Population	Baseline Type	Average Daily Use	Average Baseline Predicted Use	Percent Difference	Average Customer Day Bias	Rank of Bias compared to Other Baselines Tested
All	3403	3/5	8.8	9.1	3.6%	8.5%	1
		5/10	8.8	9.1	4.0%	7.0%	2
		3/5 Weighted	8.8	9.2	4.9%	10.6%	3
		4/4	8.8	7.9	-9.5%	-8.5%	4
		Top 3 Day Match on Avg Temp	8.8	7.8	-10.5%	-6.7%	5
		Top 5 Day Match on Avg Temp	8.8	7.8	-10.6%	-7.4%	6
		Top 4 Day Match on Avg Temp	8.8	7.8	-10.7%	-6.8%	7
		Top 10 Day Match on Avg Temp	8.8	7.8	-11.1%	-9.4%	8
		Top 3 Day Match on HDD60	8.8	7.6	-12.8%	-7.8%	9
		Top 3 Day Match on Min Temp	8.8	7.6	-13.0%	-12.3%	10
		Top 5 Day Match on HDD60	8.8	7.6	-13.1%	-8.4%	11
		Base Reg. w/Month & Day of Week Vars	8.8	7.6	-13.2%	-16.4%	12
		Top 4 Day Match on HDD60	8.8	7.6	-13.2%	-7.7%	13
		Top 4 Day Match on Min Temp	8.8	7.6	-13.4%	-12.9%	14
		Top 5 Day Match on Min Temp	8.8	7.6	-13.4%	-12.8%	15
		Top 20 Day Match on Avg Temp	8.8	7.6	-13.6%	-14.9%	16
		10/10	8.8	7.5	-13.9%	-17.6%	17
		Top 10 Day Match on Min Temp	8.8	7.5	-14.3%	-14.7%	18
		Top 10 Day Match on HDD60	8.8	7.5	-14.3%	-11.7%	19
		Top 20 Day Match on Min Temp	8.8	7.4	-16.0%	-18.6%	20
		Top 20 Day Match on HDD60	8.8	7.2	-17.9%	-18.1%	21
		Regression vs HDD60	8.8	6.3	-28.4%	-39.3%	22
CTA	52	5/10	26.2	26.4	0.9%	2.5%	1
		3/5	26.2	26.7	1.9%	3.1%	2
		4/4	26.2	25.5	-2.8%	-1.5%	3
		3/5 Weighted	26.2	26.9	2.9%	4.1%	4
		Top 3 Day Match on Min Temp	26.2	24.9	-4.8%	-3.6%	5
		Top 4 Day Match on Min Temp	26.2	24.9	-4.9%	-3.9%	6
		Top 5 Day Match on Min Temp	26.2	24.8	-5.1%	-4.3%	7
		Top 10 Day Match on Avg Temp	26.2	24.7	-5.5%	-4.6%	8
		Base Reg. w/Month & Day of Week Vars	26.2	24.7	-5.6%	-4.0%	9
		Top 5 Day Match on Avg Temp	26.2	24.7	-5.7%	-4.6%	10
		Top 4 Day Match on Avg Temp	26.2	24.6	-5.9%	-4.7%	11
		Top 10 Day Match on HDD60	26.2	24.6	-6.0%	-5.3%	12
		Top 10 Day Match on Min Temp	26.2	24.6	-6.0%	-5.0%	13

Customer Segment	Population	Baseline Type	Average Daily Use	Average Baseline Predicted Use	Percent Difference	Average Customer Day Bias	Rank of Bias compared to Other Baselines Tested
		Top 5 Day Match on HDD60	26.2	24.6	-6.0%	-4.9%	14
		Top 3 Day Match on Avg Temp	26.2	24.6	-6.1%	-5.1%	15
		Top 4 Day Match on HDD60	26.2	24.6	-6.1%	-4.9%	16
		Top 3 Day Match on HDD60	26.2	24.5	-6.4%	-5.4%	17
		Top 20 Day Match on Avg Temp	26.2	24.5	-6.5%	-5.4%	18
		10/10	26.2	24.5	-6.6%	-5.1%	19
		Top 20 Day Match on HDD60	26.2	24.3	-7.2%	-6.3%	20
		Top 20 Day Match on Min Temp	26.2	24.1	-7.7%	-6.5%	21
		Regression vs HDD60	26.2	23.5	-10.3%	-8.1%	22
HWL	188	3/5	104.4	107.9	3.4%	6.4%	1
		3/5 Weighted	104.4	108.9	4.3%	7.4%	2
		5/10	104.4	109.8	5.2%	8.1%	3
		4/4	104.4	95.1	-8.9%	-5.2%	4
		Base Reg. w/Month & Day of Week Vars	104.4	94.9	-9.1%	-6.6%	5
		Top 10 Day Match on Avg Temp	104.4	93.6	-10.3%	-7.5%	6
		Top 5 Day Match on Avg Temp	104.4	93.3	-10.6%	-7.4%	7
		Top 3 Day Match on Avg Temp	104.4	93.2	-10.7%	-7.6%	8
		10/10	104.4	93.0	-10.9%	-8.1%	9
		Top 4 Day Match on Avg Temp	104.4	92.9	-11.0%	-7.8%	10
		Top 20 Day Match on Avg Temp	104.4	92.4	-11.5%	-8.8%	11
		Top 3 Day Match on Min Temp	104.4	92.2	-11.7%	-8.0%	12
		Top 4 Day Match on Min Temp	104.4	91.7	-12.1%	-9.0%	13
		Top 5 Day Match on Min Temp	104.4	91.7	-12.2%	-8.7%	14
		Top 10 Day Match on Min Temp	104.4	91.2	-12.6%	-9.3%	15
		Top 20 Day Match on Min Temp	104.4	90.4	-13.4%	-10.5%	16
		Top 3 Day Match on HDD60	104.4	90.1	-13.7%	-10.3%	17
		Top 5 Day Match on HDD60	104.4	89.8	-13.9%	-10.1%	18
		Top 4 Day Match on HDD60	104.4	89.4	-14.3%	-10.4%	19
		Top 10 Day Match on HDD60	104.4	89.4	-14.4%	-11.4%	20
		Top 20 Day Match on HDD60	104.4	87.0	-16.6%	-13.3%	21
		Regression vs HDD60	104.4	82.2	-21.3%	-18.8%	22
My Account	2351	5/10	2.7	2.8	2.3%	7.5%	1
		3/5	2.7	2.9	4.5%	9.1%	2
		3/5 Weighted	2.7	2.9	6.8%	11.5%	3
		Top 4 Day Match on Avg Temp	2.7	2.5	-10.4%	-6.0%	4
		Top 3 Day Match on Avg Temp	2.7	2.5	-10.5%	-5.8%	5
		Top 5 Day Match on Avg Temp	2.7	2.4	-11.0%	-6.8%	6
		Top 4 Day Match on HDD60	2.7	2.4	-11.3%	-6.7%	7

Customer Segment	Population	Baseline Type	Average Daily Use	Average Baseline Predicted Use	Percent Difference	Average Customer Day Bias	Rank of Bias compared to Other Baselines Tested
		Top 3 Day Match on HDD60	2.7	2.4	-11.3%	-6.9%	8
		4/4	2.7	2.4	-11.7%	-8.5%	9
		Top 5 Day Match on HDD60	2.7	2.4	-12.0%	-7.6%	10
		Top 10 Day Match on Avg Temp	2.7	2.4	-13.3%	-8.9%	11
		Top 10 Day Match on HDD60	2.7	2.3	-15.2%	-11.2%	12
		Top 3 Day Match on Min Temp	2.7	2.3	-16.8%	-11.7%	13
		Top 5 Day Match on Min Temp	2.7	2.3	-17.0%	-12.1%	14
		Top 4 Day Match on Min Temp	2.7	2.3	-17.1%	-12.3%	15
		Top 10 Day Match on Min Temp	2.7	2.2	-18.8%	-14.3%	16
		Top 20 Day Match on Avg Temp	2.7	2.2	-19.0%	-14.7%	17
		10/10	2.7	2.2	-21.6%	-18.0%	18
		Top 20 Day Match on HDD60	2.7	2.1	-21.8%	-17.9%	19
		Top 20 Day Match on Min Temp	2.7	2.1	-22.9%	-18.5%	20
		Base Reg. w/Month & Day of Week Vars	2.7	2.1	-23.1%	-16.0%	21
		Regression vs HDD60	2.7	1.5	-46.6%	-39.7%	22
Non-My Account	812	5/10	2.9	2.9	1.5%	5.6%	1
		3/5	2.9	3.0	3.8%	7.5%	2
		3/5 Weighted	2.9	3.1	5.8%	9.4%	3
		Top 3 Day Match on Avg Temp	2.9	2.5	-12.1%	-9.1%	4
		Top 4 Day Match on Avg Temp	2.9	2.5	-12.1%	-9.0%	5
		4/4	2.9	2.5	-12.2%	-9.5%	6
		Top 5 Day Match on Avg Temp	2.9	2.5	-12.7%	-9.6%	7
		Top 3 Day Match on HDD60	2.9	2.5	-13.1%	-10.0%	8
		Top 4 Day Match on HDD60	2.9	2.5	-13.2%	-10.0%	9
		Top 5 Day Match on HDD60	2.9	2.5	-13.9%	-10.7%	10
		Top 10 Day Match on Avg Temp	2.9	2.5	-14.3%	-11.6%	11
		Top 10 Day Match on HDD60	2.9	2.4	-16.3%	-13.6%	12
		Top 3 Day Match on Min Temp	2.9	2.4	-18.2%	-15.6%	13
		Top 4 Day Match on Min Temp	2.9	2.4	-18.5%	-16.0%	14
		Top 5 Day Match on Min Temp	2.9	2.3	-18.8%	-16.3%	15
		Top 20 Day Match on Avg Temp	2.9	2.3	-20.1%	-17.4%	16
		Top 10 Day Match on Min Temp	2.9	2.3	-20.2%	-17.9%	17
		10/10	2.9	2.3	-22.2%	-19.5%	18
		Top 20 Day Match on HDD60	2.9	2.2	-23.4%	-20.8%	19
		Top 20 Day Match on Min Temp	2.9	2.2	-23.9%	-21.5%	20
		Base Reg. w/Month & Day of Week Vars	2.9	2.2	-24.1%	-20.4%	21
		Regression vs HDD60	2.9	1.5	-48.5%	-44.7%	22

Table B-2: Full Proxy Day Results for Customers with a Full Panel of Data

Customer Segment	Population	Baseline Type	Average Daily Use	Average Baseline Predicted Use	Percent Difference	Average Customer Day Bias	Rank of Bias compared to Other Baselines Tested
All	1817	3/5	13.5	14.0	3.6%	9.1%	1
		5/10	13.5	14.1	4.5%	7.8%	2
		3/5 Weighted	13.5	14.2	4.7%	11.4%	3
		4/4	13.5	12.3	-9.1%	-8.0%	4
		Top 5 Day Match on Avg Temp	13.5	12.1	-10.7%	-8.2%	5
		Top 3 Day Match on Avg Temp	13.5	12.1	-10.8%	-7.2%	6
		Top 10 Day Match on Avg Temp	13.5	12.1	-10.8%	-9.6%	7
		Top 4 Day Match on Avg Temp	13.5	12.1	-11.0%	-7.7%	8
		Base Reg. w/Month & Day of Week Vars	13.5	12.0	-11.3%	-12.6%	9
		Top 3 Day Match on Min Temp	13.5	11.9	-12.4%	-11.7%	10
		Top 20 Day Match on Avg Temp	13.5	11.8	-12.6%	-14.4%	11
		10/10	13.5	11.8	-12.7%	-17.1%	12
		Top 5 Day Match on Min Temp	13.5	11.8	-12.8%	-12.5%	13
		Top 4 Day Match on Min Temp	13.5	11.8	-12.8%	-12.6%	14
		Top 3 Day Match on HDD60	13.5	11.7	-13.3%	-8.9%	15
		Top 10 Day Match on Min Temp	13.5	11.7	-13.5%	-14.3%	16
		Top 5 Day Match on HDD60	13.5	11.7	-13.6%	-9.4%	17
		Top 4 Day Match on HDD60	13.5	11.7	-13.8%	-8.9%	18
		Top 10 Day Match on HDD60	13.5	11.6	-14.4%	-12.6%	19
		Top 20 Day Match on Min Temp	13.5	11.5	-14.9%	-18.1%	20
		Top 20 Day Match on HDD60	13.5	11.2	-17.3%	-18.3%	21
		Regression vs HDD60	13.5	10.2	-24.7%	-34.0%	22
CTA	42	5/10	25.8	25.9	0.3%	2.1%	1
		3/5	25.8	26.1	1.1%	2.5%	2
		3/5 Weighted	25.8	26.3	2.2%	3.5%	3
		4/4	25.8	24.9	-3.4%	-2.0%	4
		Top 3 Day Match on Min Temp	25.8	24.4	-5.3%	-4.0%	5
		Top 4 Day Match on Min Temp	25.8	24.4	-5.4%	-4.5%	6
		Top 5 Day Match on Min Temp	25.8	24.3	-5.6%	-4.8%	7
		Base Reg. w/Month & Day of Week Vars	25.8	24.3	-5.8%	-3.8%	8
		Top 10 Day Match on Avg Temp	25.8	24.2	-6.2%	-5.2%	9
		Top 5 Day Match on Avg Temp	25.8	24.0	-6.7%	-5.5%	10
		Top 10 Day Match on Min Temp	25.8	24.0	-6.8%	-5.8%	11
		Top 10 Day Match on HDD60	25.8	24.0	-6.8%	-6.0%	12
		Top 20 Day Match on Avg Temp	25.8	24.0	-7.1%	-6.0%	13
		Top 4 Day Match on Avg Temp	25.8	23.9	-7.2%	-5.6%	14

Customer Segment	Population	Baseline Type	Average Daily Use	Average Baseline Predicted Use	Percent Difference	Average Customer Day Bias	Rank of Bias compared to Other Baselines Tested
		Top 5 Day Match on HDD60	25.8	23.9	-7.2%	-6.0%	15
		10/10	25.8	23.9	-7.2%	-5.4%	16
		Top 4 Day Match on HDD60	25.8	23.9	-7.4%	-5.9%	17
		Top 3 Day Match on Avg Temp	25.8	23.8	-7.5%	-6.3%	18
		Top 3 Day Match on HDD60	25.8	23.8	-7.9%	-6.7%	19
		Top 20 Day Match on HDD60	25.8	23.8	-7.9%	-6.9%	20
		Top 20 Day Match on Min Temp	25.8	23.5	-8.7%	-7.4%	21
		Regression vs HDD60	25.8	23.2	-10.1%	-7.7%	22
HWL	184	3/5	104.3	108.0	3.5%	6.7%	1
		3/5 Weighted	104.3	109.0	4.4%	7.6%	2
		5/10	104.3	109.9	5.3%	8.3%	3
		4/4	104.3	95.2	-8.8%	-5.0%	4
		Base Reg. w/Month & Day of Week Vars	104.3	94.9	-9.1%	-6.5%	5
		Top 10 Day Match on Avg Temp	104.3	93.7	-10.2%	-7.3%	6
		Top 5 Day Match on Avg Temp	104.3	93.5	-10.4%	-7.2%	7
		Top 3 Day Match on Avg Temp	104.3	93.3	-10.6%	-7.4%	8
		10/10	104.3	93.1	-10.8%	-7.9%	9
		Top 4 Day Match on Avg Temp	104.3	93.0	-10.9%	-7.6%	10
		Top 20 Day Match on Avg Temp	104.3	92.5	-11.3%	-8.6%	11
		Top 3 Day Match on Min Temp	104.3	92.2	-11.6%	-7.9%	12
		Top 5 Day Match on Min Temp	104.3	91.8	-12.0%	-8.5%	13
		Top 4 Day Match on Min Temp	104.3	91.8	-12.1%	-8.9%	14
		Top 10 Day Match on Min Temp	104.3	91.3	-12.5%	-9.2%	15
		Top 20 Day Match on Min Temp	104.3	90.5	-13.3%	-10.3%	16
		Top 3 Day Match on HDD60	104.3	90.2	-13.6%	-10.1%	17
		Top 5 Day Match on HDD60	104.3	89.9	-13.8%	-9.9%	18
		Top 4 Day Match on HDD60	104.3	89.5	-14.2%	-10.2%	19
		Top 10 Day Match on HDD60	104.3	89.5	-14.3%	-11.1%	20
		Top 20 Day Match on HDD60	104.3	87.1	-16.5%	-13.1%	21
		Regression vs HDD60	104.3	82.2	-21.2%	-18.6%	22
My Account	1087	5/10	2.7	2.7	2.2%	9.1%	1
		3/5	2.7	2.8	4.7%	10.5%	2
		3/5 Weighted	2.7	2.9	7.2%	13.3%	3
		4/4	2.7	2.3	-11.8%	-7.9%	4
		Top 3 Day Match on Avg Temp	2.7	2.3	-12.2%	-6.0%	5
		Top 4 Day Match on Avg Temp	2.7	2.3	-12.4%	-6.7%	6
		Top 5 Day Match on Avg Temp	2.7	2.3	-12.7%	-7.5%	7
		Top 3 Day Match on HDD60	2.7	2.3	-13.5%	-7.8%	8

Customer Segment	Population	Baseline Type	Average Daily Use	Average Baseline Predicted Use	Percent Difference	Average Customer Day Bias	Rank of Bias compared to Other Baselines Tested
		Top 4 Day Match on HDD60	2.7	2.3	-13.7%	-7.6%	9
		Top 5 Day Match on HDD60	2.7	2.3	-14.1%	-8.4%	10
		Top 10 Day Match on Avg Temp	2.7	2.3	-14.5%	-8.9%	11
		Top 10 Day Match on HDD60	2.7	2.2	-17.0%	-12.2%	12
		Top 3 Day Match on Min Temp	2.7	2.2	-17.0%	-10.7%	13
		Top 5 Day Match on Min Temp	2.7	2.2	-17.3%	-11.5%	14
		Top 4 Day Match on Min Temp	2.7	2.2	-17.4%	-11.7%	15
		Top 10 Day Match on Min Temp	2.7	2.1	-19.2%	-13.8%	16
		Top 20 Day Match on Avg Temp	2.7	2.1	-19.5%	-14.1%	17
		Base Reg. w/Month & Day of Week Vars	2.7	2.1	-21.8%	-10.8%	18
		10/10	2.7	2.1	-22.0%	-17.6%	19
		Top 20 Day Match on HDD60	2.7	2.0	-22.9%	-18.1%	20
		Top 20 Day Match on Min Temp	2.7	2.0	-23.4%	-18.1%	21
		Regression vs HDD60	2.7	1.5	-43.3%	-33.7%	22
Non-My Account	504	5/10	2.8	2.9	1.1%	5.2%	1
		3/5	2.8	2.9	3.7%	7.4%	2
		3/5 Weighted	2.8	3.0	5.8%	9.4%	3
		Top 3 Day Match on Avg Temp	2.8	2.5	-12.2%	-9.7%	4
		4/4	2.8	2.5	-12.4%	-9.8%	5
		Top 4 Day Match on Avg Temp	2.8	2.5	-12.7%	-10.0%	6
		Top 5 Day Match on Avg Temp	2.8	2.5	-13.1%	-10.5%	7
		Top 3 Day Match on HDD60	2.8	2.4	-13.7%	-10.9%	8
		Top 4 Day Match on HDD60	2.8	2.4	-14.2%	-11.4%	9
		Top 5 Day Match on HDD60	2.8	2.4	-14.6%	-11.9%	10
		Top 10 Day Match on Avg Temp	2.8	2.4	-14.7%	-12.3%	11
		Top 10 Day Match on HDD60	2.8	2.4	-17.1%	-14.7%	12
		Top 3 Day Match on Min Temp	2.8	2.3	-18.2%	-15.9%	13
		Top 4 Day Match on Min Temp	2.8	2.3	-18.5%	-16.3%	14
		Top 5 Day Match on Min Temp	2.8	2.3	-18.9%	-16.5%	15
		Top 10 Day Match on Min Temp	2.8	2.3	-20.1%	-18.1%	16
		Top 20 Day Match on Avg Temp	2.8	2.3	-20.2%	-18.0%	17
		10/10	2.8	2.2	-22.7%	-20.2%	18
		Base Reg. w/Month & Day of Week Vars	2.8	2.2	-23.5%	-19.6%	19
		Top 20 Day Match on Min Temp	2.8	2.2	-23.9%	-21.8%	20
		Top 20 Day Match on HDD60	2.8	2.2	-24.0%	-21.7%	21
		Regression vs HDD60	2.8	1.5	-45.9%	-42.5%	22

Table B-3: Full Proxy Day Results for Customers with a Full Panel of Data & HDD60 Correlation Greater than 0.8

Customer Segment	Population	Baseline Type	Average Daily Use	Average Baseline Predicted Use	Percent Difference	Average Customer Day Bias	Rank of Bias compared to Other Baselines Tested
All	389	3/5 Weighted	7.7	7.3	-5.7%	1.4%	1
		3/5	7.7	7.1	-8.2%	-1.3%	2
		5/10	7.7	6.8	-12.2%	-5.7%	3
		4/4	7.7	6.4	-17.2%	-14.6%	4
		Top 5 Day Match on Avg Temp	7.7	6.0	-22.1%	-17.9%	5
		Top 5 Day Match on HDD60	7.7	6.0	-22.4%	-18.6%	6
		Top 10 Day Match on Avg Temp	7.7	6.0	-22.4%	-18.8%	7
		Top 10 Day Match on HDD60	7.7	5.9	-23.0%	-19.8%	8
		Top 4 Day Match on Avg Temp	7.7	5.9	-23.1%	-18.4%	9
		Top 4 Day Match on HDD60	7.7	5.9	-23.4%	-18.9%	10
		Top 3 Day Match on Avg Temp	7.7	5.9	-23.4%	-18.2%	11
		Top 3 Day Match on Min Temp	7.7	5.9	-23.4%	-21.8%	12
		Top 3 Day Match on HDD60	7.7	5.9	-23.6%	-18.7%	13
		Top 5 Day Match on Min Temp	7.7	5.9	-23.9%	-21.9%	14
		Top 4 Day Match on Min Temp	7.7	5.8	-24.4%	-21.9%	15
		Base Reg. w/Month & Day of Week Vars	7.7	5.8	-25.5%	-25.9%	16
		Top 20 Day Match on Avg Temp	7.7	5.7	-25.7%	-23.7%	17
		Top 10 Day Match on Min Temp	7.7	5.7	-26.0%	-23.9%	18
		Top 20 Day Match on HDD60	7.7	5.7	-26.7%	-25.6%	19
		10/10	7.7	5.5	-28.3%	-26.2%	20
		Top 20 Day Match on Min Temp	7.7	5.4	-30.2%	-28.4%	21
		Regression vs HDD60	7.7	4.4	-43.4%	-47.6%	22
CTA	10	3/5 Weighted	37.3	36.2	-2.9%	-2.6%	1
		3/5	37.3	35.6	-4.5%	-4.2%	2
		5/10	37.3	35.0	-6.1%	-5.9%	3
		4/4	37.3	34.0	-9.0%	-8.8%	4
		Base Reg. w/Month & Day of Week Vars	37.3	33.3	-10.7%	-10.5%	5
		Top 4 Day Match on Min Temp	37.3	32.7	-12.3%	-12.0%	6
		Top 5 Day Match on Min Temp	37.3	32.7	-12.5%	-12.1%	7
		Top 3 Day Match on Min Temp	37.3	32.4	-13.1%	-12.7%	8
		Top 10 Day Match on Avg Temp	37.3	32.4	-13.3%	-13.2%	9
		Top 10 Day Match on HDD60	37.3	32.2	-13.6%	-13.6%	10
		Top 10 Day Match on Min Temp	37.3	32.1	-13.9%	-13.6%	11
		Top 20 Day Match on Avg Temp	37.3	32.1	-14.0%	-13.9%	12
		Top 20 Day Match on HDD60	37.3	32.0	-14.4%	-14.4%	13
		Top 5 Day Match on Avg Temp	37.3	31.8	-14.7%	-14.7%	14

Customer Segment	Population	Baseline Type	Average Daily Use	Average Baseline Predicted Use	Percent Difference	Average Customer Day Bias	Rank of Bias compared to Other Baselines Tested
		Top 5 Day Match on HDD60	37.3	31.7	-15.0%	-15.1%	15
		Top 3 Day Match on Avg Temp	37.3	31.6	-15.2%	-15.0%	16
		10/10	37.3	31.6	-15.4%	-15.2%	17
		Top 3 Day Match on HDD60	37.3	31.6	-15.4%	-15.3%	18
		Top 4 Day Match on Avg Temp	37.3	31.4	-15.8%	-15.7%	19
		Top 4 Day Match on HDD60	37.3	31.3	-16.1%	-16.1%	20
		Top 20 Day Match on Min Temp	37.3	31.2	-16.5%	-16.1%	21
		Regression vs HDD60	37.3	30.5	-18.4%	-18.3%	22
HWL	16	3/5 Weighted	93.1	82.6	-11.3%	-11.6%	1
		3/5	93.1	80.0	-14.0%	-14.4%	2
		5/10	93.1	76.2	-18.2%	-18.3%	3
		4/4	93.1	73.5	-21.0%	-21.5%	4
		Top 3 Day Match on Min Temp	93.1	68.8	-26.1%	-26.7%	5
		Top 5 Day Match on Avg Temp	93.1	68.4	-26.5%	-27.2%	6
		Top 5 Day Match on HDD60	93.1	68.3	-26.6%	-27.2%	7
		Top 10 Day Match on Avg Temp	93.1	68.0	-26.9%	-27.4%	8
		Top 10 Day Match on HDD60	93.1	67.8	-27.2%	-27.6%	9
		Top 5 Day Match on Min Temp	93.1	67.5	-27.5%	-27.6%	10
		Top 4 Day Match on HDD60	93.1	67.0	-28.0%	-28.5%	11.5
		Top 4 Day Match on Avg Temp	93.1	67.0	-28.0%	-28.5%	11.5
		Base Reg. w/Month & Day of Week Vars	93.1	67.0	-28.0%	-28.3%	13
		Top 4 Day Match on Min Temp	93.1	66.6	-28.4%	-28.6%	14
		Top 3 Day Match on Avg Temp	93.1	66.3	-28.8%	-29.3%	15.5
		Top 3 Day Match on HDD60	93.1	66.3	-28.8%	-29.3%	15.5
		Top 20 Day Match on Avg Temp	93.1	65.5	-29.7%	-30.2%	17
		Top 10 Day Match on Min Temp	93.1	65.1	-30.0%	-30.3%	18
		Top 20 Day Match on HDD60	93.1	65.1	-30.1%	-30.6%	19
		10/10	93.1	62.6	-32.7%	-33.3%	20
		Top 20 Day Match on Min Temp	93.1	61.0	-34.4%	-34.8%	21
		Regression vs HDD60	93.1	50.8	-45.4%	-46.1%	22
My Account	245	3/5	3.1	3.1	-0.7%	0.7%	1
		3/5 Weighted	3.1	3.2	1.9%	3.6%	2
		5/10	3.1	2.9	-5.4%	-4.0%	3
		4/4	3.1	2.7	-14.1%	-13.6%	4
		Top 5 Day Match on Avg Temp	3.1	2.6	-17.8%	-16.7%	5
		Top 5 Day Match on HDD60	3.1	2.5	-18.4%	-17.3%	6
		Top 3 Day Match on Avg Temp	3.1	2.5	-18.5%	-17.2%	7
		Top 4 Day Match on Avg Temp	3.1	2.5	-18.5%	-17.2%	8

Customer Segment	Population	Baseline Type	Average Daily Use	Average Baseline Predicted Use	Percent Difference	Average Customer Day Bias	Rank of Bias compared to Other Baselines Tested
		Top 10 Day Match on Avg Temp	3.1	2.5	-18.7%	-17.7%	9
		Top 3 Day Match on HDD60	3.1	2.5	-18.9%	-17.7%	10
		Top 4 Day Match on HDD60	3.1	2.5	-19.0%	-17.6%	11
		Top 10 Day Match on HDD60	3.1	2.5	-19.7%	-18.8%	12
		Top 4 Day Match on Min Temp	3.1	2.4	-22.1%	-20.7%	13
		Top 3 Day Match on Min Temp	3.1	2.4	-22.1%	-20.6%	14
		Top 5 Day Match on Min Temp	3.1	2.4	-22.3%	-21.1%	15
		Top 20 Day Match on Avg Temp	3.1	2.4	-23.5%	-22.7%	16
		Top 10 Day Match on Min Temp	3.1	2.4	-24.2%	-23.1%	17
		Top 20 Day Match on HDD60	3.1	2.3	-25.2%	-24.6%	18
		10/10	3.1	2.3	-25.9%	-25.3%	19
		Base Reg. w/Month & Day of Week Vars	3.1	2.3	-26.3%	-25.4%	20
		Top 20 Day Match on Min Temp	3.1	2.2	-28.6%	-27.7%	21
		Regression vs HDD60	3.1	1.6	-48.0%	-47.5%	22
Non-My Account	118	3/5 Weighted	3.2	3.2	-1.8%	-0.9%	1
		3/5	3.2	3.1	-4.2%	-3.4%	2
		5/10	3.2	3.0	-8.4%	-7.6%	3
		4/4	3.2	2.7	-16.4%	-16.1%	4
		Top 3 Day Match on Avg Temp	3.2	2.6	-20.0%	-19.1%	5
		Top 5 Day Match on Avg Temp	3.2	2.6	-20.3%	-19.6%	6
		Top 3 Day Match on HDD60	3.2	2.6	-20.6%	-19.8%	7
		Top 4 Day Match on Avg Temp	3.2	2.6	-20.6%	-19.7%	8
		Top 5 Day Match on HDD60	3.2	2.5	-21.0%	-20.3%	9
		Top 10 Day Match on Avg Temp	3.2	2.5	-21.0%	-20.3%	10
		Top 4 Day Match on HDD60	3.2	2.5	-21.2%	-20.4%	11
		Top 10 Day Match on HDD60	3.2	2.5	-22.1%	-21.5%	12
		Top 5 Day Match on Min Temp	3.2	2.4	-24.6%	-23.8%	13
		Top 4 Day Match on Min Temp	3.2	2.4	-25.0%	-24.4%	14
		Top 3 Day Match on Min Temp	3.2	2.4	-25.3%	-24.4%	15
		Top 10 Day Match on Min Temp	3.2	2.4	-26.2%	-25.7%	16
		Top 20 Day Match on Avg Temp	3.2	2.4	-26.3%	-25.8%	17
		Top 20 Day Match on HDD60	3.2	2.3	-28.3%	-27.9%	18
		10/10	3.2	2.3	-28.3%	-28.0%	19
		Base Reg. w/Month & Day of Week Vars	3.2	2.3	-28.6%	-27.8%	20
		Top 20 Day Match on Min Temp	3.2	2.2	-30.3%	-30.0%	21
		Regression vs HDD60	3.2	1.6	-50.8%	-50.4%	22

Appendix C Pilot Rebate Program Baseline Advisory Day Results

Table C-1: Full Advisory Day Results

Customer Segment	Baseline Type	Average Daily Use	Average Baseline Predicted Use	Average Percent Difference	Total Rebate
CTA	Top 10 Day Match on Avg Temp	26.2	24.1	-7.8%	$ 121
	Top 20 Day Match on Avg Temp	26.2	23.7	-9.2%	$ 110
	Top 3 Day Match on Avg Temp	26.2	24.3	-6.9%	$ 225
	Top 4 Day Match on Avg Temp	26.2	24.3	-7.2%	$ 174
	Top 5 Day Match on Avg Temp	26.2	24.3	-7.1%	$ 170
	5/10	26.2	25.8	-1.5%	$ 288
	4/4	26.2	24.6	-5.9%	$ 115
	Top 10 Day Match on HDD60	26.2	24.1	-7.9%	$ 122
	Top 20 Day Match on HDD60	26.2	23.7	-9.5%	$ 109
	Top 3 Day Match on HDD60	26.2	24.4	-6.8%	$ 229
	Top 4 Day Match on HDD60	26.2	24.3	-7.2%	$ 174
	Top 5 Day Match on HDD60	26.2	24.2	-7.3%	$ 170
	Top 10 Day Match on Min Temp	26.2	23.7	-9.3%	$ 142
	Top 20 Day Match on Min Temp	26.2	23.4	-10.5%	$ 128
	Top 3 Day Match on Min Temp	26.2	24.2	-7.5%	$ 200
	Top 4 Day Match on Min Temp	26.2	24.1	-7.8%	$ 168
	Top 5 Day Match on Min Temp	26.2	23.9	-8.6%	$ 151
	Regression vs HDD60	26.2	22.0	-15.7%	$ 91
	Base Reg. w/Month & Day of Week Vars	26.2	24.0	-8.1%	$ 159
	10/10	26.2	23.9	-8.5%	$ 92
	3/5	26.2	25.6	-2.0%	$ 238
	3/5 Weighted	26.2	26.0	-0.7%	$ 280
HWL	Top 10 Day Match on Avg Temp	114.8	96.9	-15.6%	$ 13,619
	Top 20 Day Match on Avg Temp	114.8	97.0	-15.5%	$ 13,829
	Top 3 Day Match on Avg Temp	114.8	94.9	-17.3%	$ 15,107
	Top 4 Day Match on Avg Temp	114.8	95.1	-17.1%	$ 13,860
	Top 5 Day Match on Avg Temp	114.8	95.2	-17.0%	$ 12,908
	5/10	114.8	117.1	2.0%	$ 27,668
	4/4	114.8	103.1	-10.2%	$ 15,881
	Top 10 Day Match on HDD60	114.8	95.4	-16.9%	$ 13,628
	Top 20 Day Match on HDD60	114.8	94.8	-17.4%	$ 13,868
	Top 3 Day Match on HDD60	114.8	94.7	-17.5%	$ 15,362
	Top 4 Day Match on HDD60	114.8	94.9	-17.3%	$ 13,785
	Top 5 Day Match on HDD60	114.8	94.8	-17.4%	$ 13,486
	Top 10 Day Match on Min Temp	114.8	96.1	-16.3%	$ 14,173
	Top 20 Day Match on Min Temp	114.8	94.6	-17.6%	$ 13,404

Customer Segment	Baseline Type	Average Daily Use	Average Baseline Predicted Use	Average Percent Difference	Total Rebate
	Top 3 Day Match on Min Temp	114.8	96.9	-15.6%	$ 17,072
	Top 4 Day Match on Min Temp	114.8	97.8	-14.8%	$ 16,453
	Top 5 Day Match on Min Temp	114.8	97.6	-15.0%	$ 16,254
	Regression vs HDD60	114.8	81.6	-28.9%	$ 15,215
	Base Reg. w/Month & Day of Week Vars	114.8	102.7	-10.5%	$ 18,913
	10/10	114.8	100.7	-12.2%	$ 15,287
	3/5	114.8	114.5	-0.2%	$ 25,796
	3/5 Weighted	114.8	115.6	0.7%	$ 26,747
My Account	Top 10 Day Match on Avg Temp	3.6	2.5	-31.2%	$ 3,352
	Top 20 Day Match on Avg Temp	3.6	2.3	-35.7%	$ 2,644
	Top 3 Day Match on Avg Temp	3.6	2.4	-35.5%	$ 4,172
	Top 4 Day Match on Avg Temp	3.6	2.5	-32.7%	$ 3,986
	Top 5 Day Match on Avg Temp	3.6	2.5	-31.6%	$ 3,869
	5/10	3.6	3.0	-16.7%	$ 6,235
	4/4	3.6	2.6	-28.7%	$ 3,116
	Top 10 Day Match on HDD60	3.6	2.5	-32.2%	$ 3,299
	Top 20 Day Match on HDD60	3.6	2.3	-37.5%	$ 2,567
	Top 3 Day Match on HDD60	3.6	2.3	-36.1%	$ 4,188
	Top 4 Day Match on HDD60	3.6	2.4	-33.4%	$ 3,992
	Top 5 Day Match on HDD60	3.6	2.5	-32.4%	$ 3,866
	Top 10 Day Match on Min Temp	3.6	2.5	-32.5%	$ 3,247
	Top 20 Day Match on Min Temp	3.6	2.3	-37.9%	$ 2,573
	Top 3 Day Match on Min Temp	3.6	2.6	-29.3%	$ 4,521
	Top 4 Day Match on Min Temp	3.6	2.6	-29.9%	$ 4,004
	Top 5 Day Match on Min Temp	3.6	2.5	-30.2%	$ 3,823
	Regression vs HDD60	3.6	1.5	-59.3%	$ 1,456
	Base Reg. w/Month & Day of Week Vars	3.6	2.6	-28.1%	$ 3,867
	10/10	3.6	2.4	-32.9%	$ 2,638
	3/5	3.6	2.9	-20.5%	$ 5,250
	3/5 Weighted	3.6	3.0	-18.3%	$ 5,932
Non-My Account	Top 10 Day Match on Avg Temp	3.9	2.7	-29.7%	$ 1,084
	Top 20 Day Match on Avg Temp	3.9	2.6	-33.5%	$ 866
	Top 3 Day Match on Avg Temp	3.9	2.6	-33.2%	$ 1,482
	Top 4 Day Match on Avg Temp	3.9	2.7	-30.8%	$ 1,352
	Top 5 Day Match on Avg Temp	3.9	2.7	-29.8%	$ 1,312
	5/10	3.9	3.3	-15.2%	$ 1,869
	4/4	3.9	2.8	-26.5%	$ 992
	Top 10 Day Match on HDD60	3.9	2.7	-30.4%	$ 1,059

Customer Segment	Baseline Type	Average Daily Use	Average Baseline Predicted Use	Average Percent Difference	Total Rebate
	Top 20 Day Match on HDD60	3.9	2.5	-34.8%	$ 817
	Top 3 Day Match on HDD60	3.9	2.6	-33.7%	$ 1,446
	Top 4 Day Match on HDD60	3.9	2.6	-31.3%	$ 1,325
	Top 5 Day Match on HDD60	3.9	2.7	-30.2%	$ 1,288
	Top 10 Day Match on Min Temp	3.9	2.6	-31.6%	$ 1,004
	Top 20 Day Match on Min Temp	3.9	2.5	-36.3%	$ 822
	Top 3 Day Match on Min Temp	3.9	2.8	-28.2%	$ 1,456
	Top 4 Day Match on Min Temp	3.9	2.7	-29.0%	$ 1,311
	Top 5 Day Match on Min Temp	3.9	2.7	-29.6%	$ 1,194
	Regression vs HDD60	3.9	1.5	-60.8%	$ 367
	Base Reg. w/Month & Day of Week Vars	3.9	2.7	-29.2%	$ 1,004
	10/10	3.9	2.6	-31.6%	$ 841
	3/5	3.9	3.2	-17.5%	$ 1,748
	3/5 Weighted	3.9	3.3	-15.5%	$ 1,930

Appendix D Overview of “SoCalGas Advisory Thermostat Program”

June 2017

OVERVIEW OF SOCALGAS(R) WINTER THERMOSTAT DEMAND RESPONSE PILOT

Summary and Key Outcomes

In the winter of 2017 Southern California Gas Company (SoCalGas) partnered with ecobee and EnergyHub to implement the "SoCalGas Advisory Thermostat Program." This pilot program was an element of the "Natural Gas Conservation Pilot Rebate Program" as described in SoCalGas Advice Letter 5035. The pilot was an innovative gas demand response program intended to reduce gas demand by direct control of customer thermostats. The pilot used the Bring Your Own Thermostat™ (BYOT) model to recruit existing customers with ecobee thermostats into the program by offering up to $50 of incentives. The following are the pilot's key stats and outcomes:

- 2,488 eligible ecobee thermostats within SoCalGas territory
- 411 thermostats applied
- 396 thermostats successfully enrolled
- 16% enrollment rate (above the industry average for first year)

Program Design

Season	January 19, 2017-March 31, 2017
Control Parameters	Up to 4-degree offset; Events from 5am-9am and/or 5pm-9pm; Opt-out allowed
Number of events per season	No more than 5
Customer eligibility criteria	Must be an ecobee owner within SoCalGas territory with active SoCalGas account and an activated Advanced Meter, but outside of SCE territory. Ecobee thermostat must control heat.
Program Name and messaging	"SoCalGas Advisory Thermostat Program"
Customer rebate (upfront and ongoing)	$25 for signing up, $25 end of season for staying in the program. Incentive paid to customers via check.

Engagement Strategy

EnergyHub and ecobee implemented a digital engagement campaign to recruit SoCalGas customers from the existing base of 2,488 ecobee thermostats. The campaign included

EnergyHub | ecobee

www.energyhub.com | www.ecobee.com

advertisements and rebate information on ecobee’s webpage, outbound emails, and a SoCalGas branded enrollment site. Eligible SoCalGas customers began enrolling after January 19th, with the first enrollments processed and available for direct thermostat control on January 30th. Examples of some of the materials are provided below.

Cobranded Enrollment Page

Outbound Email

The email campaigns had higher than typical engagement levels experienced in similar ecobee promotional campaigns with 55% of recipients opening the email and 16% clicking through to the enrollment page. In total, 396 thermostats were successfully enrolled representing a 16% total enrollment rate which is high considering the limited recruitment time. A total of 14 thermostats were rejected from enrollment. Reasons for rejection include no SoCalGas account found (7), outside the service territory (6), or name of the application did not match account (1).

Demand Response Results

Because there were no further SoCalGas Advisory days called after the point at which customers were enrolled in the pilot, SoCalGas did not have a need to call any control events using the EnergyHub Demand Response Management System (DRMS). It is not uncommon for utilities to not run control events given weather conditions or other factors.

EnergyHub

www.energyhub.com

ecobee

www.ecobee.com