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2009 Load Impact Evaluation for Pacific Gas and Electric Company's Residential SmartRate™—Peak Day Pricing and TOU Tariffs and SmartAC Program

Volume 1: Ex Post Load Impacts

Final Report

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1. EXECUTIVE SUMMARY

This report is the first of two volumes that document the load impact analysis, methodology, and results for the following Pacific Gas and Electric Company (PG&E) demand response tariffs and programs:

- Residential SmartRate™[1], in both its current form as well as in a revised structure (explained in Volume 2) that will go into effect starting in 2011;
- Non-residential SmartRate;
- Residential time-of-use (TOU) tariffs E-6 (ex post and ex ante) and E-7 (ex post only);
- The SmartAC™ program for residential and non-residential customers.

This volume documents the ex post analysis for the above programs and tariffs for the 2009 program year.[2] Volume 2 documents the ex ante analysis.

1.1. RESIDENTIAL SMART RATE LOAD IMPACT SUMMARY

The SmartRate pricing structure is an overlay on top of PG&E's other tariff offerings. SmartRate pricing consists of an incremental charge that applies during the peak period on Smart Days and a per kilowatt-hour credit that applies for all other hours from June through September. For residential customers, the additional peak-period charge on Smart Days is 60¢/kWh, and applies between 2 pm and 7 pm. For non-residential customers, the incremental charge is 75¢/kWh and applies from 2 pm to 6 pm. Up to 15 Smart Days can be called during non-holiday weekdays from May 1st to October 31st.

Residential SmartRate enrollment roughly doubled during the 2009 program year, increasing from approximately 8,500 in May to more than 21,000 by September. By the end of calendar year 2009, enrollment had reached over 25,000 accounts. Average residential customer enrollment across the 15 Smart Days that were called in 2009 equaled 15,882.

Table 1-1 summarizes the average load reduction across the five-hour event window provided by residential SmartRate customers on each event day during the summer of 2009. the average load reduction across the five-hour event window provided by residential SmartRate customers on each event day during the summer of 2009. As seen, the average percent reduction ranged from a low of 12.2% on July 21st to a high of 17.2% on September 10th. An average reduction of 15 percent was obtained across the 15 event days. The average load reduction per participant ranged from a low of 0.26 kW to a high of 0.44 kW. The average reduction across all 15 days was 0.31 kW. The combination of enrollment and average load impacts created aggregate reductions in peak demand on Smart Days ranging from a low of 3.1 MW on July13th to a high of 6.9 MW by

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[1] Any use of the term SmartMeter, SmartRate or SmartAC in this document is intended to refer to the trademarked term, whether or not TM is included. SmartMeter™ is a trademark of SmartSynch, Inc. and is used by permission.

[2] Comparisons with the 2008 analysis can be made by referring to: Stephen S. George, Josh Bode and Matt Mercurio. *2008 Load Impact Evaluation for PG&E's SmartRate, SmartAC and Residential TOU Programs. Final Report.* May 1, 2009. Prepared for Pacific Gas & Electric Co.

the last event day of the summer. Average, aggregate load reductions for the summer equaled 5.0MW.

Table 1-1
Residential SmartRate Average Hourly Load Reduction for Event Period by Event Day (All Enrolled Participants)

Date	Day of Week	Enrolled participants	Avg. Reference Load	Avg. Estimated Load with DR	Avg. Load Reduction	Percent Load Reduction	Aggregate Load Reduction	Daily Minimum Temperature	Daily Maximum Temperature
			(kW)	(kW)	(kW)	(%)	(MW)	(°F)	(°F)
29-Jun-09	M	10,892	2.70	2.26	0.44	16.2%	4.8	76.8	105.4
30-Jun-09	T	10,975	2.33	2.02	0.32	13.6%	3.5	77.2	100.7
13-Jul-09	M	11,449	1.93	1.66	0.27	13.9%	3.1	67.2	94.5
14-Jul-09	T	11,462	2.31	1.99	0.32	13.8%	3.6	70.4	99.7
16-Jul-09	Th	11,488	2.59	2.21	0.37	14.4%	4.3	74.4	102.8
21-Jul-09	T	11,558	2.31	2.03	0.28	12.2%	3.3	72.1	98.4
27-Jul-09	M	12,299	2.49	2.13	0.35	14.3%	4.4	73.6	101.8
10-Aug-09	M	16,741	2.12	1.79	0.33	15.6%	5.5	71.2	97.6
11-Aug-09	T	17,177	2.06	1.80	0.26	12.7%	4.5	70.8	95.5
18-Aug-09	T	19,182	1.85	1.59	0.26	14.1%	5.0	66	94.6
27-Aug-09	Th	20,779	1.82	1.52	0.29	16.1%	6.1	64.3	95.5
28-Aug-09	F	20,903	1.95	1.64	0.32	16.2%	6.6	68.1	96.9
2-Sep-09	W	20,966	1.97	1.67	0.30	15.3%	6.3	70.6	96.8
10-Sep-09	Th	21,163	1.79	1.48	0.31	17.2%	6.5	65.5	94.9
11-Sep-09	F	21,200	1.90	1.58	0.32	17.0%	6.9	68.8	94.8
Total	**N/A**	**15,882**	**2.08**	**1.77**	**0.31**	**15.0%**	**5.0**	**69.7**	**97.4**

As discussed in Section 2, customers are asked at the time they sign up for the SmartRate tariff to indicate whether or not they want to be notified about events and, if so, to provide up to four different notification options (e.g., one or more email addresses, one or more telephone numbers). On average, 19% of customers were not successfully notified on most event days. Almost 42% of customers were notified once, 28% were notified twice and approximately 11% were notified three or four times on most events.

Event notification has a significant impact on load reductions. The average load reduction across all 15 events increases from 15.0% to almost 19.2% when customers who were not notified are dropped from the sample, and the average load impact rose from 0.31 kW to 0.41 kW. On the highest impact day, June 29th, the average load reduction for notified customers exceeded 0.5 kW. Both the average and percentage load reductions increase more than three-fold between customers who are successfully notified through one option to those that receive four successful notifications. The percent and average load reduction for customers who receive only a single notification, respectively, are 12.8% and 0.26 kW. The same values for customers who receive four successful notifications are 43.0% and 0.94 kW. The percent and average reductions for customers receiving two notifications equal 21.8% and 0.48 kW, and customers successfully notified three times reduced load on average by 31.7% and 0.74 kW.

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CARE stands for California Alternate Rates for Energy and is a program through which enrolled, low income consumers receive lower rates than non-CARE customers. Qualification for CARE is based on self-reported, household income and varies with the number of persons per household. There are significant differences in prices between CARE and non-CARE customers, especially in rate Tiers 3, 4 and 5, and the peak-period price differentials between the underlying tariff and SmartRate prices on Smart Days are also quite different. As was found to be true in the 2008 load impact evaluation, customers on PG&E's CARE rate participated at much higher rates than did non-CARE customers relative to their share of the PG&E population as a whole. Indeed, more than half of SmartRate participants were CARE customers, while only 23.5% of PG&E's customer population was on the CARE tariff over the same time frame. The average load reduction for CARE customers equaled 0.15 kW, or 7.5%, which was roughly one third as much as the 0.49 kW, or 22.7%, average reduction for non-CARE customers.

The much lower load response provided by CARE customers does not necessarily mean that CARE customers are inherently less price responsive. Two factors strongly related to load impacts – notification rates, and central air conditioning ownership – differ significantly between CARE and non-CARE customers and may explain much of the difference in average response rates between the two customer segments.

On average, 69.6% of CARE customers were successfully notified of events while 83.1%of non-CARE customers received event notification. As discussed above, event notification is a strong driver of load response and could explain a significant portion of the difference in load impacts.

The other factor is central air conditioning ownership. FSC estimated the likelihood of central conditioning ownership for residential accounts as input to the ex ante SmartAC evaluation (see Volume 2 for documentation). Based on this analysis, the estimated share of SmartRate customers with central air conditioning is 64% for non-CARE customers and roughly 53% for CARE customers. Customers with a high propensity of owning central air conditioning provide significantly greater load reductions than do customers who do not own central air conditioning. Evidence presented in Section 3 indicates that the average load drop for CARE customers with less than a 25% probability of owning central air conditioning is only one third as large as for CARE customers with a 75% probability of owning central air conditioning. For non-CARE customers, households with a greater than 75% probability of owning central air conditioning provide load reductions that are 4.5 times greater than households who have less than a 25% probability of owning central air conditioning.

Figure 1-1 shows the distribution of load impacts across customers. As indicated, roughly 45% of customers provide no load reduction at all, although about half of these customers did not receive event notifications. On the other hand, more than one third of all customers provide more than 0.2 kW of average load reduction, and 11.7% of all customers provide load reductions exceeding 1 kW. Clearly, if these high responders can be identified and targeted, program cost-effectiveness could be dramatically improved. At the same time, as discussed in the ex-ante volume, program effectiveness could also be improved by encouraging low responders to have their load response automated through participation in SmartAC.

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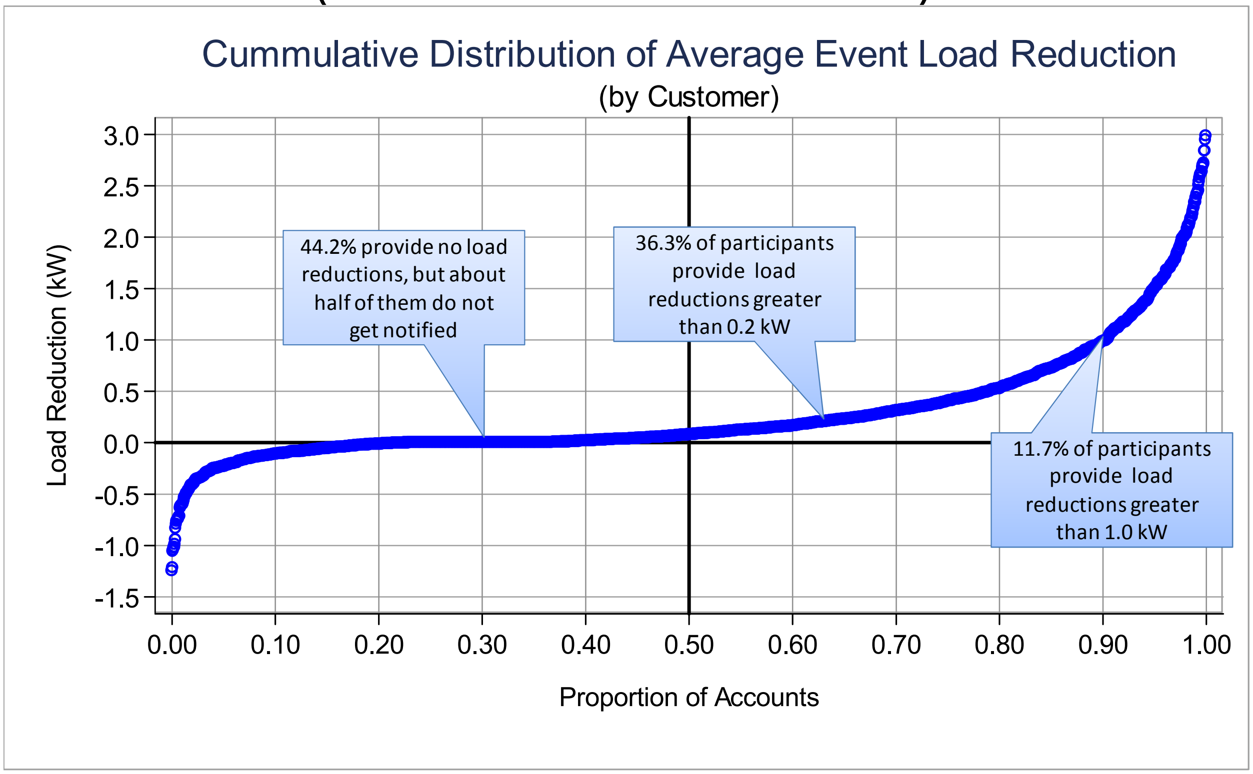
Figure 1-1
Residential SmartRate Distribution of Individual Customer Average Event Load Reduction
(Includes Customers That Were Not Notified)



1.2. NON-RESIDENTIAL SMART RATE LOAD IMPACT SUMMARY

There were only 187 non-residential accounts enrolled in SmartRate in 2009, all of them located in or near Kern County. These accounts experienced the same 15 event days as did residential SmartRate customers. This small sample size suggests that the impact estimates presented here should be viewed with significant caution. This group of current participants is not representative of PG&E's non-residential (A-1) customer population either in Kern County or for the service territory as a whole.

Table 1-2 shows the average load reduction for non-residential SmartRate customers for each event day in 2009. The average load reduction across the 15 event days is 0.44 kW, or 16.2% of the average reference load. The load reduction ranges from a low of 0.14 kW, or 6.8% on July 16th, to a high of 0.66 kW, or 23.9%, on September 2nd.

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Table 1-2
Load Impacts by Event Day for Non-Residential SmartRate Customers

Date	Day of Week	# of Enrolled Customers	Maximum Temp (°F)	Minimum Temp (°F)	Average Hourly Load (kW)	Average Load Reduction (kW)	Average % Load Reduction
29-Jun-09	M	187	108	78.5	3.13	0.54	17.2
30-Jun-09	T	187	103.5	82	2.94	0.41	13.9
13-Jul-09	M	187	95	69	2.78	0.48	17.3
14-Jul-09	T	187	100	71	2.94	0.48	16.2
16-Jul-09	Th	187	105	77.5	2.03	0.14	6.8
21-Jul-09	T	187	102	75.5	3.05	0.51	16.8
27-Jul-09	M	187	104	77.5	3.12	0.61	19.5
10-Aug-09	M	187	99	73.5	2.87	0.44	15.3
11-Aug-09	T	187	102	74.5	2.98	0.4	13.6
18-Aug-09	T	187	99	70	2.88	0.37	12.9
27-Aug-09	Th	187	97	68	1.87	0.19	10.4
28-Aug-09	F	187	97	70	2.83	0.51	17.9
2-Sep-09	W	187	98	72.5	2.77	0.66	23.9
10-Sep-09	Th	187	96.5	68	1.82	0.21	11.4
11-Sep-09	F	187	97	71.5	2.73	0.63	23.1
Average	**n/a**	**187**	**100.2**	**73.3**	**2.73**	**0.44**	**16.2**

1.3. RESIDENTIAL TOU TARIFF EX POST LOAD IMPACT SUMMARY

PG&E has two residential TOU tariffs – E7 and E6. Currently, roughly 78,000 customers are enrolled on E7, and approximately 7,400 customers are enrolled on E6. Enrollment for E7 is closed while enrollment for E6 remains open. The E-7 tariff is a two-period, five-tier tariff. The peak period for the E7 tariff, which is the same all year long, is from noon to 6 pm on weekdays, with off-peak prices in effect at all other times. With the E6 tariff, the peak period is from 1 pm to 7 pm in the summer months. The partial peak period in the summer is from 10 am to 1 pm and 7 pm to 9 pm, Monday through Friday and from 5 pm to 8 pm on Saturdays and Sundays. In the winter, peak period prices do not apply, and partial peak prices occur from 5 pm to 8 pm on weekdays only. There are two versions of each rate, one for CARE customers and one for non-CARE customers.

Table 1-3 shows the average change in peak-period energy use for a typical weekday for each month.[3] The average peak period reduction across the year is 0.14 kW. The greatest average week day load reduction, 0.21 kW, occurs in September and the lowest average, 0.11 kW, is found in each month from November through April. The percentage reduction in peak period usage peaks in September, at 12.2%, and is lowest in December, at 6.8%. While the average kW reduction is essentially the same during all winter months, the percentage reduction varies.

[3] Keep in mind that the impacts are for October 2008 through the end of September 2009, as this is the time period covered by the available data.

Table 1-3:
Average Weekday Peak Period Load Reduction for the E7 Tariff by Month
(October 2008 through September 2009, Peak Period from noon to 6 pm)

Month	Reference Load	Estimated Load with DR	Impact	Percent Reduction	Average Temp
	(kW)	(kW)	(kW)	(%)	(°F)
Jan-09	1.40	1.29	0.11	7.6%	58.1
Feb-09	1.35	1.25	0.11	7.9%	57.3
Mar-09	1.24	1.13	0.11	8.6%	63.0
Apr-09	1.25	1.14	0.11	8.5%	66.9
May-09	1.36	1.22	0.14	10.0%	76.1
Jun-09	1.52	1.37	0.15	10.0%	77.6
Jul-09	1.91	1.70	0.20	10.7%	83.8
Aug-09	1.79	1.59	0.20	11.3%	83.4
Sep-09	1.72	1.51	0.21	12.2%	83.4
Oct-08	1.27	1.14	0.14	10.7%	75.4
Nov-08	1.26	1.15	0.11	8.5%	63.4
Dec-08	1.56	1.45	0.11	6.8%	52.4
Total	**1.47**	**1.33**	**0.14**	**9.6%**	**70.2**

Table 1-4 shows the average load reduction on monthly system peak days for E7 customers. The percentage load reductions are comparable to those observed on the average week day and the absolute load reductions during winter months are nearly identical on the average week day and the monthly system peak day. However, the absolute peak-period load reduction during the key summer months of June through August are significantly higher than on the average week day. For example, the peak period reduction on the July system peak day is 0.36 kW, which is roughly 80% higher than the peak-period reduction on an average week day.

Table 1-4:
E7 Monthly System Peak Day Load Reductions by Month (12-6 pm)
October 2008 to September 2009

Month	Reference Load	Estimated Load with DR	Impact	Percent Reduction	Average Temp
	(kW)	(kW)	(kW)	(%)	(°F)
Jan-09	1.49	1.59	0.11	7.2%	45.9
Feb-09	1.40	1.50	0.11	7.6%	51.9
Mar-09	1.11	1.22	0.11	9.6%	58.8
Apr-09	1.57	1.67	0.11	6.8%	83.9
May-09	2.25	2.53	0.27	12.2%	94.1
Jun-09	2.20	2.56	0.36	16.4%	93.1
Jul-09	2.42	2.83	0.40	16.6%	95.5
Aug-09	2.21	2.55	0.34	15.4%	92.6
Sep-09	2.13	2.50	0.37	17.3%	94.0
Oct-08	1.31	1.51	0.20	15.3%	84.2
Nov-08	1.19	1.30	0.11	9.0%	73.9
Dec-08	1.68	1.79	0.11	6.3%	45.3
Total	**1.78**	**2.00**	**0.22**	**12.3%**	**76.5**

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1.4. RESIDENTIAL SMARTAC EX POST LOAD IMPACT SUMMARY

PG&E's SmartAC™ program involves the installation of programmable communicating thermostats (PCTs) and/or direct load control switches (switches) in households and small/medium businesses with central [or packaged] air conditioning (CAC). The control devices allow air conditioners to be cycled or thermostats to be adjusted when an event is triggered, thereby reducing energy demand associated with air conditioning load. SmartAC events can only be called under emergency or in anticipation of emergency conditions between May 1st and October 31st and for an event period of six hours or less for no more than 100 hours per season. One territory-wide test event was called in 2009, on September 10th. Devices were controlled from 3 pm to 7 pm. Residential customer enrollment on SmartAC on September 10th was roughly 107,000 accounts.

Under contract to PG&E, FSC selected a sample of SmartAC participants and installed end-use loggers on the air conditioning units for these households to obtain data for use in both ex post and ex ante load impact analysis for 2009. Unfortunately, a programming error by PG&E's SmartAC program contractor created a situation where the switches and PCTs that control air conditioners for the research sample did not operate when signaled. Thus, the original evaluation plan, which would have provided a more robust database for analysis, had to be abandoned.

The load impact estimates presented here are based on analysis of whole building energy use for a sample of SmartAC participants for which SmartMeters had been installed prior to the September 10th event date. The sample was reweighted to properly represent the distribution of SmartAC customers across climate regions. The results reflect a downward bias correction that we believe reflects the actual event impact more accurately. In other words, regression based estimates were revised downward substantially for reasons detailed in the report. The impacts presented are conservative, as reflected by the fact that the estimates for the two hour immediately after the events – the snapback period – are both more than 140% of the largest load reduction over the event period.

The average estimated load reduction for residential SmartAC participants on September 10th was 0.19 kW, which constitutes about 10% of the total household load for this group of customers. September 10th was a relatively cool day, with the average temperature across the four hour event period equal to only 93.8°F and the maximum temperature equal to only 95°F.

Load impact estimates were developed separately for SmartAC customers with PCTs and switches. Almost 80% of SmartAC households are controlled using switches, and the remaining 20% are controlled using PCTs. The average impact on September 10th for households with switches was 0.19 kW, or 9.5%. The average impact for households with PCTs was 0.21 kW, which is slightly higher in absolute terms than for households with switches. However, households with PCTs have higher reference loads (2.3 kW) than do households with switches (2.0 kW).

1.5. NON-RESIDENTIAL SMARTAC EX POST LOAD IMPACT SUMMARY

A non-residential whole-building sample was drawn to estimate load impacts in light of the error by PG&E operations contractor. However, the non-residential whole-building sample was limited to 190 customers due to schedule of the smart meter roll out schedule and the timing of the event. The background whole-building load is larger for non-residential compared to the residential sample. In the residential sample, the peak event day reference load for the average customer is

2.18 kW. In the non-residential sample, it is 7.33—more than three times greater. Patterns in AC load (the signal) stand out much more among a smaller background reference load (the noise).

As the result, to calculate load impacts, the measured percent impact values taken from the analysis done on the 2008 SmartAC Residential Sample were applied to the directly measured, unperturbed, per customer air conditioner load on the event day – September 10, 2009. This was possible because the measurement and evaluation sample end use recording devices worked as planned.

Average per customer impact over the event period is 0.71 kW. Impact is higher in the first two hours of the event—around 0.8 kW—before falling off in the last two hours. The end-use data provided valuable information about non-residential air conditioner loads. Overall, non-residential air conditioner loads are nearly twice as large per unit as residential air conditioners under similar weather conditions. This is partly due to different occupancy and air conditioner use patterns, and partly due to differences in the size of air conditioners. In addition, non-residential customers are more likely to have multiple air conditioner units per site, leading to potential efficiencies in recruitment and installation.

2. PROGRAM SUMMARIES

This report is the first of two volumes that document the load impact analysis, methodology, and results for the following Pacific Gas and Electric Company (PG&E) demand response tariffs and programs:

- Residential SmartRate™[4], in both its current form as well as in a revised structure (explained in Volume 2) that will go into effect starting in 2011;
- Non-residential SmartRate;
- Residential time-of-use (TOU) tariffs E-6 (ex post and ex ante) and E-7 (ex post only);
- The SmartAC™ program for residential and non-residential customers.

This volume documents the ex post analysis for the above programs and tariffs for the 2009 program year.[5] Volume 2 documents the ex ante analysis. The load impact estimates presented here are intended to conform to the CPUC Load Impact Protocols.[6]

2.1. SMARTRATE PROGRAM OVERVIEW

In May, 2008, Pacific Gas and Electric Company (PG&E) began offering a critical peak pricing tariff known as SmartRate to residential and small commercial customers in the Bakersfield and greater Kern County area. This region was the first in PG&E's service territory to receive new meters under the Company's advanced metering infrastructure deployment, branded as the SmartMeter™ Program. By the end of the 2008 program year, enrollment in the Kern County area exceeded 10,000 customers. SmartRate marketing was suspended from the fall of 2008 through early spring 2009. Starting in May 2009, enrollment expanded both in terms of the number of customers and the geographic regions covered. At the beginning of the 2009 program season, roughly 8, 500 residential customers were enrolled in the program and by the end of September 2009, more than 22,000 customers were enrolled. At the time this report was written, active enrollment equaled approximately 25,500 customers. Figure 2-1 summarizes SmartRate program enrollment in 2009.

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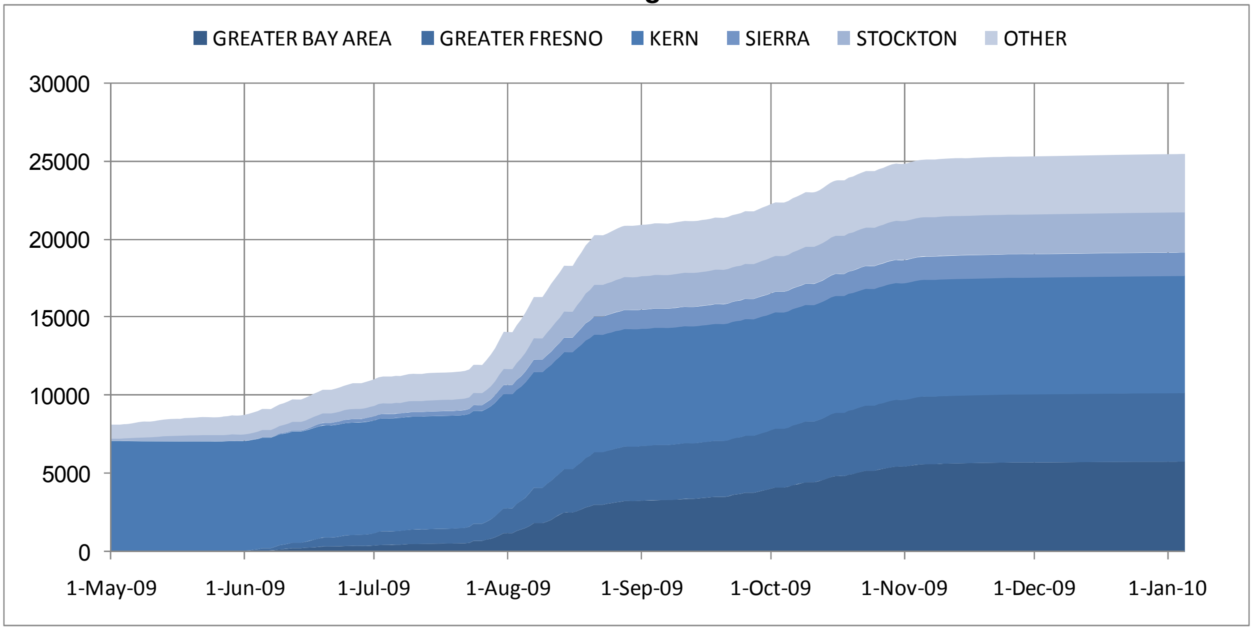
[5] Comparisons with the 2008 analysis can be made by referring to: Stephen S. George, Josh Bode and Matt Mercurio. *2008 Load Impact Evaluation for PG&E's SmartRate, SmartAC and Residential TOU Programs. Final Report.* May 1, 2009. Prepared for Pacific Gas & Electric Co.

[6] Attachment A to CPUC D.08-04-050, issued on April 28, 2008. Hereafter referred to as the Load Impact Protocols.

Figure 2-1
2009 SmartRate Program Enrollment



SmartRate is a voluntary rate supplement that features critical peak pricing. Under critical peak pricing, peak period prices are significantly higher than the otherwise applicable price on a limited number of "event" days (up to 15), known as SmartDays, during the summer season. The peak period on SmartDays is from 2 pm to 7 pm for residential customers and from 2 pm to 6 pm for non-residential customers. The summer season runs from May 1st through October 31st. Prices only vary by time of day on SmartDays, unless a customer's underlying rate is a time-of-use (TOU) rate.[7] Customers are notified that the next day will be a SmartDay by 3 pm on the preceding day. Customers have several options for receiving event notification (e.g., email, phone, etc.), including not being notified at all. Roughly 30% of customers either chose not to be notified or provided notification information that was initially incorrect or became outdated.

The SmartRate pricing structure is an overlay on top of PG&E's other tariff offerings. SmartRate pricing consists of an incremental charge that applies during the peak period on SmartDays and a per kilowatt-hour credit that applies for all other hours from June through September. For residential customers, the additional peak-period charge on SmartDays is 60¢/kWh. For non-residential customers, the incremental charge is 75¢/kWh. SmartDays can only be called during non-holiday weekdays from May 1st to October 31st.

The SmartRate credit has two components, both of which apply only during the months of June through September.[8] The first SmartRate credit applies to all usage other than peak-period usage

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[7] The number of E-7 and E-6 customers that are also on SmartRate is trivial at this time.
[8] Credits were applied only during the four month period from June through September rather than for the whole summer in an attempt to smooth out the bill impacts across the summer months. Since most event days are likely to fall in the months of June through September (indeed, all of the 2008 events occurred in these months), having the discount apply only in these months would do a better job of partially offsetting the negative bill impacts associated with the higher prices on event days.

on SmartDays. For residential customers, the credit equals roughly 3¢/kWh. An additional credit of 1¢/kWh applies to tier 3 and higher usage for residential customers regardless of time period.

PG&E's standard residential tariff, E-1, is a five-tier, increasing block rate, with the price per kWh increasing nearly fourfold between Tier 1 and Tier 5. The usage level where prices change is tied to a baseline usage amount that varies by climate zone. Table 2-1 shows the prices for each tier for the E-1 tariff for both CARE and non-CARE customers who are not all-electric homes. CARE stands for California Alternate Rates for Energy and is a program through which enrolled, low income consumers receive lower rates than non-CARE customers.[9] As shown in Table 2-1, the CARE discount is quite significant, especially for low income households that have usage in Tier 3 and above. The ratio of marginal prices between E-1 and CARE customers is more than 4 to 1 in Tier 5, for example, and the average price ratio is more than 2.5 to 1.

Table 2-1
E-1 CARE and Non-CARE Prices for PG&E[10]

Usage Tier	% of Baseline Usage	E-1 Price for Tier	Average E-1 Price Based on Mid-Tier Usage	CARE Price for Tier	Average CARE Price Based on Mid-Tier Usage
		(¢/kWh)	(¢/kWh)	(¢/kWh)	(¢/kWh)
1	100%	11.5	11.5	8.3	8.3
2	130%	13.1	11.7	9.6	8.5
3	200%	26.0	14.9	9.6	8.8
4	300%	37.9	21.0	9.6	9.1
5	>300%	44.1	26.7	9.6	9.2

With the tiered pricing used in PG&E's service territory, the price ratio between peak-period prices on SmartDays and the average price on normal days on the SmartRate tariff (which is roughly 3¢/kWh lower than the averages in Table 2-2 because of the SmartRate credit during those hours), varies significantly with usage and also varies between CARE and non-CARE customers. For example, for a Tier 1 customer on the E-1 tariff, the peak-period price on SmartDays is more than 8 times higher than on non-SmartDays.[11] On the other hand, for a Tier 5 customer, the peak period price would equal roughly 85¢/kWh and the price ratio would be less than 4 to 1. For CARE customers, the SmartDay peak-period price is approximately 69¢/kWh and the price ratio between SmartDay peak-period prices and non-SmartDay prices is almost 12 to 1.

In 2008, a disproportionate number of CARE customers enrolled in SmartRate relative to the share of CARE customers in the Kern County and neighboring area. This initial trend continued

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[9] Qualification for CARE is based on self-reported, household income and varies with the number of persons per household. The maximum qualifying income for a household with 1 or 2 people is $30,500. For a four-person household, the maximum qualifying income is $43,200.
[10] For E-1 customers, the fixed monthly charge is approximately $4.44. For CARE customers, it equals roughly $3.55.
[11] The peak period price would equal 11.5 + 60 = 71.5. The price at all other times during the summer period would equal 11.5 – 3 = 8.5. The price ratio equals 8.4.

as SmartRate expanded to other regions. Table 2-2 shows the proportion of CARE and non-CARE customers in the population, and in the SmartRate program, by LCA. In every LCA except Sierra, CARE customers constitute a significantly higher share of SmartRate customers than their share in the population as a whole. In the Fresno LCA, for example, over two-thirds of SmartRate participants are CARE customers while CARE customers comprise only about 40% of the Fresno LCA. In the Greater Bay Area and Stockton LCAs, the share of SmartRate customers that on the CARE rate is almost twice as high as their share in the population as a whole.

Table 2-2
CARE and non-CARE Customers
in Population and SmartRate Program by Local Capacity Area[12]

Local Capacity Area	SmartRate Participants (End of 2009)				PG&E Residential Population			
	Standard Tariff	%	Low Income Tariff (CARE)	%	Standard Tariff	%	Low Income Tariff (CARE)	%
Greater Bay Area	1,814	31.5%	3,936	68.5%	1,674,914	82.0%	367,523	18.0%
Greater Fresno	2,694	61.4%	1,693	38.6%	275,250	59.8%	185,395	40.2%
Humboldt	NA	NA	NA	NA	38,803	68.5%	17,828	31.5%
Kern	4,398	58.5%	3,117	41.5%	107,075	61.5%	67,104	38.5%
Northern Coast	NA	NA	NA	NA	375,693	81.2%	86,960	18.8%
Sierra	330	21.8%	1,181	78.2%	202,617	77.5%	58,679	22.5%
Stockton	1,310	50.9%	1,266	49.1%	152,046	71.2%	61,614	28.8%
Other or Unclassified	1,886	50.4%	1,854	49.6%	606,776	74.2%	210857	25.8%
Total	**12,432**	**48.8%**	**13,047**	**51.2%**	**3,438,262**	**76.5%**	**1,056,722**	**23.5%**

*NA = Not applicable, no customers eligible because smart meter deployment had not yet reached area.

To date, SmartRate has been marketed through direct mail. PG&E has experimented with a variety of incentives, ranging from an initial offer of a $50 Visa gift card during the 2008 campaign, to no incentive at all for several of the 2009 promotional campaigns. A detailed discussion of the various offers, messages and multiple-mailing strategies used to market SmartRate is contained in Volume 2.

All SmartRate promotional materials include an offer of first-year bill protection in order to address the risk aversion that pilot programs and market research have shown to be a significant barrier to participation for customers considering dynamic rate options. The first year bill protection ensures that, initially at least, customer's bills would not increase under the new rate option relative to what they would have been over the same period under the prior tariff.

In 2009, for the first time, SmartRate was also offered to a subset of SmartAC program participants, and the enrollment rate for this group of customers was significantly greater than for customers who were not enrolled in SmartAC. Of the roughly 25,500 customers who signed up for SmartRate by the end of 2009, approximately 4,700 were also enrolled in PG&E's SmartAC

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[12] SmartRate was offered to households with smart meters, a pre-condition for eligibility, and not to the entire population in each local capacity area.

program. Customers who enroll in both programs are given the option of having their air conditioner cycled 50% of the time or their thermostat set point increased by 4 degrees during the peak period on Smart Days. The fact that many of these dual enrolled customers signed up late in the season combined with a lag in reprogramming the cycling devices meant that only about 910 dually enrolled customers actually had their cycling devices controlled during the majority of events in 2009. The impact evaluation presented in Section 3 shows the incremental effect of the cycling device on the average load impact for SmartRate customers.

The maximum number of Smart Days were called in 2009. Table 2-3 shows the dates for each Smart Day event, and the number of customers enrolled on each date, and the enrollment weighted average temperature. As seen, the hottest average temperature among the 15 days was on the first event day of the season, June 29th, when the average was almost 105°F. The coolest day, at 93.4°F, was on July 13th. Unlike in 2008, when the nine event days were comprised of three, three-day event sequences, there were no three-day event periods in 2009. However, there were five two-day event periods. There were two event days in late June, five each in July and August, and three in September, with the last one occurring on September 11th.

Table 2-3
2009 Smart Day Dates, Customer Enrollment and Event Period Average Temperature

Date	Enrolled participants	Temperature (participant weighted average across five event hours) (°F)
29-Jun-09	10,892	104.9
30-Jun-09	10,975	100.1
13-Jul-09	11,449	93.4
14-Jul-09	11,462	98.7
16-Jul-09	11,488	102.2
21-Jul-09	11,558	98.5
27-Jul-09	12,299	101.0
10-Aug-09	16,741	96.8
11-Aug-09	17,177	95.1
18-Aug-09	19,182	94.0
27-Aug-09	20,779	94.2
28-Aug-09	20,903	96.0
2-Sep-09	20,966	96.0
10-Sep-09	21,163	94.1
11-Sep-09	21,200	94.3

2.2. TOU TARIFF OVERVIEW

PG&E has had a traditional TOU rate in place for many years. The E-7 tariff is a two-period, five-tier tariff. The peak period for the E7 tariff is from noon to 6 pm on weekdays, with off-peak prices in effect at all other times. The peak period is the same the entire year. The E7 rate has been closed to new customers since 2007. It was replaced by the E-6 tariff, which is a three-period, five-tier TOU rate. With the E6 tariff, the peak period is from 1 pm to 7 pm in the summer months. The partial peak period in the summer is from 10 am to 1 pm and 7 pm to 9 pm, Monday through Friday and from 5 pm to 8 pm on Saturdays and Sundays. In the winter, peak period prices do not apply, and partial peak prices occur from 5 pm to 8 pm on weekdays only. There are two versions of each rate, one for CARE customers and one for non-CARE customers. Table 2-4 shows the electricity price by rate period for E-6 and E-7 customers.

Table 2-4
E-6 and E-7 Prices[13]

Rate	Rate Description	Minimum Charge (cents)	Meter Charge (cents per meter per day)	Season	TOU Period	Energy Charge (¢/kWh)					Average Total Rate (c/kWh)
						Tier 1 (baseline)	Tier 2 (101-130% of baseline)	Tier 3 (131-200% of baseline)	Tier 4 (201-300% of baseline)	Tier 5 (300% of baseline+)	
E7	Residential time-of-use (4 periods)	14.8	11.5	Summer	Peak	28.1	29.7	42.6	54.5	60.8	18.5
					Off-Peak	7.1	8.7	21.6	33.5	39.8	
				Winter	Peak	10.0	11.6	24.5	36.4	42.6	
					Off-Peak	7.4	9.0	21.9	33.9	40.1	
EL-7	Residential time-of-use, Care (4 periods)	14.8	0.0	Summer	Peak	26.8	26.8	26.8	26.8	26.8	8.7
					Off-Peak	6.1	6.1	6.1	6.1	6.1	
				Winter	Peak	8.9	8.9	8.9	8.9	8.9	
					Off-Peak	6.4	6.4	6.4	6.4	6.4	
E6	Residential time-of-use (6 periods)	14.8	25.3	Summer	Peak	29.3	30.8	43.7	55.6	61.7	17.9
					Part-Peak	14.4	16.0	28.9	40.7	47.0	
					Off-Peak	8.4	10.0	22.9	34.8	41.0	
				Winter	Peak	10.0	11.6	24.4	36.3	42.5	
					Off-Peak	8.8	10.4	23.3	35.2	41.4	
EL-6	Residential time-of-use, Care (6 periods)	11.8	20.2	Summer	Peak	20.8	22.0	22.0	22.0	22.0	8.7
					Part-Peak	10.2	11.5	11.5	11.5	11.5	
					Off-Peak	6.0	7.2	7.2	7.2	7.2	
				Winter	Peak	7.1	8.3	8.3	8.3	8.3	
					Off-Peak	6.2	7.5	7.5	7.5	7.5	

Table 2-5 shows the number of customers that are on the E-6 and E-7 rates, broken down by CARE and non-CARE status. In total, there are approximately 85,000 customers currently being served under the four versions of the TOU tariffs, with almost 78,000 on E-7 and 7,410 on E-6. About 9% of the E-7 customers are on the CARE tariff and only about 4% of E-6 customers are CARE customers.

[13] http://www.pge.com/nots/rates/tariffs/electric.shtml#RESELEC_TOU

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Table 2-5
E6 an E7 TOU Tariff Enrollment by Local Capacity Area and CARE status

Local Capacity Area	E7 Time of Use Rate			E6 Time of Use Rate		
	Standard tariff	Low Income Tariff (CARE)	Total	Standard tariff	Low Income Tariff (CARE)	Total
Greater Bay Area	26,788	1,706	28,494	3,136	88	3,224
Greater Fresno	6,166	828	6,994	574	40	614
Humboldt	1,631	352	1,983	67	22	89
Kern	1,411	190	1,601	74	5	79
NONE	75	1	76	9	1	10
Northern Coast	12,409	1,031	13,440	1,274	67	1,341
Other	13,274	1,325	14,599	1,201	52	1,253
Sierra	6,660	726	7,386	582	26	608
Stockton	2,977	372	3,349	180	12	192
Total	**71,391**	**6,531**	**77,922**	**7,097**	**313**	**7,410**

Table 2-6 describes the share of TOU participants with net metering. Net metered customers typically have very different load patterns compared with standard metered customers, as they very often have solar power or some other form of distributed generation. Approximately 16 % of E-7 customers are net metered but roughly 81% of E-6 customers are net metered. The load impact estimates presented in Section 5 have excluded net metered customers, as the data used in the analysis only apply to standard metered customers.

Table 2-6
E6 an E7 TOU Tariff Enrollment with Standard and Net Meters

Local Capacity Area	E7 Time of Use Rate			E6 Time of Use Rate		
	Standard	Net metered	Total	Standard	Net metered	Total
Greater Bay Area	23,158	5,336	28,494	457	2767	3,224
Greater Fresno	6,305	689	6,994	131	483	614
Humboldt	1,792	191	1,983	39	50	89
Kern	1,517	84	1,601	19	60	79
NONE	67	9	76		10	10
Northern Coast	10,764	2,676	13,440	296	1045	1,341
Other	12,520	2,079	14,599	279	974	1,253
Sierra	6,269	1117	7,386	140	468	608
Stockton	3,017	332	3,349	53	139	192
Total	**65,409**	**12,513**	**77,922**	**1,414**	**5996**	**7,410**

2.3. SMARTAC PROGRAM OVERVIEW

PG&E's SmartAC™ program involves the installation of programmable communicating thermostats (PCTs) and/or direct load control switches (switches) in households and small/medium businesses with central [or packaged] air conditioning (CAC). The control devices allow CAC equipment to be cycled or thermostats to be adjusted[14] when an event is triggered, thereby reducing energy demand associated with air conditioning load. SmartAC events can only be called under emergency or in anticipation of emergency conditions between May 1st and October 31st and for an event period of six hours or less for no more than 100 hours per season. One territory-wide test event was called in 2009, on September 10th. Devices were controlled from 3 pm to 7 pm.

PG&E began marketing the SmartAC program in early 2007. Most marketing has been done through direct mail, although PG&E is testing alternative methods for marketing to small and medium businesses (SMB) in 2010, including direct mail with telemarketing or email follow up and the use of account representatives for SMBs that are assigned accounts. To date, most residential participants were paid a one-time fee of $25 to allow installation of one or more devices at their premise.[15]

Table 2-7 shows the number of active, enrolled customers and devices on September 10, 2009 (the test event day) by customer type, device type and local capacity area. It is important to distinguish between enrolled customers and enrolled devices, as many customers, especially SMB customers, have multiple air conditioning units and, therefore, multiple control devices.

As seen in the table, the majority of SmartAC customers and devices are among residential households. Indeed, the residential segment comprises 99% of all SmartAC customers and 98% of devices. Out of more than 100,000 active accounts on the program on September 10th, only 1,001 are commercial customers. Commercial accounts have roughly 2.5 devices per customer, whereas residential accounts have 1.1 devices per customer.

The differential participation rates between residential and non-residential accounts is more a reflection of the lack of marketing to commercial accounts to date than it necessarily is a reflection of the lack of interest of commercial customers participating in the program. As mentioned above, PG&E is significantly increasing its marketing activity among small and medium business accounts in 2010 and it is expected that SMB accounts will comprise a larger share of the total number of SmartAC accounts and devices during the summer of 2010.

Roughly one third of all SmartAC accounts active on September 10th were located in the Greater Bay Area LCA and about one quarter were in the Fresno LCA. The low participation in the Kern County LCA reflects the fact that SmartAC was not marketed in Kern County before 2009 because of the initial decision to not market SmartRate and SmartAC simultaneously. In 2009, PG&E offered SmartAC to SmartRate customers in Kern County and the take rate was quite high, with almost 5,000 SmartRate customers accepting the SmartAC offer. However, as previously

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[14] Air conditioner cycling can be done with either load control devices or thermostats, while thermostats can also be used to reduce air conditioning use by adjusting temperature settings.

[15] Future marketing plans and enrollment estimates are discussed at length in Volume 2 of this report. Some of the methods being tested are also described in PG&E's *SmartAC 2009 Annual Report*, December 31, 2009.

discussed, most of the SmartRate participant devices were not installed before the end of the summer, which is a key reason why the participation rate for Kern County shown in Table 2-7 is this low.

Table 2-7
SmartAC Active Accounts and Control Devices
September 10, 2009 Event Day

Customer Class	Local Capacity Area	PCT		Switch		Total	
		Accounts	Devices	Accounts	Devices	Accounts	Devices
Non Residential	Greater Bay Area	341	768	61	105	402	873
	Greater Fresno	132	378	83	198	215	576
	Kern	18	47	1	6	19	53
	Northern Coast	30	84	16	52	46	136
	Other	89	308	52	144	141	452
	Sierra	42	92	24	55	66	147
	Stockton	62	164	50	108	112	272
	Total	**714**	**1,841**	**287**	**668**	**1,001**	**2,509**
Residential	Greater Bay Area	7,146	7,894	30,326	34,082	37,472	41,976
	Greater Fresno	7,001	7,704	17,363	19,293	24,364	26,997
	Kern	1,003	1,116	344	392	1,347	1,508
	Northern Coast	425	443	2,562	2,675	2,987	3,118
	Other	3,470	3,669	13,840	14,886	17,310	18,555
	Sierra	1,136	1,333	10,332	12,100	11,468	13,433
	Stockton	2,528	2,682	9,145	9,945	11,673	12,627
	Total	**22,709**	**24,841**	**83,912**	**93,373**	**106,621**	**118,214**

2.4. REPORT ORGANIZATION

The remainder of this report is organized as follows. Section 3 contains the 2009 ex post load impact estimates for the SmartRate tariff for residential customers. This section contains estimates for the average SmartRate participant as well as for many different customer segments, including households who were enrolled in both SmartRate and SmartAC. Section 4 presents load impact estimates for the small group of non-residential SmartRate customers. Section 5 contains ex post load impact estimates for residential TOU rates E-6 and E-7 while Section 6 contains the load impact estimates for both residential and SMB SmartAC customers. The appendices contain various supporting material.

Each report section is organized similarly, although some differences exist. In general, a section begins with a brief discussion of the types of load impacts that will be reported. The CPUC Load Impact Protocols dictate the minimum requirements for load impact output, some of which are reported here and some of which are contained only in electronic tables that are provided separately. However, in some instances, results that go beyond the minimum requirements are reported. For example, for SmartRate, an important policy issue concerns whether load impacts persist across multiple days and years. This report presents evidence based on the same group of customers who participated in 2008 and 2009 showing that average impacts are comparable across the two years in which the rate has been available.

Following the objectives section is a discussion of the analysis methodology used to produce the impacts. Regression analysis is used in all cases, and the model specifications are delineated. Graphs showing how the models perform under various conditions are presented to demonstrate the validity of the impact estimates. The final subsection in each chapter presents the load impact results.

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3. RESIDENTIAL SMARTRATE EX POST LOAD IMPACT ANALYSIS

PG&E's SmartRate tariff is the largest residential dynamic pricing program in the country. While there have been numerous pilot programs that have confirmed that residential customers can and do respond to dynamic prices, to date, few utilities have implemented a dynamic rate for residential consumers. PG&E's 2008 load impact evaluation has received nationwide interest in that it addressed a number of important pricing policy issues, including:

- Load impacts on the third day of multiple-event day periods are actually higher than on prior days, which contradicted assumptions made by many who thought that customer response would degrade significantly across multiple days;
- Low income (CARE) customers participate at a high rate and provide statistically significant load reductions, albeit lower reductions than the average non-CARE customer;
- The average impact across nine event days for non-CARE customers was roughly 23 percent, without any enabling technology, which contradicts the assumptions made by many policymakers that consumers will not provide significant reductions without automating technology.

This year's load impact evaluation supports those initial findings and provides a wide variety of highly valuable, additional evidence that dynamic pricing is a viable and reliable demand response resource. The 2009 analysis includes:

- An assessment of how impacts vary across a wide spectrum of climate zones and local capacity areas;[16]
- An assessment of load impacts across 15 event days, most of which involve cooler temperatures than those underlying the 2008 load impact estimates;[17]
- An assessment of the incremental impact of air conditioning load control on Smart Days, based on customers who are enrolled in both SmartRate and SmartAC;
- An assessment of the persistence of load impacts across multiple years for customers who were enrolled in SmartRate in both 2008 and 2009.

In keeping with the requirements for ex post load impact evaluations, results are presented for each hour of each event day for the average customer and for all customers enrolled at the time. The distribution across customers of the average impact across all event hours and event days is also provided (e.g., What percent of customers produce average impacts that exceed 10 percent?). Average impacts are also produced for customers who were and were not notified, as some customers either chose to participate without notification or did not provide accurate contact information.

[16] SmartRate enrollment in 2008 was constrained to the Kern County region where SmartMeters were initially installed, and therefore only represented a single climate region and LCA.
[17] Seven of the nine event days in 2008 had maximum temperatures exceeding 100°F.

3.1. ANALYSIS APPROACH

The 2009 load impacts for the SmartRate tariff were estimated through individual customer time-series regressions. Individual customer regressions were used for several reasons. Most importantly, PG&E does not typically collect data on a key explanatory variable – the size and type of air conditioning at each household. Given the climatic diversity of PG&E's service territory – where temperatures of 60°F and 105°F can experienced in the same day by customers 100 miles apart – both AC ownership and the amount of customer weather related energy demand vary substantially across the territory.

By employing individual customer regressions, the presence and use of air conditioning is captured through temperature variables and their interaction with hourly binary variables. In other words, the presence of air conditioning or lack thereof is a fixed effect that interacts with weather. By allowing individual customer coefficients to vary, the results are more accurate at the customer level – an important feature when results are desired for various customer segments in addition to the average for all participants. In addition, individual customer regressions can be employed to describe accurately the distribution of customer load reductions as well as the distribution of percent load reductions.

The main regression alternatives, panel regressions and segmented aggregate time series, were not used due to the unique features of the data and the evolving customer mix and enrollment rates over time. Unlike individual customer regressions, panel regressions can make use of both control groups and pre-enrollment data and can provide very robust average customer impact estimates by controlling for certain omitted or unobservable variables.[18] While panel regression can increase the accuracy of impact estimates for the average customer, it cannot be employed to describe meaningfully the distribution of impacts among the participant population. Importantly, the lack of data on the type and size of air conditioners at the customer level precluded the use of panel regression. Because air conditioning is a key driver of electricity demand that interacts with weather and has previously been show to be related to load impacts, its omission in a panel regression without a randomly assigned control group would likely lead to inaccurate results. The other alternative, running time series on customer load aggregated by segment, could not adequately control for the evolving customer mix or provide insights into the distribution of impacts among the participant population. Except for the lower amount of effort required, segmented time series regressions did not yield methodological benefits that were not also captured through individual customer regressions.

The impact estimates presented in the next section are based on time-series regressions for individual customers. The analysis is based on a proportional random sample of approximately 2,500 customers drawn from the participant population of roughly 25,000 that were enrolled and

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[18] Panel regression can account for omitted variables that are unique to customers and relatively time invariant over the analysis time frame (fixed effects) such as household income. It can also account for omitted variables that are common across the participant population but unique to specific time periods (time effects). They cannot, however, account for omitted variables that vary both by participant and by time period or for household characteristics (e.g., central air conditioning) that interact with variables that vary over time, such as weather and occupancy.

experienced events by the end of the summer 2009.[19] The dependent variable in each regression is average hourly demand (kW). The explanatory variables can be grouped into three main categories:

- Variables that reflect the average load shape of customers, absent the need for cooling;
- Variables that explain deviations in hourly usage from the average load shape; and
- Variables that estimate the change in energy use during event days and the factors that influence the load reductions.

The explanatory variables include hourly binary variables to capture the inherent variation in usage across hours of the day, day-of-week binary variables to capture variation in usage between week days and weekends and across weekdays, weather variables to capture the influence of temperature on electricity use, and event-day and event-hour variables to estimate the impact of the higher SmartDay prices on energy use during each hour of the event period as well as hours leading up to and following the event period. The event variables are interacted with weather throughout the season in order to explain how the impacts vary as a result of changes in those conditions. The notification delivery success for each event was interacted with the event variables for customers without automated price response (over 95%). For some customers, notification delivery success can vary from event to event. This may occur because of changes in contact information without corresponding updates to PG&E, or because some customers do not have voicemail. By interacting notification delivery success with the event variables, the impacts for these non-notified customers are effectively constrained to equal zero. However, both basic logic and the empirical data presented later in this chapter indicate that participants cannot respond to an event if they are unaware of it.

The model specification was intentionally designed to capture a wide variation of household operating schedules as well as different hourly responses to weather and event conditions. The specification performed well for most customers, although for specific customers, some of the parameters may have been irrelevant.[20]

The regressions were estimated using generalized least squares (GLS) and Huber-White robust standard errors in order to ensure that the confidence bands around the impact variables were not overstated either due to auto-correlation or heteroskedasticity.[21] The following equation summarizes the model specification. Given the large number of regressions (e.g., 2,500), it was not feasible to customize regressions for each customer. Importantly, the model performed well in the aggregate, as shown below in Sections 3.1.1 and 3.1.2.

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[19] The exact number of participants and sample points vary by date as enrollment grew over time during the 2009 summer months.
[20] Irrelevant parameters can lead to wider standard errors, but do not bias the significant parameters. Given that the number of observations per regression generally exceeded 2,000, statistical power was not a major concern.
[21] The GLS method used relied on the Prais-Winsten technique – a form of iterated GLS.

$$
\begin{aligned}
kW_t = {} & a + \sum_{x=5}^{10} b_x \cdot month_x + \sum_{y=2}^{24} c_y \cdot hour_y + \sum_{y=2}^{24} d_y \cdot hour_y \cdot weekend + \sum_{y=2}^{24} e_y \cdot hour_y \cdot daylight_t \\
& + f \cdot cdh_t + g \cdot (cdh_t)^2 + h \cdot cdh_t \cdot \ln(nitecdh_u + 1) + i \cdot (cdh_t \cdot \ln(nitecdh_u + 1))^2 \\
& + \sum_{y=2}^{24} j_y \cdot cdh_t \cdot hour_y + \sum_{y=2}^{24} k_y \cdot (cdh_t \cdot hour_y)^2 \\
& + \sum_{y=2}^{24} l_y \cdot cdh_t \cdot hour_y \cdot daylight_t + \sum_{y=2}^{24} m_y \cdot (cdh_t \cdot hour_y \cdot daylight_t)^2 \\
& + \sum_{y=2}^{24} n_y \cdot eventday_t \cdot hour_y + \sum_{y=2}^{24} o_y \cdot eventday_t \cdot hour_y \cdot cdh_t + \sum_{y=2}^{24} p_y \cdot (eventday_t \cdot hour_y \cdot cdh_t)^2 \\
& + \varepsilon_t
\end{aligned}
$$

Table 3-1
SmartRate Regression Model Variables and Description

Variable	Description
a	a is an estimated constant
b - p	b-p are estimated parameters
month	Dummy variables for month of the summer, designed to pick up seasonal effects
hour	Dummy variables representing the hours of the day, designed to estimate the effect of occupancy schedule on weather insensitive energy consumption
$hour \cdot weekend$	Dummy variables representing the weekend hours, designed to estimate differences in energy consumption due to weekend occupancy schedule
$hour \cdot daylight$	Variables that identify the fraction of the hour with daylight. It is designed to estimate the effect of daylight on energy consumption and is incorporated due to changes in daylight hours over the year
cdh	Cooling degree hours (defined as the maximum of 0 or temperature – 65 F°), which is correlated with cooling load
$cdh \cdot \ln(nitecdh + 1)$	The interaction of cooling degree hours with overnight heat intensity, as measure by the natural log of total daily cooling degree hours from 12pm- 6am. One is added to the total because the log of zero is unidentified
$cdh \cdot hour \cdot daylight$	The interaction between cooling degree hours, time of day, and daylight. It is designed to estimate the effect of daylight on occupancy and, by connection, air conditioner use
$eventday \cdot hour$	Dummy variables for each of hour of the event day. They are incorporated to estimate non-weather sensitive load shifting and reductions due the higher event period prices. All hours of the day are included because notice of events is provided on day-ahead basis
$eventday \cdot hour \cdot cdh$	The interaction between event day hours and weather, as measured by cooling degree hours. The variables are designed to estimate weather sensitive load shifting and reductions due the higher event period prices. All hours of the day are included because notice of events is provided on day-ahead basis and some participants alter AC usage throughout the day (make sure they shut off AC when they leave for work) and others provide load response solely during the event period.
t, u, x, y	Indicators to track the count or hourly time periods, days, month, and hour of day respectively
ε	The error term

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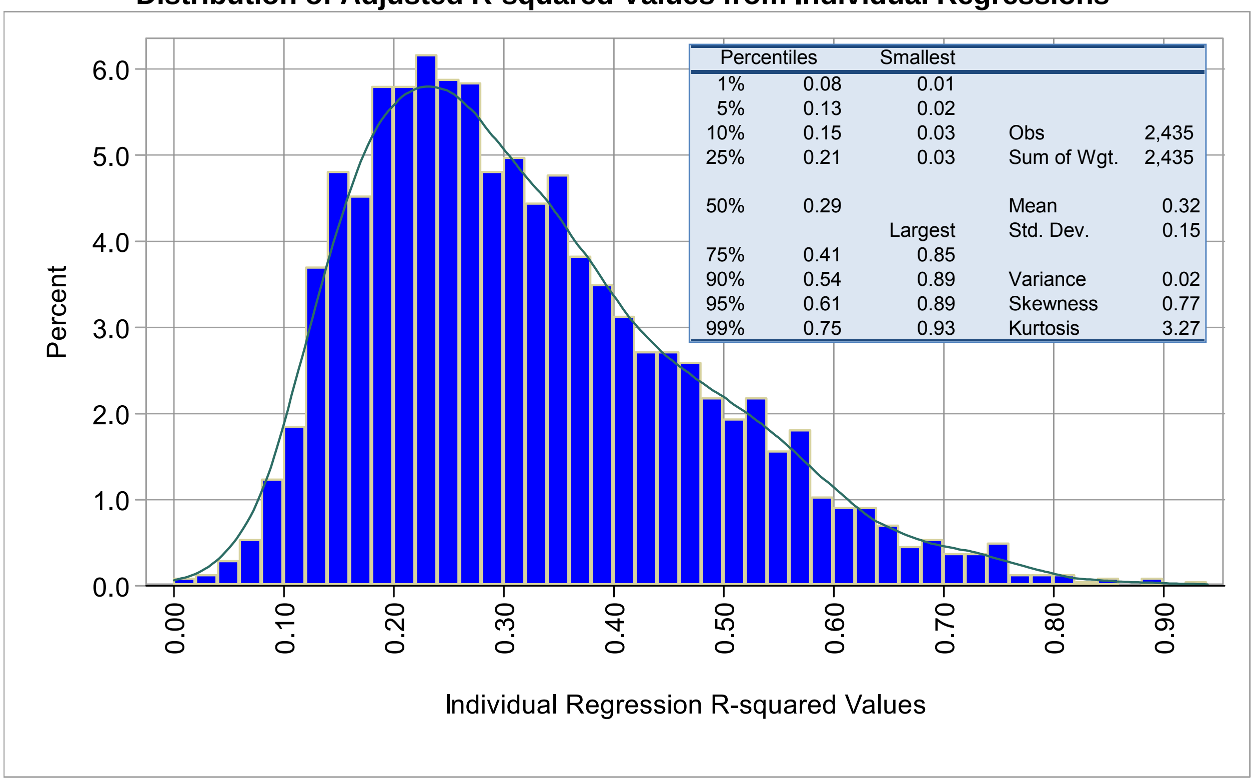
3.1.1. *Goodness of Fit Measures*

Although the regressions were estimated at the individual customer level, from a policy standpoint, the focus is less on how the regressions perform for individual customers than it is on how the regressions perform for the average participant and for specific customer segments. Overall, individual customers exhibited more variation and less consistent energy use patterns than the aggregate participant population. Likewise, the regressions explained better the variation in electricity consumption and load impacts for the average customer (or average customer within a specific segment) than for individual customers. In other words, it is more difficult to explain fully how a specific CARE customer behaves on an hourly basis than it is to explain how the average CARE customer behaves on an hourly basis. Because of this, we present measures of the explained variation, as described by the R-squared goodness-of-fit statistic, for the individual regressions and for specific segments as well as for the average customer overall.

Figure 3-1 shows the distribution of R-squared values from the individual residential customer regressions. As the peak period use, annual consumption, and ratio of summer to non-summer usage increase, the goodness-of-fit from the regressions generally improves.

Figure 3-1
Distribution of Adjusted R-squared Values from Individual Regressions



While the individual customer regressions do a reasonably good job of explaining the variation in electricity use, in aggregate, nearly all of the variation in energy use across hours is explained by the model specification. When the predicted and actual values are aggregated across the individual results, the model explains 98.2% of the variation in energy use. Put another way, less than 2% of the variation in average customer energy use over time is explained by variables that are not included in the model. In order to estimate the average customer R-squared values, the regression-predicted and actual electricity usage values were averaged across all customers for each date and hour. This process produced regression predicted and actual values for the average customer, which enabled the calculation of errors for the average customer and the calculation of the R-squared value. The same process was performed to estimate the amount of explained variation for the average customer in specific segments. [22]

Table 3-2 summarizes the amount of variation explained by the regression model for the average customer for specific segments. Overall, depending on the specific group assessed, between 93% and 99% of the average customer variation is explained through the individual regressions.

Table 3-2
Residential SmartRate Adjusted R-squared Values for the Average Customer by Segment

Local Capacity Area	R^2
GREATER BAY AREA	93.2%
GREATER FRESNO	97.7%
KERN	98.0%
SIERRA	94.8%
STOCKTON	95.3%
OTHER	96.4%

Daily maximum temperature (F)	R^2
90 or less	96.5%
90-95 (F)	97.4%
95-100 (F)	98.5%
100-105 (F)	99.0%
105 or higher	98.9%

Load Response Rank (Quintile)	R^2
Top 20%	97.3%
20th to 40th percentiles	97.8%
40th to 60th percentiles	97.9%
60th to 80th percentiles	97.9%
Bottom 20%	97.9%

Consumption rank (Quintile)	R^2
Top 20%	97.9%
20th to 40th percentiles	98.1%
40th to 60th percentiles	98.1%
60th to 80th percentiles	97.8%
Bottom 20%	96.8%

AC likelihood	R^2
Less than 25%	93.3%
25-50%	97.9%
50-75%	98.3%
75% or more	97.9%

CARE status	R^2
Standard tariff	97.8%
Low income tariff (CARE)	98.3%

The regressions explain almost all the variation for average customers across geographical locations, heat intensity, load responsiveness, overall energy consumption, low income tariff

[22] The R-squared values for the average participant and for the average customer by segment were estimated using the following formula:

$$R^2 = 1 - \frac{\sum_t (\hat{y}_t - y_t)^2}{\sum_t (\hat{y}_t - \bar{y})^2}$$

Where y_t is the actual energy use at time t and $\hat{y}_t$ is the regression predicted energy use at time t and $\bar{y}$ is the actual mean energy use across all time periods. Technically, the R-squared values need to be adjusted based on the number of parameters and observations from each regression. Given that the number of observations per regression was typically well over three thousand, the effects of the adjustment were anticipated to be minimal.

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status, and AC likelihood. Importantly, the regressions predict behavior well for high temperature days in which events are most likely to occur. They also predict well for customers that are highly responsive and those that are not, indicating that the high and low responder are not due to estimation error. However, R-squared values are a measure of precision, and high values do not automatically indicate lack of bias (i.e., accuracy).

3.1.2. Model Accuracy and Validity Assessment

The most important feature of load impact analysis is the ability to predict accurately customer load and load reductions under the extreme conditions under which demand response resources are most likely to be called. The accuracy of load impact estimates depend more on the accuracy of the regression coefficients representing the load impacts than on how well the regression predicts customer load. For SmartRate, we are not only confident that the load impact parameters are accurate, but the regression predicted values of energy consumption closely mirror and are often nearly indistinguishable from actual energy consumption, further validating the accuracy of the load impact estimates. Given the ramp up of the program over time, it is possible to assess the accuracy of the models under event and non-event conditions (within customer comparisons) and also to compare predicted values to those of future participants that had not yet enrolled for a specific events – referred to as a non-equivalent control group in technical terms.

Figure 3-2 shows the compares actual and regression predicted average hourly energy use for participants during event and non-events days with daily maximum temperature over 95°F. The figure highlights the ability to accurately predict hourly energy demand for similar event and non-event days. On non-event days, the actual and regression predicted values are nearly indistinguishable. This is also true for event days. Importantly, the regression predicted reference load, or counterfactual, also mirrors the loads for non-event days with similar daily maximum temperatures.

Figure 3-3 is similar, with one key difference – it compares event day hourly average demand for enrollees in late summer, a natural control group, to participants who enrolled in 2008 or in the early summer. Both groups eventually self-select into the program, but one group experiences the event while the other does not. The regression predicted estimates closely align with actual hourly average demand for both sets of customers. The differences in the load levels reflect differences in the group. Most late summer 2009 enrollees were located in generally cooler areas with lower central air conditioner saturation.

Figure 3-2
Comparison of Average Participant Actual and Predicted Hourly Demand For Event and Non-Event Days with Daily Maximum Temperatures Above 95°F

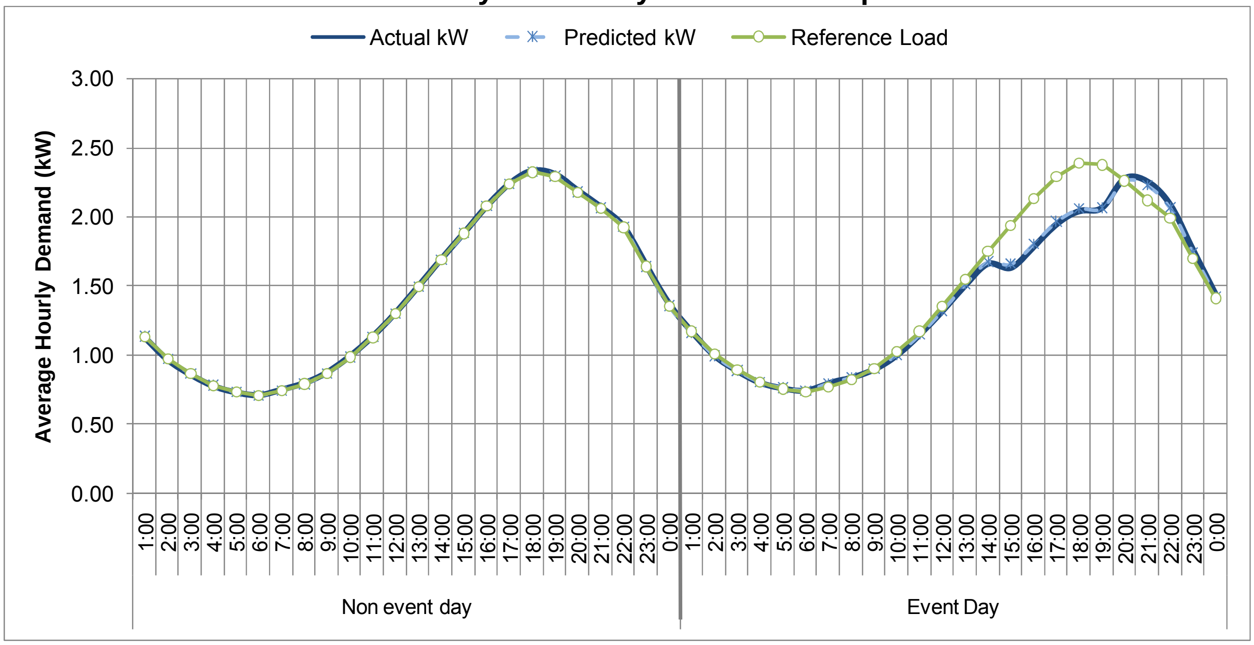


Figure 3-3
Actual and Predicted Hourly Demand for Participants and Natural Control Group Event Days with Daily Maximum Temperatures Above 95°F

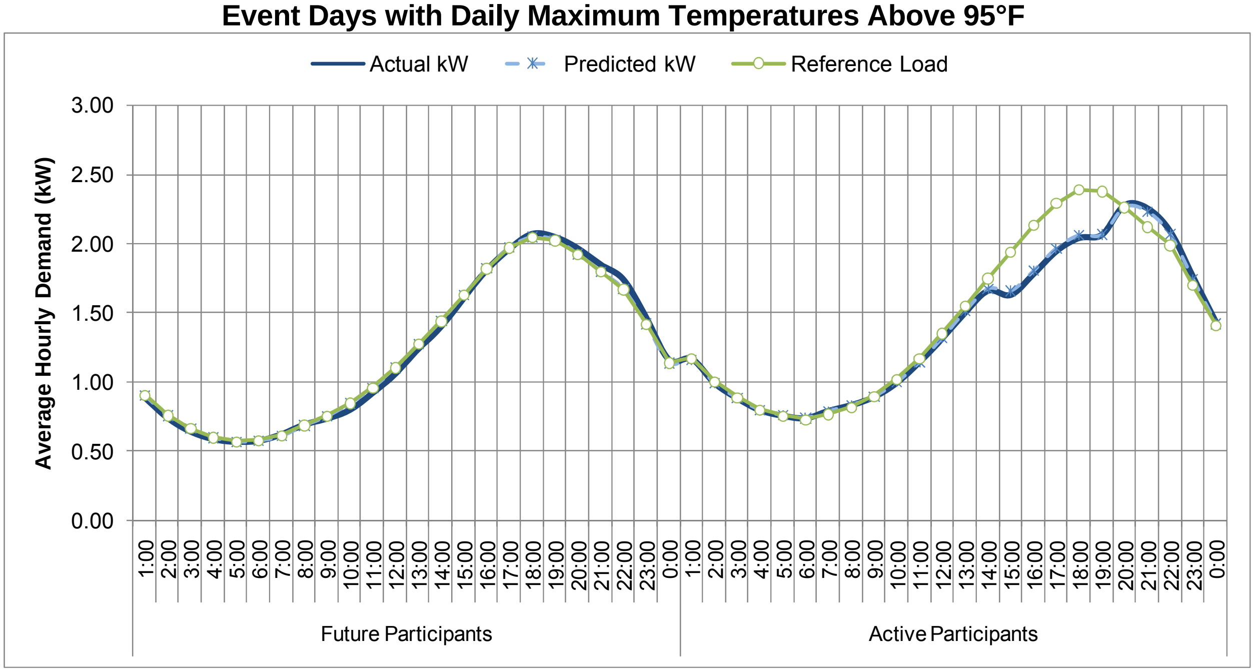
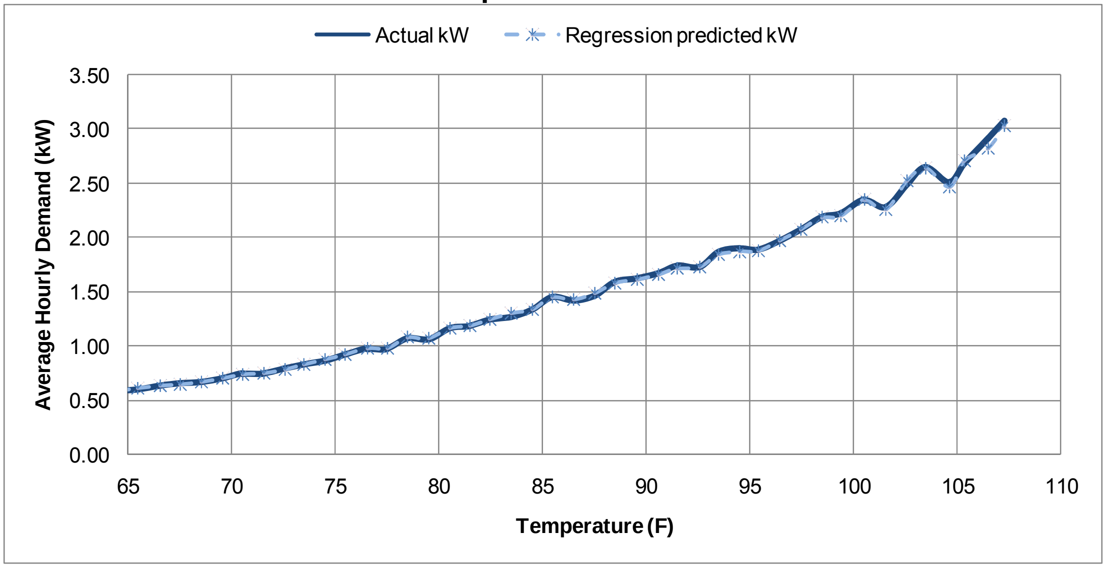


Figure 3-4 compares the actual and predicted values by temperature, based on average customer temperature variation for summer 2009, and illustrates the model's ability to accurately predict customer behavior under event conditions for a wide range of temperatures.

Figure 3-4
Actual and Predicted Average Participant Hourly Demand by Temperature
All Participants Summer 2009



Similar comparisons of actual and predicted values were conducted by month, day of week, individual event days, and various other iterations – all of which indicated that the results were not only unbiased for the average day and average customer, but also unbiased across multiple customer segments and temporal characteristics.

3.2. LOAD IMPACT RESULTS

The remainder of this section discusses the ex post load impact estimates for the SmartRate tariff. It begins with a discussion of results for the average participant, which includes roughly 910 customers who were dually enrolled in SmartRate and SmartAC and had their air conditioning units cycled on Smart Days. The incremental effect of cycling is discussed separately. Load impacts for a wide variety of customer groups that differ with respect to underlying tariff (CARE, non-CARE), climate region, air conditioning ownership, LCA, whether or not they were notified and other important factors are also presented.

3.2.1. Average SmartRate Participant

Figure 3-5 shows the hourly load impacts for the average SmartRate customer across the fifteen event days and contains the numerical values underlying the figure. The average impact across the five hour event window is 0.31 kW, or 15.0%. The percent load reduction is highest in the first two event hours, between 2 and 4 pm, and lowest in the last hour, from 6 to 7 pm. Load impacts vary from a low of 0.27 kW in the first hour to a high of 0.32 kW in the second and fourth event hours. The reference load increases from a low of 1.78 kW between 2 and 3 pm, when the temperature is 95.5°F, to a high of 2.23 kW between 5 and 6 pm, when the temperature

Figure 3-5
Average Load Impact per Hour for All 2009 Event Days
(Average SmartRate Participant)

TABLE 1: Menu options

Type of Results	Average Customer
Event	Average event
Participant Category	ALL Active

TABLE 2: Event Day Information

Event Date	Average event
Event Notification	Day Ahead
Event Start	14:00
Event End	18:00
ACCOUNTS FOR EVENT	15,882
TOTAL ENROLLED ACCOUNTS	15,882
Avg. Load Reduction for Event Window	0.31
% Load Reduction for Event Window	14.9%

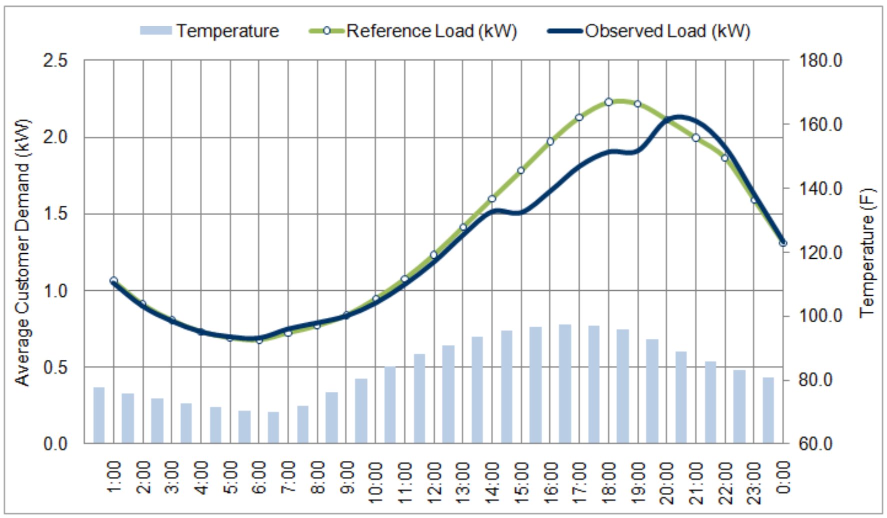


TABLE 3: Ex-Ante Load Impact Results

Hour Ending	Reference Load (kW)	Observed Load (kW)	Load Impact (kW)	%Load Reduction	Weighted Temp (F)	Uncertainty Adjusted Impact - Percentiles 10th	30th	50th	70th	90th
1:00	1.06	1.05	0.01	1.4%	77.6	0.01	0.01	0.01	0.02	0.02
2:00	0.91	0.90	0.01	1.5%	75.9	0.01	0.01	0.01	0.02	0.02
3:00	0.81	0.80	0.01	1.0%	74.3	0.00	0.01	0.01	0.01	0.01
4:00	0.73	0.73	0.00	0.4%	72.8	0.00	0.00	0.00	0.01	0.01
5:00	0.69	0.70	0.00	-0.6%	71.4	-0.01	-0.01	0.00	0.00	0.00
6:00	0.68	0.69	-0.01	-1.3%	70.3	-0.01	-0.01	-0.01	-0.01	0.00
7:00	0.73	0.75	-0.02	-3.3%	69.9	-0.03	-0.03	-0.02	-0.02	-0.02
8:00	0.77	0.79	-0.02	-2.2%	71.9	-0.02	-0.02	-0.02	-0.02	-0.01
9:00	0.84	0.83	0.01	0.8%	76.1	0.00	0.00	0.01	0.01	0.01
10:00	0.95	0.92	0.03	3.1%	80.4	0.02	0.03	0.03	0.03	0.03
11:00	1.08	1.04	0.04	3.5%	84.4	0.03	0.04	0.04	0.04	0.04
12:00	1.23	1.19	0.05	3.8%	88.0	0.04	0.05	0.05	0.05	0.05
13:00	1.42	1.36	0.05	3.7%	91.0	0.05	0.05	0.05	0.05	0.06
14:00	1.60	1.52	0.09	5.3%	93.5	0.08	0.08	0.09	0.09	0.09
15:00	1.78	1.51	0.27	15.3%	95.5	0.27	0.27	0.27	0.28	0.28
16:00	1.97	1.65	0.32	16.3%	96.7	0.32	0.32	0.32	0.32	0.33
17:00	2.13	1.81	0.32	14.9%	97.3	0.31	0.32	0.32	0.32	0.32
18:00	2.23	1.91	0.32	14.4%	97.1	0.32	0.32	0.32	0.32	0.33
19:00	2.22	1.91	0.30	13.7%	95.7	0.30	0.30	0.30	0.31	0.31
20:00	2.12	2.12	0.00	-0.1%	92.7	-0.01	0.00	0.00	0.00	0.00
21:00	2.00	2.11	-0.11	-5.6%	88.9	-0.12	-0.11	-0.11	-0.11	-0.11
22:00	1.86	1.93	-0.07	-3.8%	85.9	-0.08	-0.07	-0.07	-0.07	-0.07
23:00	1.59	1.62	-0.03	-2.2%	83.2	-0.04	-0.04	-0.03	-0.03	-0.03
0:00	1.31	1.32	-0.01	-0.6%	80.8	-0.01	-0.01	-0.01	-0.01	0.00
	Reference Energy Use (kWh)	Observed Energy Use (kWh)	Change in Energy Use (kWh)	% Daily Load Reduction	Cooling Degree Hours (Base 75)	Uncertainty Adjusted Impact - Percentiles 10th	30th	50th	70th	90th
Daily	32.71	31.16	1.56	4.8%	130.9					

has increased to 97.1°F. There is a small snapback effect that peaks at roughly 5 percent, or 0.11 kW, in the second post-event hour, from 8 to 9 pm.

Table 3-3 summarizes the average load reduction across the five-hour event window provided by residential SmartRate customers on each event day during the summer of 2009. As seen, the average percent reduction ranged from a low of 12.2% on July 21st to a high of 17.2% on September 10th. An average reduction of 15% was obtained across the 15 event days. The average load reduction per participant ranged from a low of 0.26 kW to a high of 0.44 kW. The average reduction across all 15 days was 0.31 kW.

As seen in the table, program enrollment grew steadily throughout the summer period, with 10,892 customers on the SmartRate tariff on the first event day and 21,200 on the last event day.[23] The combination of enrollment and average load impacts created aggregate reductions in peak demand on Smart Days ranging from a low of 3.1 MW on July 13th to a high of 6.9 MW by the last event day of the summer. Average, aggregate load reductions for the summer equaled 5.0MW.

Table 3-3
Average Hourly Load Reduction for SmartRate Event Period by Event Day
(All Enrolled Participants)

Date	Day of Week	Enrolled participants	Avg. Reference Load	Avg. Estimated Load with DR	Avg. Load Reduction	Percent Load Reduction	Aggregate Load Reduction	Daily Minimum Temperature	Daily Maximum Temperature
			(kW)	(kW)	(kW)	(%)	(MW)	(°F)	(°F)
29-Jun-09	M	10,892	2.70	2.26	0.44	16.2%	4.8	76.8	105.4
30-Jun-09	T	10,975	2.33	2.02	0.32	13.6%	3.5	77.2	100.7
13-Jul-09	M	11,449	1.93	1.66	0.27	13.9%	3.1	67.2	94.5
14-Jul-09	T	11,462	2.31	1.99	0.32	13.8%	3.6	70.4	99.7
16-Jul-09	Th	11,488	2.59	2.21	0.37	14.4%	4.3	74.4	102.8
21-Jul-09	T	11,558	2.31	2.03	0.28	12.2%	3.3	72.1	98.4
27-Jul-09	M	12,299	2.49	2.13	0.35	14.3%	4.4	73.6	101.8
10-Aug-09	M	16,741	2.12	1.79	0.33	15.6%	5.5	71.2	97.6
11-Aug-09	T	17,177	2.06	1.80	0.26	12.7%	4.5	70.8	95.5
18-Aug-09	T	19,182	1.85	1.59	0.26	14.1%	5.0	66	94.6
27-Aug-09	Th	20,779	1.82	1.52	0.29	16.1%	6.1	64.3	95.5
28-Aug-09	F	20,903	1.95	1.64	0.32	16.2%	6.6	68.1	96.9
2-Sep-09	W	20,966	1.97	1.67	0.30	15.3%	6.3	70.6	96.8
10-Sep-09	Th	21,163	1.79	1.48	0.31	17.2%	6.5	65.5	94.9
11-Sep-09	F	21,200	1.90	1.58	0.32	17.0%	6.9	68.8	94.8
Total	**N/A**	**15,882**	**2.08**	**1.77**	**0.31**	**15.0%**	**5.0**	**69.7**	**97.4**

Interpreting the pattern of load impacts across events is difficult because multiple factors vary across days, including temperature, the normal pattern of energy use (as reflected in day-of-week variables in the regression models) and, most importantly, enrollment. Not only does the level of enrollment vary across event days (which primarily affects the aggregate load reduction), but the

[23] As indicated in Section 2, enrollment continued to increase after the end of the season and equaled more than 25,000 customers by the end of the year.

characteristics of the underlying population also vary. For example, as the summer progressed, enrollment evolved from being dominated by the hotter climate zones of Bakersfield and Fresno, and the socio-demographic characteristics of those cities, to greater participation by households from the more moderate climate zones and different socio-demographic population found in the Bay Area. The percent of customers notified also increased from the beginning to the end of the season, while the average saturation of air conditioners declined. These changing factors help explain, for example, why the average load impact on June 30th, 0.32 kW, is the same as the average on September 11th, even though the maximum and minimum temperatures are much lower on September 11th than on June 30th.

3.2.2. The Influence of Event Notification

As discussed in Section 2, customers are asked at the time they sign up for the SmartRate tariff to indicate whether or not they want to be notified about events and, if so, to provide up to four different notification options (e.g., one or more email addresses, one or more telephone numbers). Table 3-4 shows the percent of customers who were successfully notified through one or more options by event. The column labeled "none" in the table includes both customers who did not provide notification information as well as those who provided information that subsequently became invalid. As seen, on average, 19.2% of customers were not successfully notified. Almost 42% of customers were notified once, 28% were notified twice and about 11% were notified three or four times on most events.

Table 3-4
Percent of SmartRate Customers Notified by Event

Date	Number of successful notifications				
	None	1	2	3	4
29-Jun-09	19.9%	43.6%	26.7%	8.2%	1.6%
30-Jun-09	21.5%	43.0%	26.3%	7.8%	1.5%
13-Jul-09	22.7%	41.9%	25.9%	8.0%	1.5%
14-Jul-09	23.4%	41.2%	26.0%	8.1%	1.4%
16-Jul-09	22.9%	41.6%	25.8%	8.2%	1.5%
21-Jul-09	23.3%	41.7%	25.7%	7.8%	1.5%
27-Jul-09	22.3%	41.7%	26.2%	8.0%	1.8%
10-Aug-09	18.7%	41.1%	27.9%	9.5%	2.8%
11-Aug-09	18.4%	41.2%	28.0%	9.4%	2.9%
18-Aug-09	17.2%	41.7%	28.6%	9.6%	2.9%
27-Aug-09	16.9%	41.7%	28.9%	9.5%	3.0%
28-Aug-09	17.3%	41.3%	28.7%	9.7%	2.9%
2-Sep-09	17.5%	41.2%	28.7%	9.7%	2.8%
10-Sep-09	17.5%	41.4%	28.4%	9.7%	3.0%
11-Sep-09	17.4%	41.4%	28.5%	9.7%	2.9%
Total	**19.2%**	**41.6%**	**27.7%**	**9.1%**	**2.4%**

Table 3-4 shows the load impacts for successfully notified customers and compares them with the average load impacts for all customers, including those that were not notified. As seen, the

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average load reduction across all 15 events increases from 15% to more than 19% when customers who were not notified are excluded, and the average load impact rose from 0.31 kW to 0.41 kW. On September 10th and 11th, the load reduction for notified customers exceeded 21.4 percent. On the highest impact day, June 29th, the average load reduction for notified customers exceeded 0.59 kW.

Table 3-5
Comparison of Load Impacts Between Notified and Un-notified SmartRate Customers

Date	Enrolled participants	Participants for whom notification was attempted	Number notified about event	% Notified	Notified Customers		All Customers	
					Avg. Impact (kW)	% Load reduction	Avg. Impact (kW)	% Load reduction
29-Jun-09	10,892	10,168	8,726	80.11%	0.59	20.8%	0.44	16.2%
30-Jun-09	10,975	10,200	8,620	78.54%	0.43	17.7%	0.32	13.6%
13-Jul-09	11,449	10,439	8,845	77.26%	0.38	18.8%	0.27	13.9%
14-Jul-09	11,462	10,461	8,780	76.60%	0.45	18.7%	0.32	13.8%
16-Jul-09	11,488	10,478	8,853	77.06%	0.53	19.5%	0.37	14.4%
21-Jul-09	11,558	10,522	8,870	76.74%	0.40	16.3%	0.28	12.2%
27-Jul-09	12,299	11,249	9,556	77.70%	0.50	19.0%	0.35	14.3%
10-Aug-09	16,741	15,650	13,608	81.29%	0.43	19.7%	0.33	15.6%
11-Aug-09	17,177	16,079	14,010	81.56%	0.34	16.3%	0.26	12.7%
18-Aug-09	19,182	18,034	15,874	82.75%	0.33	17.7%	0.26	14.1%
27-Aug-09	20,779	19,578	17,264	83.08%	0.37	20.0%	0.29	16.1%
28-Aug-09	20,903	19,689	17,277	82.65%	0.40	20.1%	0.32	16.2%
2-Sep-09	20,966	19,810	17,290	82.47%	0.39	19.1%	0.30	15.3%
10-Sep-09	21,163	19,978	17,449	82.45%	0.39	21.4%	0.31	17.2%
11-Sep-09	21,200	20,012	17,501	82.55%	0.41	21.2%	0.32	17.0%
Total	**15,882**	**14,823**	**12,835**	**80.81%**	**0.41**	**19.2%**	**0.31**	**15.0%**

Table 3-6 shows the average impact and percent load reduction by number of successful notifications for each event. It should not be surprising to see that average load impacts increase when customers who are not notified are dropped from the sample. Perhaps more surprising is the fact that load impacts increase significantly across customers who are successfully notified more than once. Both the average and percentage load reductions increase more than threefold between customers who are successfully notified through one option to those that receive four successful notifications. The percent and average load reduction for customers who receive only a single notification, respectively, are 12.8% and 0.26 kW. The same values for customers who receive four successful notifications are 43.0% and 0.94 kW. The percent and average reductions for customers receiving two notifications equal 21.8% and 0.48 kW, and customers successfully notified three times reduced load on average by 31.7% and 0.74 kW.

It is difficult to determine from the existing data whether the significant increase in load reductions with the number of notifications is due to self selection, greater event awareness or both. While it seems reasonable to assume that customers who are notified through multiple channels are more likely to be made aware of an upcoming event than are customers who are only notified through a

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single channel, it may also be true that those who provide multiple notification options are more interested in avoiding the high-priced periods on Smart Days. Which of these two explanations is the key driver of increased responsiveness could be determined if PG&E were to contact customers who only provided a single notification option, solicit additional notification information and then observe whether these customers provided larger responses in future events. An alternative approach would be to conduct post-event surveys (shortly after events, so recall is not a problem) among samples of customers who received 1, 2, 3 and 4 successful notifications to determine if event awareness increases with the number of successful notifications. Given the very significant differences in average impacts between customers who are and are not notified and who are notified more frequently, improvements in notification information could be fertile ground for increasing average load impacts.

Table 3-6
Average SmartRate Load Impacts and Percent Load Reductions by Number of Successful Notifications

Date	One		Two		Three		Four	
	Avg. Impact	% Impact	Avg. Impact	% Impact	Avg. Impact	% Impact	Avg. Impact	% Impact
29-Jun-09	0.38	14.7%	0.71	23.1%	1.21	36.9%	1.49	43.7%
30-Jun-09	0.27	11.8%	0.54	21.1%	0.80	28.1%	1.33	53.2%
13-Jul-09	0.23	12.3%	0.48	22.4%	0.75	32.4%	0.92	37.3%
14-Jul-09	0.28	12.5%	0.59	23.2%	0.76	27.3%	1.52	40.8%
16-Jul-09	0.34	13.5%	0.62	22.1%	0.99	32.6%	1.55	41.8%
21-Jul-09	0.25	10.8%	0.54	21.0%	0.58	22.2%	0.96	39.5%
27-Jul-09	0.29	11.3%	0.67	24.7%	0.86	31.5%	1.13	42.2%
10-Aug-09	0.26	12.6%	0.51	21.9%	0.79	32.0%	1.07	47.5%
11-Aug-09	0.19	9.6%	0.39	18.0%	0.70	30.4%	0.68	36.6%
18-Aug-09	0.20	11.0%	0.40	20.5%	0.62	31.4%	0.64	35.7%
27-Aug-09	0.23	13.5%	0.42	21.6%	0.68	33.5%	0.75	41.0%
28-Aug-09	0.26	13.9%	0.43	21.0%	0.71	33.8%	0.94	42.7%
2-Sep-09	0.24	12.2%	0.46	22.1%	0.66	31.1%	0.89	41.7%
10-Sep-09	0.28	15.9%	0.40	21.6%	0.65	34.1%	0.98	49.6%
11-Sep-09	0.27	14.4%	0.45	22.9%	0.73	34.0%	1.00	48.2%
Total	**0.26**	**12.8%**	**0.48**	**21.8%**	**0.74**	**31.7%**	**0.94**	**43.0%**

3.2.3. CARE Customer Responsiveness

As previously discussed, CARE stands for California Alternate Rates for Energy and is a program through which enrolled, low income consumers receive lower rates than non-CARE customers. Qualification for CARE is based on self-reported, household income and varies with the number of persons per household. For consumers whose energy use falls in Tier 1 of California's five-tier, increasing block tariff, the price per kWh is about 40% more on the E-1 tariff than on the E-1 CARE tariff. In Tier 5, E-1 customers pay almost five times more for an additional kWh than do CARE customers.

An important finding from PG&E's 2008 load impact evaluation report was that CARE customers participated in the SmartRate program at a much higher rate than did non-CARE customers, but the average percent reduction of CARE customers was roughly half that of non-CARE customers. Both of these facts also apply to the 2009 participant population. Indeed, the difference in responsiveness between CARE and non-CARE customers is even greater in the 2009 program year.

The percent of CARE and non-CARE customers who are enrolled in each CAISO local capacity area and the percent of the PG&E population that are CARE and non-CARE customers in each region was shown previously in Table 2-2. Overall, 23.5% of the PG&E population was comprised of CARE customers in 2009 but more than half of SmartRate participants were CARE customers. The participant differential relative to the population share is greatest in Fresno, where almost two thirds of all SmartRate customers are CARE customers whereas only 40% of the Fresno LCA population is on the CARE tariff. It is interesting that the high sign up rate by CARE customers has continued in 2009 in spite of the fact that, unlike in 2008, most customers were not offered a sign up incentive. One theory concerning why so many CARE customers signed up in 2008 was the offer of a $50 Visa gift card during that initial promotional effort, which could be more attractive and useful to low-income CARE customers than to non-CARE customers. In 2009, most promotional mailings did not offer any incentive. Clearly, low income CARE customers in PG&E's service territory are significantly more likely to sign up for SmartRate regardless of the promotional strategy used.

Table 3-7 shows the average load reduction (kW) and percent load reduction for CARE and non-CARE customers for each planning region. The average load reduction for CARE customers is roughly one third of the magnitude of non-CARE customers. Across the 15 event days in 2009, CARE customers reduced their peak period load on average by 0.15 kW, or 7.5%. Non-CARE customers, on the other hand, reduced load on average by 0.49 kW, or 22.7%.[24]

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[24] See pages 37 and 38 of the 2008 ex post load impact report (*2008 Ex Post Load Impact Evaluation for Pacific Gas and Electric Company's SmartRate^{TM} Tariff,* Final Report, December 30, 2008) for some hypotheses concerning why response rates may be lower for CARE customers.

Table 3-7
Load Reductions for CARE and Non-CARE SmartRate Participants by Local Capacity Area

CARE Status	Local Capacity Area	Reference Load	Impact	Percent Load Reduction	Notification Rate	Estimated Share with central AC	Avg. Event Temp
		(kW)	(kW)	(%)	(%)	(%)	(°F)
Non CARE Participants	Greater Bay Area	0.87	0.20	23.2%	90.2%	19.6%	82.03
	Greater Fresno	2.36	0.60	25.6%	83.7%	74.5%	99.59
	Kern	2.72	0.55	20.3%	79.9%	73.8%	99.22
	Sierra	2.50	0.68	27.3%	84.9%	78.8%	95.38
	Stockton	2.16	0.48	22.2%	77.8%	75.2%	94.49
	Other or Unclassified	1.77	0.47	26.4%	85.4%	68.8%	96.40
	Total	**2.15**	**0.49**	**22.7%**	**83.1%**	**64.0%**	**95.03**
CARE Participants	Greater Bay Area	0.85	0.10	11.9%	81.6%	15.3%	84.12
	Greater Fresno	2.21	0.11	4.8%	64.2%	52.1%	99.55
	Kern	2.33	0.20	8.5%	70.6%	59.4%	99.25
	Sierra	1.55	0.16	10.0%	78.4%	63.8%	95.02
	Stockton	1.96	0.11	5.8%	68.2%	65.1%	94.51
	Other or Unclassified	1.57	0.10	6.4%	66.9%	44.7%	97.84
	Total	**2.05**	**0.15**	**7.5%**	**69.6%**	**53.5%**	**97.65**

For each region, the estimated load without DR, or reference load, is almost equivalent between CARE and non-CARE. However, the load reductions for CARE customers are consistently lower across all regions. The difference in load response does not necessarily imply that CARE customers are inherently less price responsive. Two factors strongly related to load impacts – notification rates, and central air conditioning ownership – differ significantly between CARE and non-CARE customers and may explain much of the difference in average response rates between the two customer segments.

On average, 69.6% of CARE customers were directly notified of events while 83.1% of non-CARE customers received event notification. As discussed in the previous subsection, event notification is a strong driver of load response and could explain a significant portion of the difference in load impacts.

The other factor is central air conditioning ownership. FSC estimated the likelihood of central air conditioning ownership for residential accounts as input to the ex ante SmartAC evaluation (see Volume 2, Section 3 for documentation). Based on this analysis, the estimated share of SmartRate customers with central air conditioning is 64% for non-CARE customers and roughly 53% for CARE customers. Air conditioning ownership is a strong driver of demand response for customers on dynamic tariffs.[25]

[25] See for example, Stephen S. George and Ahmad Faruqui. *Impact Evaluation of California's Statewide Pricing Pilot.* Final Report, March 16, 2005.

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3.2.4. Load Impacts by Local Capacity Area

PG&E's service territory is climatically diverse and the variation in temperature and cooling requirements is quite significant, especially during the summer, when the coastal fog is often quite thick on the same days that the inland valleys are hottest. PG&E is comprised of eight CAISO local capacity areas that differ significantly in terms of climate and population characteristics. As previously discussed, the Kern and Fresno LCAs are the hottest which, all other things equal, would produce larger load impacts compared with milder climate regions. However, as discussed in Section 3.2.3, enrollment in some of these warmer LCAs is dominated by CARE customers, who respond significantly less than non-CARE customers. As such, the average load reduction across LCAs is influenced by at least two countervailing factors.

Table 3-8 shows the average hourly load reduction for each LCA in PG&E's service territory. The Sierra region has the largest absolute and percentage reduction among the six regions, with an absolute load reduction nearly two times larger than the program average and more than three times larger than the reduction in the Greater Bay Area LCA. These two regions have the lowest share of participants who are CARE customers, but the Sierra LCA is much warmer than the Bay Area and has a reference load that is more than 2.5 times larger than in the Bay Area. It should be noted that most customers in the Bay Area that were enrolled in SmartRate in 2009 were from the very moderate climate zones in the South Bay, rather than the much warmer East Bay climate region. This is due to the fact that SmartMeters were deployed in the South Bay before the East Bay. As SmartMeter deployment is completed throughout the Bay Area, and SmartMeter marketing focuses on the warmer Bay Area climate zones, we would expect the average load reduction in the Bay Area LCA should increase.

Table 3-8
SmartRate Average Hourly Load Reduction for Event Period by Local Capacity Area
(All Enrolled Participants)

Local Capacity Area	Avg. Ref. Load (kW)	Estimated Load w/o DR (kW)	Load Reduction (kW)	% Load Reduction	Avg. Temp. (°F)
Greater Bay Area	0.86	0.69	0.18	20.3%	82.6
Greater Fresno	2.26	1.95	0.30	13.5%	99.6
Kern	2.47	2.13	0.34	13.8%	99.2
Sierra	2.26	1.71	0.56	24.6%	95.3
Stockton	2.08	1.76	0.32	15.5%	94.5
Other or Unclassified	1.64	1.39	0.25	15.5%	97.3
Total	2.08	1.77	0.31	15.0%	96.4

3.2.5. Load Impacts by Central Air Conditioning Saturation and Temperature

Load impacts for SmartRate participants vary substantially by central air conditioning ownership and temperature. Higher load reductions coincide with greater saturation of central air conditioning and with hotter temperatures. Central air conditioning is a substantial household load that can be readily adjusted by participants. The same behavior by participants - e.g., setting their thermostat temperature up by four or six degrees – can produce substantially larger load reductions for hotter days. Figure 3-6 shows the load impacts associated with SmartRate households with a high likelihood of owning central air conditioning (likelihood between 75 and

100%), on days when maximum temperatures are high. As seen, both loads and load impacts increase significantly as temperature increases.

Figure 3-6
Load Impacts for SmartRate Customers with a High Likelihood of Owning Central Air Conditioning by Maximum Daily Temperature Bin

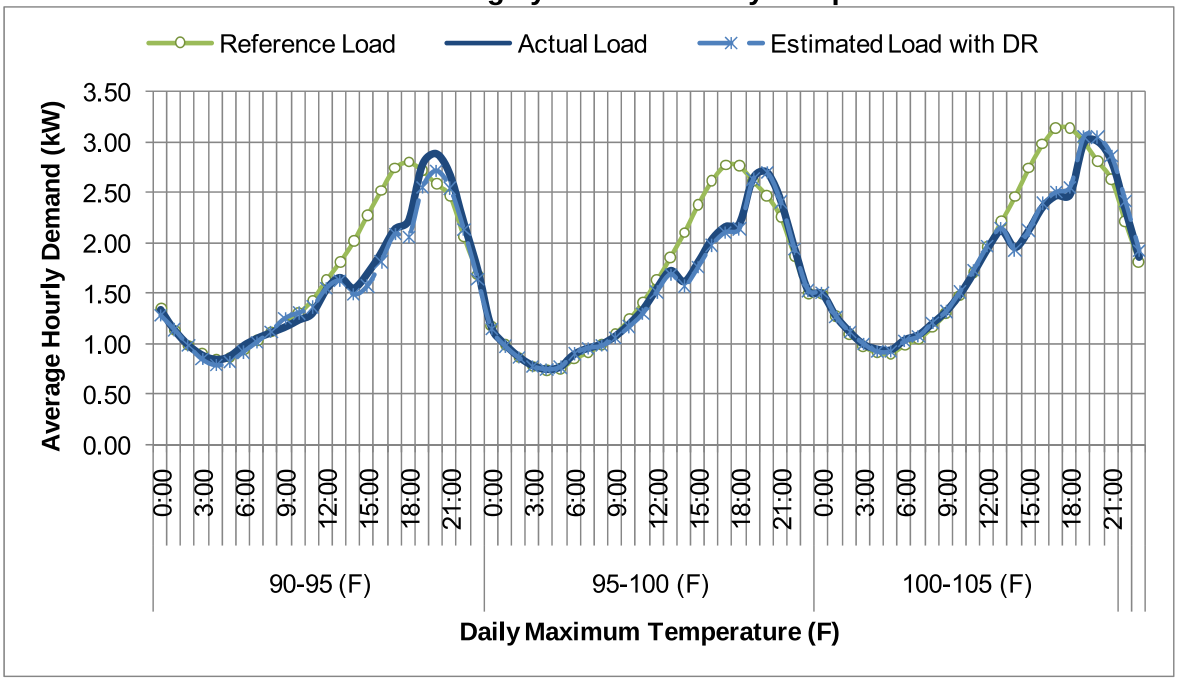

Table 3-9 provides a deeper picture of the relationship between air conditioning ownership, temperature and another important driver of demand response, CARE status. Several trends are noteworthy. First, the percent load reduction is relatively constant across temperature bins, although the absolute load reduction increases as maximum temperatures increase, especially for customers with a high likelihood of owning central air conditioning. Second, the absolute load reduction increases significantly from households with less than a 25% probability of owning central air conditioning to those with more than a 75% likelihood of owning it, even within each temperature bin. Finally, should also be noted that even customers with a low likelihood of owning central air conditioning provide a large percent reduction in electricity use—23% for non-CARE customers and 14% for CARE customers with less than a 25% likelihood of owning central air conditioning. While the absolute load reductions are much smaller for this group than for those who are more likely to have air conditioning, the percent reduction shows that customers are clearly willing to reduce or shift the use of not only air conditioning, but of other end uses as well.

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Table 3-9
SmartRate Load Impacts by Central Air Conditioning Ownership Likelihood, Temperature and CARE Status

CARE Status	Central AC Likelihood	90-95 (F)		95-100 (F)		100-105 (F)		Total[1]	
		Impact (kW)	%	Impact (kW)	%	Impact (kW)	%	Impact (kW)	%
Non-CARE	0-25%	0.18	23.1	0.17	22.7	-	-	0.17	22.9
	25-50%	0.15	10.7	0.26	19.3	0.23	13.5	0.26	18.3
	50-75%	0.25	13.6	0.33	16.8	0.27	10.6	0.32	15.2
	75-100%	0.66	27.1	0.75	28.1	0.92	28.1	0.77	28.1
	Total	**0.37**	**22.2**	**0.54**	**24.1**	**0.64**	**21.9**	**0.54**	**23.5**
CARE	0-25%	0.1	10.7	0.17	18.9	-	-	0.13	14.2
	25-50%	0.07	4.8	0.07	4.2	0.12	5.9	0.08	4.5
	50-75%	0.15	7.2	0.15	6.6	0.21	7.8	0.16	7
	75-100%	0.35	13.5	0.37	13.4	0.49	14.7	0.39	13.7
	Total	**0.14**	**8.2**	**0.16**	**7.5**	**0.23**	**9**	**0.17**	**7.8**
ALL	0-25%	0.15	17.6	0.17	21	-	-	0.16	19.1
	25-50%	0.08	5.5	0.11	6.9	0.13	6.7	0.11	6.8
	50-75%	0.19	9.4	0.22	10.4	0.23	8.8	0.22	10
	75-100%	0.57	23.1	0.65	24.2	0.8	24.4	0.67	24.2
	Total	**0.25**	**14.7**	**0.34**	**15.6**	**0.41**	**15.1**	**0.34**	**15.4**

[1] Total includes all days, including those below 95 (F). Low central AC likelihood participants experienced events in cooler days

3.2.6. Distribution of Load Impacts

Figure 3-7 shows the distribution of load impacts across customers. As indicated, 44.2% of customers provide no load reduction at all, although almost half of these customers (19.2% overall) did not receive event notifications. On the other hand, more than one third of all customers provide more than 0.2 kW of average load reduction, and 11.7% of all customers provide load reductions exceeding 1 kW. Similar distributions for each event day are shown in Table 3-9. The basic pattern is quite consistent across event days. It is noteworthy that on the hottest event day of the season, June 29th, 19% of all customers provided load reductions exceeding 1 kW. Clearly, if these high responders can be identified and targeted, program cost-effectiveness could be dramatically improved. At the same time, as discussed in the ex-ante volume, program effectiveness could also be improved by encouraging low responders to have their load response automated through participation in SmartAC.

Figure 3-7
Distribution of Individual SmartRate Customer Average Event Load Impact (Includes Customers That Were Not Notified)

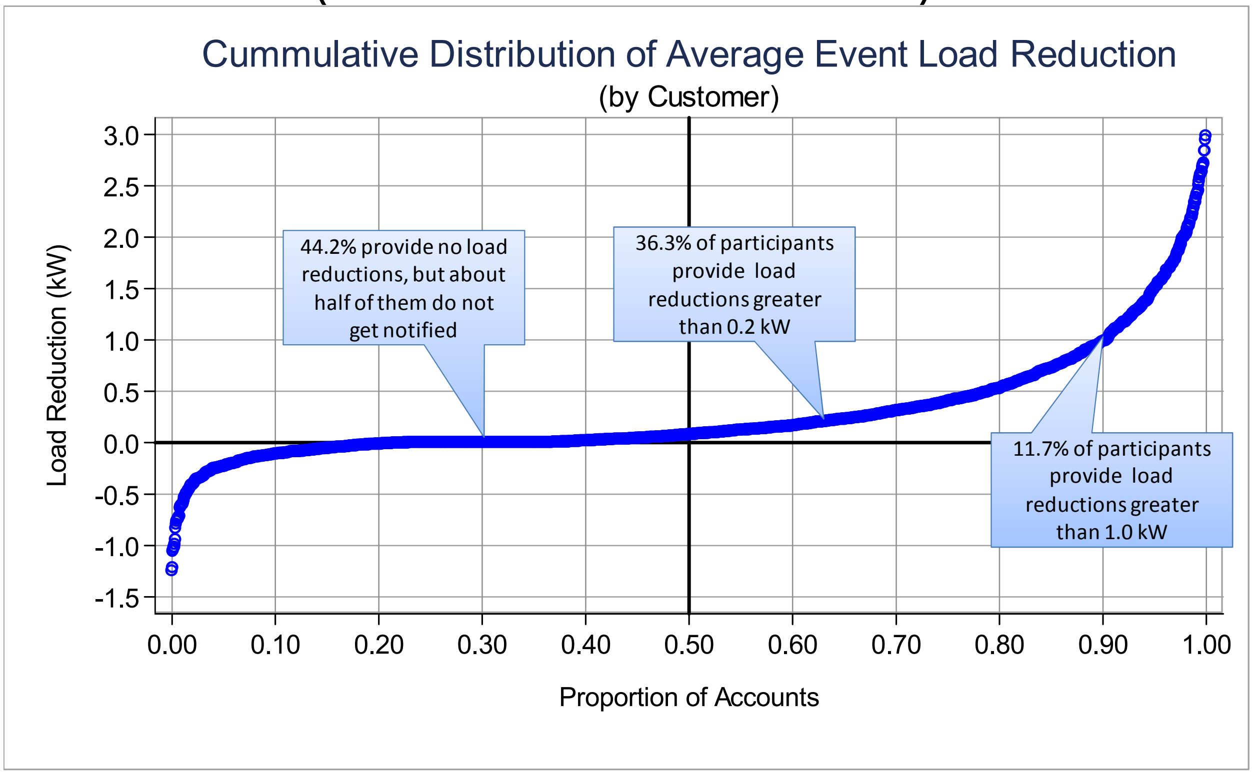
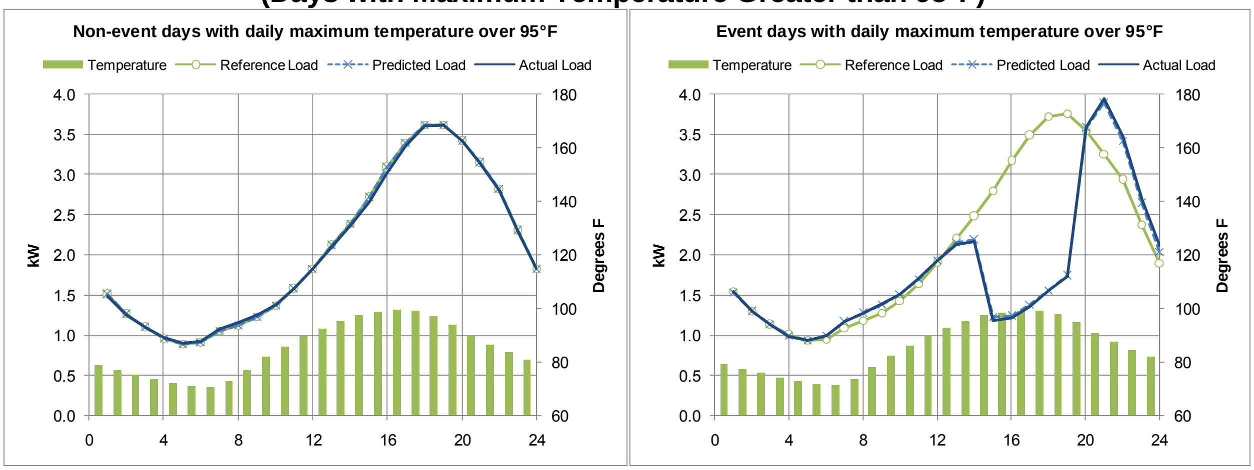


Table 3-9
Share of SmartRate Customers Exceeding Load Reduction Thresholds by Event (Includes Customers Not Notified)

Event Date	Share of accounts providing load reductions greater than					
	0.0 kW	0.2 kW	0.4 kW	0.6 kW	0.8 kW	1.0 kW
29-Jun-09	51.8%	38.6%	30.9%	25.8%	21.9%	19.0%
30-Jun-09	52.7%	33.0%	23.5%	17.9%	14.0%	11.4%
13-Jul-09	51.6%	34.8%	23.5%	16.7%	12.5%	10.4%
14-Jul-09	52.7%	33.8%	24.4%	18.1%	14.4%	11.1%
16-Jul-09	52.4%	35.6%	26.0%	20.8%	17.7%	14.4%
21-Jul-09	51.0%	31.6%	22.6%	15.9%	12.7%	10.4%
27-Jul-09	52.1%	35.1%	25.4%	20.3%	16.6%	13.5%
10-Aug-09	57.7%	37.1%	26.0%	19.9%	15.7%	11.8%
11-Aug-09	53.2%	32.2%	22.9%	16.2%	12.9%	10.2%
18-Aug-09	55.7%	33.8%	23.0%	16.9%	13.1%	9.8%
27-Aug-09	58.7%	38.6%	26.0%	18.7%	13.7%	10.0%
28-Aug-09	58.6%	40.2%	28.6%	20.7%	15.3%	11.7%
2-Sep-09	58.0%	37.2%	25.5%	19.3%	14.8%	11.0%
10-Sep-09	59.4%	38.7%	27.6%	20.0%	14.9%	11.0%
11-Sep-09	59.0%	38.7%	28.0%	21.0%	16.4%	12.6%
Total	**55.8%**	**36.3%**	**25.7%**	**19.2%**	**15.0%**	**11.7%**

Because the distribution of impacts has several implications for targeting and dual marketing of dynamic pricing and load control, it was critical to ensure the high response estimates were valid and not an artifact of estimation error or bias. Figure 3-8 shows the average reference load and load reductions for the top 10% of participants with the largest impacts. The graph includes both event and non-event days where the daily maximum temperature exceeded 95° F.

Figure 3-8
Accuracy of Reference Loads and Impacts for SmartRate High Responders (Top 10%) (Days with Maximum Temperature Greater than 95°F)



The figure not only shows the magnitude of the load reduction, but also shows that the regressions accurately explain high responder behavior for both event and non event days under conditions when events have a higher probability of being called. The regression estimated load mirrors the actual so precisely that the two curves are nearly indistinguishable.

Table 3-11 shows the distribution of percent load reductions by estimated central air conditioning likelihood and CARE status. The table is presented because of the implications for automated price response through direct load control devices. Given PG&E's air conditioning load control strategy, the existing switches and thermostats reduce between 30 to 45% of the air conditioning load, depending on weather conditions, which translates to approximately a 15 to 30% load reduction of the whole house load.

As Table 3-11 shows, many of the customers on SmartRate provide more than 30% load reduction on their own. That is, they employ more aggressive load reduction strategies than is typically produced by the SmartAC load control program. As such, it is unlikely that putting a load control switch on these households will provide any incremental load reduction, as it appears that these households have already made adjustments that would produce air conditioning duty cycles that are unlikely to be reduced by the 50% cycling strategy used in the SmartAC program. Even if some incremental effect is obtained (through adaptive cycling for example), with such low duty cycles, the incremental impact is not likely to be enough to justify the cost of a control device or programmable thermostat.

On the other hand, there is a substantial number of SmartRate customers who do little or nothing on their own, either because they choose not to be notified, or are not price responsive. Automating their demand response under SmartRate with load control devices would yield incremental load impacts.

Table 3-11
Percent of SmartRate Customers Exceeding Percentage Reduction Thresholds (Includes Customers Not Notified)

Event Date	AC likelihood	Share of accounts providing load reductions greater than					
		0%	10%	20%	30%	40%	50%
Standard Tariff Participants	0-25%	68.3%	60.2%	42.5%	30.6%	18.8%	11.8%
	25-50%	62.9%	48.6%	41.9%	30.5%	19.0%	14.3%
	50-75%	62.6%	51.2%	42.8%	34.7%	26.3%	19.5%
	75-100%	70.8%	63.1%	53.4%	46.4%	38.1%	30.5%
	Total	**67.3%**	**57.8%**	**47.4%**	**38.8%**	**29.5%**	**22.5%**
Low Income (CARE) Participants	0-25%	45.8%	36.4%	22.0%	15.3%	9.3%	5.1%
	25-50%	42.2%	27.4%	17.5%	12.3%	8.7%	4.5%
	50-75%	46.3%	32.6%	25.8%	18.8%	14.2%	9.3%
	75-100%	56.8%	45.1%	32.7%	22.8%	15.4%	13.0%
	Total	**46.5%**	**33.3%**	**23.8%**	**17.0%**	**12.1%**	**7.9%**
All Participants	0-25%	59.5%	51.0%	34.5%	24.7%	15.1%	9.2%
	25-50%	47.1%	32.5%	23.3%	16.7%	11.2%	6.9%
	50-75%	53.0%	40.2%	32.7%	25.3%	19.1%	13.5%
	75-100%	67.2%	58.5%	48.1%	40.4%	32.3%	26.0%
	Total	**57.0%**	**45.7%**	**35.7%**	**28.0%**	**20.9%**	**15.3%**

3.2.7. Incremental Load Impacts for Dually Enrolled Customers

PG&E is one of the first utilities to implement, rather than pilot, a large scale deployment of critical peak pricing for residential customers. Because 2009 was the program's second year, it provided an opportunity to test the persistence of load responsiveness outside of a pilot context and without bill protection. In addition, PG&E offered direct load control devices to a subset of participants, and as a result collected data on actual customer choices regarding their willingness to accept automation of load response and the opportunity to test incremental impacts of technology on dynamic pricing.

In order to analyze incremental effects, we took advantage of the fact that we were able to observe price responsiveness of some customers with and without technology and that not all customers that volunteered for enabling technology– in either the form of programmable thermostats or direct load control switches – had the equipment successfully installed and commissioned. There are several reasons for the difference between enrollment volunteers and actual installations, including inability to schedule appointments for installation, volunteers not fully understanding the difference between room and central air conditioning, and differences of viewpoint within household members. Regardless, the volunteer group that did not have the device installation completed was a natural control group because they self-selected themselves for enabling technology and had central air conditioning or, at the very least, room air conditioning. Information about air conditioning ownership is critical as the correct comparison is between participants with central air conditioning with and without enabling technology.

To further ensure that the groups were comparable, the estimating sample was narrowed to the hottest PG&E climate region, which encompasses the warmer parts of the Central Valley, including Fresno and Bakersfield. Table 3-12 summarizes the design of the analysis at a high level.

Table 3-12
2nd Year Load Response Persistence and Enabling Technology Incremental Impact Analysis Design

Group	1st year (2008)	2nd year (2009)
Enabling technology (DLC switch or thermostat)	▪ 1-9 events ▪ Bill protection ▪ No enabling technology ▪ 1st year participation ▪ Have central AC ▪ Located in warmest climate region	▪ 15 events ▪ No bill protection ▪ Self selected for enabling technology that automated AC price response and had it installed ▪ 2nd year participation ▪ Have central AC ▪ Located in warmest climate region
Control group (volunteered for enabling technology, but did go through with installation)	▪ 1- 9 events ▪ Bill protection ▪ No enabling technology ▪ 1st year participation ▪ Have central AC or room AC ▪ Located in warmest climate region	▪ 15 events ▪ No bill protection ▪ Self selected for enabling technology that automated AC price response and but did not have it installed ▪ Mostly 2nd year participants, includes some first year participants ▪ Have central AC or room AC ▪ Located in warmest climate region

Table 3-13 compares the reference load, impacts, and percent impacts across a range of event temperatures for customers with and without enabling technology. All customers included are in PG&E's warmest climate region, are second year participants, and replied to the offer of enabling technology. Note that the mix of customers varies by temperature bin.

For customers on the standard tariff without enabling technology, the impacts per event range from 0.43 kW to 0.73 kW, and percent load reductions range from 15.5% to 20.8%. The impacts are slightly lower than those of standard tariff customers with enabling technology. Their counterparts with enabling technology averaged between 0.58 and 1.07 kW of load reduction per event, which ranges between 22.9% and 28.8% of whole house load. Some of the difference is likely due to unsuccessful notifications since customers with enabling technology provide response regardless of whether or not the event notification was successfully transmitted. The difference in load impacts is substantially larger between low income customers with and without enabling technology. For CARE customers, in almost all temperature ranges, impacts for the customer with enabling technology are triple the impacts of those without it.

Table 3-13
Comparison of Impacts with and Without Enabling Tech
Individual Customer Regression Impacts

Customer Category	Average Event Temperature (F)	Central AC No enabling technology				Central AC Enabling technology			
		Reference Load (kW)	Impact (kW)	Impact (%)	Successful notifications (%)	Reference Load (kW)	Impact (kW)	Impact (%)	Successful notifications (%)
Standard tariff	90-95 F	2.38	0.50	20.8%	77.8%	2.40	0.58	24.2%	81.1%
	95-100 F	2.55	0.43	16.8%	78.2%	2.59	0.59	22.9%	81.4%
	100-105 F	3.18	0.49	15.5%	84.4%	3.30	0.80	24.1%	78.9%
	105-110 F	3.59	0.73	20.4%	88.9%	3.72	1.07	28.8%	81.1%
Low income tariff (CARE)	90-95 F	2.22	0.17	7.5%	71.8%	2.34	0.44	18.7%	77.8%
	95-100 F	2.50	0.13	5.2%	73.8%	2.49	0.45	18.2%	82.4%
	100-105 F	2.92	0.23	8.0%	73.1%	3.07	0.66	21.6%	83.0%
	105-110 F	3.19	0.45	14.1%	71.8%	3.34	0.95	28.3%	85.2%

On average, customers with central air conditioning provided substantial load response without enabling technology. This is particularly true in PG&E's warmest climate region. Overall, customers with 75% or higher likelihood of owning central air conditioning reduced load by 21.5%, with the percent load reduction differing between customers in the low income, 12.4%, and standard tariffs, 26.1%. This includes all customers, not just those who were used to estimate incremental effects. Impacts over and above the load reduction customers provide in the absence of enabling technology are attributable to enabling technology.

Underlying the averages is a large amount of variation ranging from participants that aggressively control air conditioning during events to customers who do not provide event notification contact information and do not respond. For a direct control program such as SmartAC, customers provide the loads (the behavioral component) and the control devices provide the load reductions. In contrast, for a critical peak pricing tariff such as SmartRate, customers provide both the loads and load reductions. Although both types of programs have behavioral aspects, participant behavior plays a larger role in critical peak pricing.

The optimal use of enabling technology is to direct it to those that provide little or no load reduction and have significant amounts of AC load. In other words, direct it at customers where it does indeed produce incremental impacts. Conversely, offering enabling technology to high performers with the current thermostat and cycling options, can actually reduce load impacts. This is not necessarily the case. By offering more aggressive cycling and/or thermostat setback strategies, enabling technology can stabilize load reductions without reducing impacts. As discussed in Volume II, individual level customer estimates of pricing load reductions and expected AC use have been developed for the PG&E residential population, allowing for improved targeting of enabling technology in the future.

There are several issues about the enabling technology analysis that are noteworthy and limit the ability to draw strong conclusions about the future incremental effects of enabling technology:

- The test reflects an untargeted offer of enabling technologies to SmartRate customers because data for more refined targeting was unavailable at the time of the offering. The average incremental effect depends on whether targeting is employed. As the prior section discussed, without targeting or more aggressive load control options, the program can reduce impacts from high responders and at the same time increase impacts from participants that previously provided little or no load response on their own.

- The data is limited solely to PG&E's warmest climate region and may have limited validity in cooler climate zones.
- The estimating sample has a large share of low income, CARE, participants. Almost 60% of customers in the enabling technology and control groups are on low income tariffs, limiting the ability to apply the results to other customers.
- Over 80% of customers received thermostats as enabling technology. Based on its revised strategy, PG&E plans to offer primarily switches to residential customers who enroll in SmartAC in the near term. In addition, the thermostats were operated as traditional (versus adaptive) 50% cycling devices for some events and with a setback ramp strategy on other events. Based on our understanding, PG&E does not plan to use thermostats as traditional cycling devices in the future.

All of the above reasons indicate that incremental effects of SmartAC enabling technology on SmartRate should be reassessed after the 2010 summer, at which point PG&E will likely have more dually enrolled customers across a broader territory footprint, with a more representative customer and device mix.

4. NON-RESIDENTIAL SMART RATE CUSTOMER LOAD IMPACT ANALYSIS

This section presents ex post load impact estimates for non-residential SmartRate participants. There were only 187 non-residential accounts enrolled in SmartRate in 2009, all of them located in or near Kern County. These accounts experienced the same 15 event days as did residential SmartRate customers. Given the small number of enrolled customers, impact estimates are only presented for the group as a whole, not by LCA or business type. The small sample size also suggests that the impact estimates presented here should be viewed with significant caution. This group of customers is not representative of PG&E’s non-residential (A-1) customer population either in Kern County or for the service territory as a whole.

Section 4.1 provides an explanation of the estimation methodology used to develop the impact estimates, and validation procedures used to assess the accuracy of the results. Section 4.2 presents the load impact estimates.

4.1. ANALYSIS APPROACH

The impact estimates for non-residential customers were based on time-series regressions for each participant for which adequate data were available. In total, up to 190 non-residential accounts were enrolled in SmartRate during 2009 (as compared to 208 participants in 2008), although the number varied depending on the date. The final estimation was based on 183 individual customer regressions using both 2008 and 2009 data for June through October.

As with the residential models, the dependent variable in each regression is average hourly demand (kW). The explanatory variables can be grouped into three main components:

- Variables that reflect the average load shape of customers, absent the need for cooling;
- Variables that explain deviation in hourly usage from the average load shape; and
- Variables that estimate the change in energy use during event days and the factors that influence the load reductions.

The explanatory variables are similar to those employed in the residential analysis, with a few exceptions. Explanatory variables include hourly binary variables for weekdays and weekends to capture the inherent variation in usage across hours of the day absent weather effects, weather variables to capture the influence of temperature on electricity use, and event-day variables and interactions to estimate the impact of the higher SmartDay prices on energy use during each hour of the event period as well as hours leading up to and following the event period. In addition, the event variables were interacted with temperature, number of consecutive event days, cumulative event days, day of week, and month variables in order to explain how load reductions vary due to those factors. The primary difference between the residential and non-residential customer regressions is in the operating schedule of businesses and homes. By modeling the effect of temperature on each hour separately, the regression identifies differences in the operating schedules and when customers use A/C load. The specification was intentionally designed to capture a wide variation of operating schedules as well as different hourly responses to weather and event conditions.

For residential customers, the regressions explicitly modeled the effects of the school calendar on the household operating schedule and energy consumption. This was not included in the non-residential regression specification. In addition, for non-residential customers, no distinction was made based on whether or not specific accounts were sent event notifications.

The regressions were developed using the same GLS estimator and robust standard error techniques used for the residential sector analysis. The following equation summarizes the model specification.

$$KW = \alpha_0 + \sum_{i=2}^{24} \beta_i \cdot HOUR_i \cdot WEEKDAY + \sum_{i=2}^{24} \delta_i \cdot HOUR_i \cdot WEEKEND + + \sum_{j=7}^{10} \phi_k \cdot MONTH_k$$

$$+ \sum_{i=1}^{24} \mu_i \cdot HOUR_i \cdot CDH + \sum_{i=1}^{24} \eta_i \cdot HOUR_i \cdot CDH^2 + \psi \cdot S \cdot CDH + \zeta \cdot S \cdot CDH^2 +$$

$$\sum_{i=2}^{24} \pi_i \cdot HOUR_i \cdot EVENTDAY + \sum_{i=1}^{24} \quad \theta_i \cdot HOUR_i \cdot EVENTDAY \cdot CDH + \sum_{i=1}^{24} \lambda_i \cdot HOUR_i \cdot EVENTDAY \cdot CDH^2{}_l +$$

$$\sum_{j=6}^{10} \varsigma_k \cdot MONTH_k \cdot EVENT + \sum_{k=1}^{3} \upsilon_k \cdot INAROW_k \cdot EVENT + \omega \cdot CUMEVENTS \cdot EVENT +$$

$$\sum_{l=2}^{7} \xi_k \cdot DOW_k \cdot EVENT + \varepsilon$$

Where:

KW = Electricity usage in Hour i for Customer j

WEEKDAY = Monday – Friday

WEEKEND = Saturday – Sunday

$HOUR_i$ = Hours of the day, numbered 1-24

$MONTH_j$ = Months of the year, numbered 1-12

CDH_i = Cooling Degree Hour for that hour of the day, defined as Max(0, Temperature(F) - 70)

CDH^2 = CDH squared

EVENTDAY = SmartRate event day (all 24 hours)

EVENT= SmartRate event window (2 - 6 pm)

INAROW = Number of consecutive events in a row

CUMEVENTS= Cumulative number of events in season

DOW = Day of week

ε = the error term

i = Subscript indicating the hour of day (1-24)

j = Subscript indicating the month of the year (1-12)

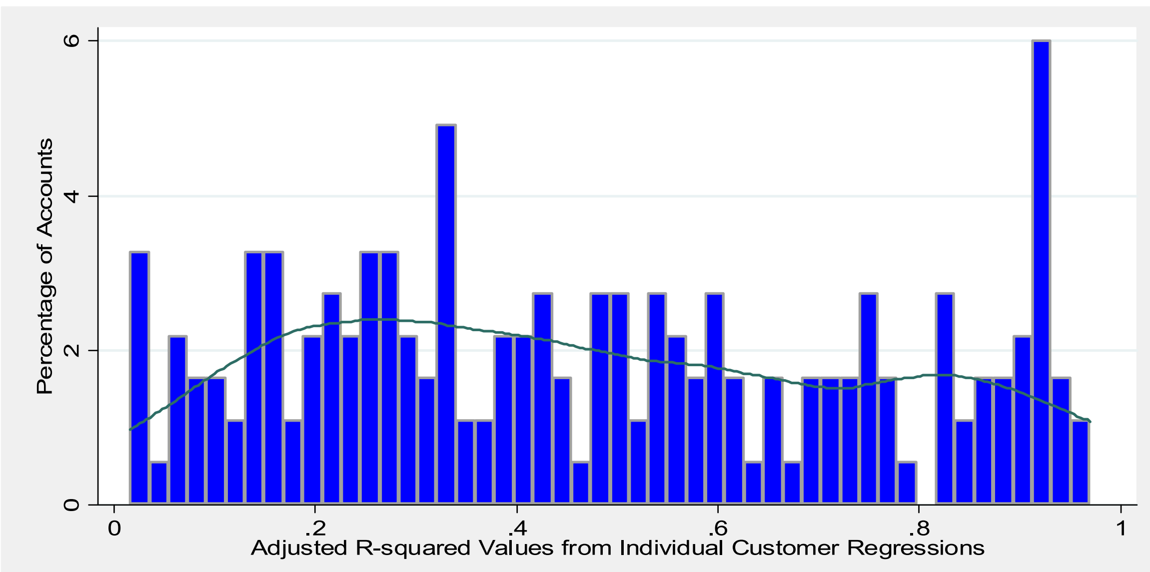
k = Subscript indicating the number of consecutive events in a row

l = Subscript indicating the day of week (1-7)

4.1.1. Goodness of Fit Measures

Figure 4-1 describes the distribution of R-squared values for the individual non-residential customer regressions. While most individual customer regressions did a good job of explaining the variation in electricity use, what matters most is how well the models do in predicting load for the average customer. In aggregate, nearly all of the variation in energy use across hours was explained by the model specification. When the predicted and actual values were aggregated across the individual results, the model explains roughly 92.9% of the variation in energy use.

Figure 4-1
Distribution of Adjusted R-squared Values from Individual Customer Regressions for the Non-Residential SmartRate Tariff



4.1.2. Model Accuracy and Validity Assessment

With any load impact analysis, the most important feature is the ability to accurately predict customer load and load reductions under the extreme conditions for which demand response is designed to provide a reliable resource. To assess the accuracy and validity of the model, we compared actual and predicted values by hour and temperature for Smart Days. Figure 4-2 compares the actual average hourly energy use of non-residential customers across event days to the regression predicted values under event and non-event conditions. Figure 4-3 compares the actual and predicted values at various hourly temperatures and illustrates that the model predicts accurately across the full range of temperatures. As in the residential section, for each figure the relevant comparison of accuracy is between the actual load under event conditions (solid line) and the regression predicted load under the same conditions (solid line with squares). We have included the regression predicted values absent the Smart Day event (dashed line) for informational purposes only. In all of the comparisons, the actual and regression predicted values

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under event conditions are virtually identical. In other words, the regressions predict how customers behave under event conditions nearly perfectly. The same is true for non-event days.

Figure 4-2
Actual and Predicted Electricity Use for the Average Smart Day
(Average Non-Residential Customer)

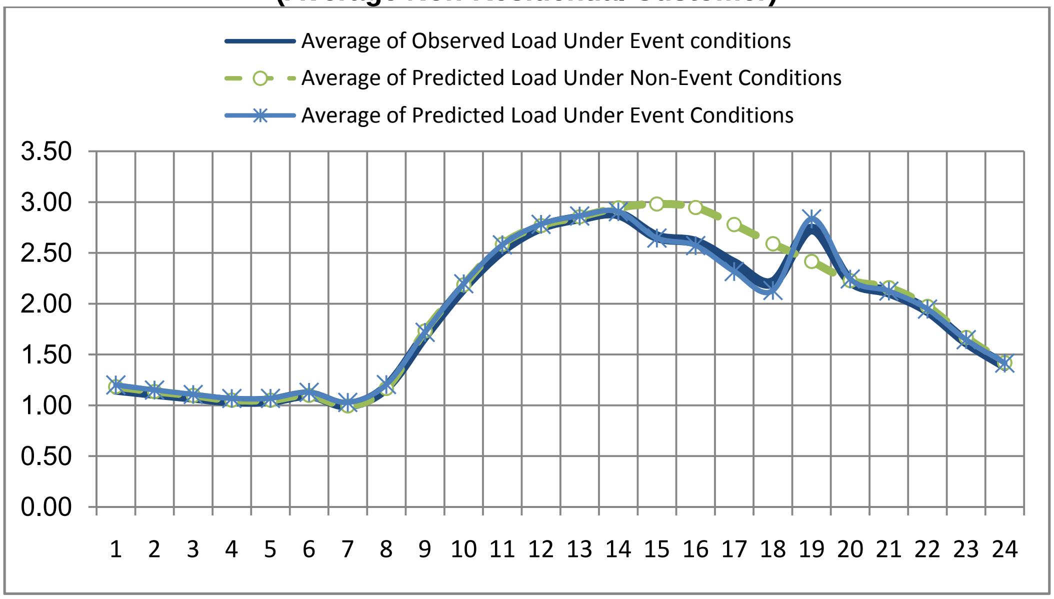
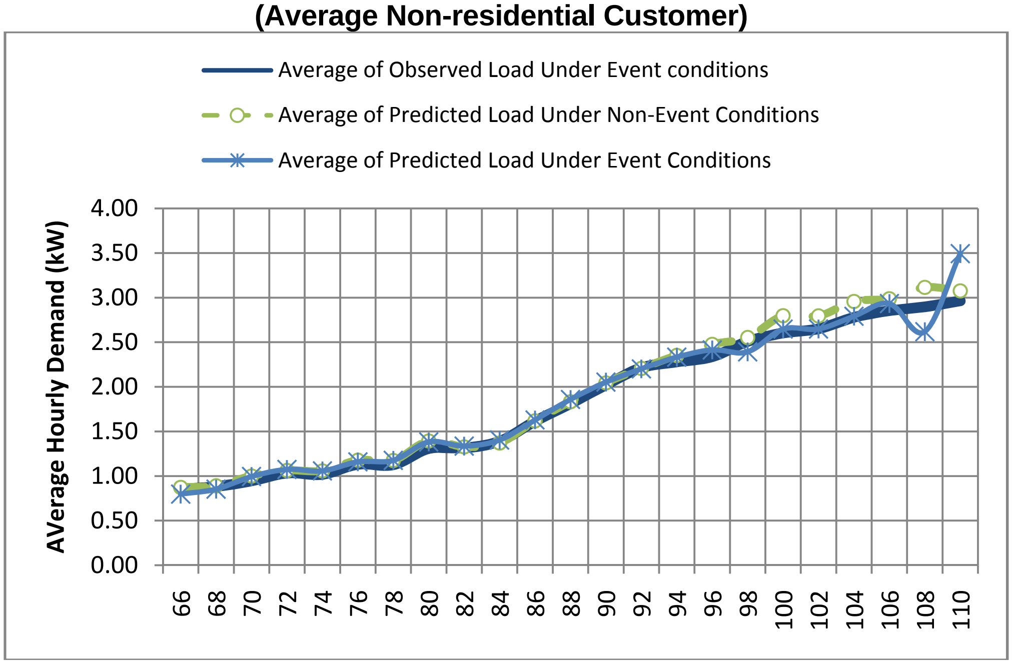


Figure 4-3
Actual and Predicted Values by Temperature for Event Days
(Average Non-residential Customer)



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4.2. LOAD IMPACT RESULTS

Figure 4-4 summarizes the load impacts for the average A-1 SmartRate customer for the average event day in 2009. It includes the hourly impact estimates and provides a snapshot of the electronic ex-post load impact tables provided jointly with this report in accordance with the California Load Impact Protocols.

The average load reduction for the 183 customers included in the estimating sample across the 15 event days in 2009 was 0.44 kW, or 16.2% of the average reference load. As seen in Table 4-1, both the percent and absolute load reductions increased across the four-hour event period, from a low of 13.5% and 0.38 kW in the first event hour to a high of 19.2% and 0.48 kW in the final event hour. It should be noted that the non-residential customers participating in SmartRate so far are not much larger than the average residential SmartRate participant. The average reference load during the event window for the 15 event days was 2.72 kW for non-residential customers and 2.08 kW for residential SmartRate customers. The average percent reduction for non-residential SmartRate customers is actually slightly larger than the 15% average load reduction that was observed for residential SmartRate customers.[26]

This result is a significant contrast to a key finding from California's Statewide Pricing Pilot,[27] which concluded that small non-residential customers do not respond to price signals in the absence of enabling technology, such as air conditioning load control, and medium non-residential customers have much lower percent reductions than do residential customers. However, as discussed at the outset of this chapter, it would be incorrect to draw any significant conclusions about non-residential customer price responsiveness from this very small, unrepresentative sample of current SmartRate participants.

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[26] It should be noted that the average percent reduction for non-residential customers is less than the average percent reduction for notified residential customers, which is almost 20%. If all or nearly all of the non-residential customers in the estimation sample were notified, the comparison with notified residential customers would be more valid than with all residential customers.

[27] See Stephen S. George, Ahmad Faruqui and John Winfield. *California's Statewide Pricing Pilot: Commercial & Industrial Analysis Update*. Final Report, June 28, 2006.

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Figure 4-4
2009 Average Event Hourly Load Impacts for Non-Residential SmartRate Customers

TABLE 1: Menu options

Type of Results	Average Customer
Event	Average Event
Participant Category	A1

TABLE 2: Event Day Information

Event Date	Average Event
Event Notification	Day Ahead
Event Start	14:00
Event End	18:00
ACCOUNTS FOR EVENT	161
TOTAL ENROLLED ACCOUNTS	161
Avg. Load Reduction for Event Window	0.44
% Load Reduction for Event Window	16.2%

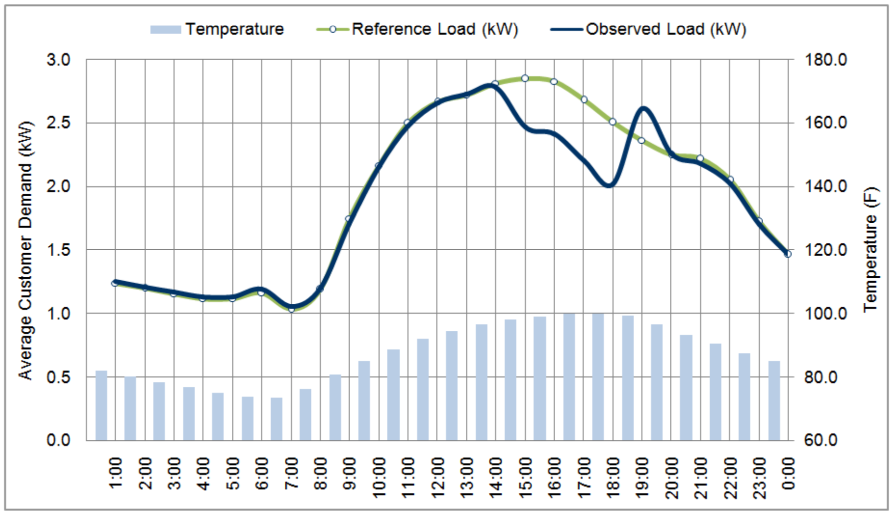

TABLE 3: Ex-Ante Load Impact Results

Hour Ending	Reference Load (kW)	Observed Load (kW)	Load Impact (kW)	%Load Reduction	Weighted Temp (F)	Uncertainty Adjusted Impact - Percentiles				
						10th	30th	50th	70th	90th
1:00	1.24	1.25	-0.01	-1.0%	81.9	-0.11	-0.05	-0.01	0.03	0.08
2:00	1.20	1.21	-0.01	-0.8%	80.1	-0.11	-0.05	-0.01	0.03	0.09
3:00	1.16	1.17	-0.01	-1.1%	78.4	-0.11	-0.05	-0.01	0.03	0.08
4:00	1.12	1.13	-0.02	-1.6%	76.8	-0.11	-0.06	-0.02	0.02	0.08
5:00	1.12	1.13	-0.02	-1.4%	75.1	-0.11	-0.06	-0.02	0.02	0.08
6:00	1.16	1.19	-0.03	-2.4%	73.8	-0.12	-0.07	-0.03	0.01	0.07
7:00	1.03	1.06	-0.02	-2.1%	73.7	-0.12	-0.06	-0.02	0.02	0.07
8:00	1.19	1.20	-0.01	-0.7%	76.2	-0.10	-0.05	-0.01	0.03	0.09
9:00	1.75	1.71	0.04	2.3%	80.9	-0.06	0.00	0.04	0.08	0.14
10:00	2.17	2.16	0.01	0.4%	85.1	-0.09	-0.03	0.01	0.05	0.11
11:00	2.50	2.48	0.02	0.8%	88.7	-0.08	-0.02	0.02	0.06	0.12
12:00	2.66	2.66	0.00	0.0%	91.9	-0.09	-0.04	0.00	0.04	0.10
13:00	2.72	2.72	0.00	0.0%	94.5	-0.10	-0.04	0.00	0.04	0.09
14:00	2.81	2.78	0.03	1.1%	96.7	-0.07	-0.01	0.03	0.07	0.13
15:00	2.85	2.47	0.38	13.5%	98.2	0.29	0.34	0.38	0.42	0.48
16:00	2.83	2.41	0.41	14.7%	99.0	0.32	0.38	0.41	0.45	0.51
17:00	2.68	2.21	0.48	17.8%	99.8	0.38	0.44	0.48	0.52	0.57
18:00	2.50	2.02	0.48	19.2%	100.0	0.38	0.44	0.48	0.52	0.58
19:00	2.37	2.61	-0.25	-10.5%	99.2	-0.35	-0.29	-0.25	-0.21	-0.15
20:00	2.25	2.25	0.00	-0.2%	96.7	-0.10	-0.04	0.00	0.04	0.09
21:00	2.22	2.18	0.04	1.8%	93.4	-0.06	0.00	0.04	0.08	0.13
22:00	2.05	2.02	0.03	1.4%	90.5	-0.07	-0.01	0.03	0.07	0.13
23:00	1.72	1.70	0.02	1.3%	87.5	-0.07	-0.02	0.02	0.06	0.12
0:00	1.47	1.47	0.00	0.1%	84.9	-0.09	-0.04	0.00	0.04	0.10

	Reference Energy Use (kWh)	Observed Energy Use (kWh)	Change in Energy Use (kWh)	% Daily Load Reduction	Cooling Degree Hours (Base 75)	Uncertainty Adjusted Impact - Percentiles				
						10th	30th	50th	70th	90th
Daily	46.76	45.19	1.57	3.4%	130.9	1.55	1.56	1.57	1.58	1.59

Table 4-2 shows the average load reduction for non-residential SmartRate customers for each event day in 2009.[28] The average load reduction ranges from a low of 0.14 kW,[29] or 6.8% on July 16th to a high of 0.66 kW, or 23.9%, on September 2nd.

Table 4-1
Load Impacts by Event Day for Non-Residential SmartRate Customers

Date	Day of Week	# of Enrolled Customers	Maximum Temp (°F)	Minimum Temp (°F)	Average Hourly Load (kW)	Average Load Reduction (kW)	Average % Load Reduction
29-Jun-09	M	187	108	78.5	3.13	0.54	17.2
30-Jun-09	T	187	103.5	82	2.94	0.41	13.9
13-Jul-09	M	187	95	69	2.78	0.48	17.3
14-Jul-09	T	187	100	71	2.94	0.48	16.2
16-Jul-09	Th	187	105	77.5	2.03	0.14	6.8
21-Jul-09	T	187	102	75.5	3.05	0.51	16.8
27-Jul-09	M	187	104	77.5	3.12	0.61	19.5
10-Aug-09	M	187	99	73.5	2.87	0.44	15.3
11-Aug-09	T	187	102	74.5	2.98	0.4	13.6
18-Aug-09	T	187	99	70	2.88	0.37	12.9
27-Aug-09	Th	187	97	68	1.87	0.19	10.4
28-Aug-09	F	187	97	70	2.83	0.51	17.9
2-Sep-09	W	187	98	72.5	2.77	0.66	23.9
10-Sep-09	Th	187	96.5	68	1.82	0.21	11.4
11-Sep-09	F	187	97	71.5	2.73	0.63	23.1
Average	n/a	187	100.2	73.3	2.73	0.44	16.2

[28] The impact estimates on 7/16, 8/27 and 9/10 were based on the impacts for all but 12 customers who displayed very unusual load patterns on those event days, with load dropping to zero during the event period and then surging to a level five to ten times higher than any other hour (on those days or other days). These were relatively large customers and the result of the unusual load pattern led to overall impacts on those days for the entire customer segment that were significantly different from the impacts on all other days. As such, we dropped those customers from the average impact estimate on the three days in question. In spite of these adjustments, impacts on those three days may still be biased. Indeed, the impact estimates for these days are the three lowest out of the 15 event days, although at least one day, July 16th, is the second hottest day.
[29] See prior footnote regarding the potential bias associated with this particular date.

5. RESIDENTIAL TIME OF USE RATES LOAD IMPACT ANALYSIS

PG&E has two residential TOU tariffs – E7 and E6. Currently, roughly 78,000 customers are enrolled on E7, and approximately 7,400 customers are enrolled on E6. Enrollment for E7 is closed while enrollment for E6 remains open. Both E7 and E6 customers are distributed throughout the PG&E service territory. The average E7 customer consumes twice as much energy annually as does the average customer on the default residential tariff, E1. The annual consumption of the average E6 customer is comparable to an E1 customer.

5.1. ANALYSIS APPROACH

Estimating load impacts for time-of-use rates presents different challenges than estimating load impacts for event based tariffs or programs. The challenges are both analytical and due to data limitations.

Time of use customers self-select into the tariff and it is necessary to control for selection effects in order to estimate load impacts. The two primary approaches used for event based programs like SmartRate – using pre-enrollment data and/or relying on behavior during non-event days (a within customer control) – are unavailable for the TOU evaluation.

For TOU tariffs, time-differentiated price signals are in effect for all weekdays of the year. As a result, it is not possible to observe the naturally occurring customer behavior in the absence of TOU pricing. Although PG&E has been installing electric smart meters throughout its territory since approximately 2007, most of E7 and E6 customers did not have a full year of interval data for evaluation. Even if available, smart meter data does not include pre-enrollment periods for E7 because the tariff has been closed for some time and all enrollments occurred prior to the installation of any smart meters.

Given the data limitations and the unique nature of the TOU programs, three primary options for estimating the effect of the time differentiated prices were considered:

1. Apply the price elasticities estimated during the course of the California Statewide Pricing Pilot (SPP), which tested TOU and CPP-TOU rates, and use them to infer changes in energy consumption by E7 and/or E6 customers. While this approach may be valid for E6 customers, who are similar to average PG&E customers, it is not valid for E7 customers. Among other differences, E7 customers consume twice as much power as customers on the standard E1 tariff. Since the SPP sample for TOU customers is not representative of the average E7 customer, it is not appropriate to use the SPP elasticities to represent E7 customer price response.

2. Use the seasonal variation in the strength of price signals to estimate the price responsiveness of TOU customers. While this approach can be employed, it may not yield accurate estimates of price responsiveness since price changes are correlated with seasonal patterns of energy use and weather. As a result, regression analysis may confound weather effects with price signals, leading to inaccurate price responsiveness estimates.

3. Use a control group. Although it is not possible to develop a randomly assigned control group since the E7 tariff is closed and participants self-select into the tariff, it is possible to draw a control group using propensity score matching. Propensity score matching is a technique designed to ensure control group members are as similar as possible to the group of interest. Using probit regression, the participant characteristics associated with enrollment are reduced to a propensity score. Matches are then determined based on the propensity score. The process allows for the development of a control group and allows for the observation of naturally occurring load patterns under flat rates for a population that matches the TOU participants.

The use of a control group developed through propensity score matching based on the E1 and E7 load research samples was employed for several reasons. In the absence of pre-enrollment data or a randomly assigned control group, in our assessment, the combination of propensity score matching with regression was the most robust analytical approach available. It explicitly addressed selection issues and controlled for any potential differences in energy use patterns between the TOU and control group. Moreover, it was possible to assess the quality of the control group by comparing how well the control group characteristics match the E7 participants. After using propensity score matching to identify the control group, regression analysis was used to identify differences in load between the TOU group and the control group. The remainder of this section details the control group development and the selection of regression models.

5.1.1. Development of Control Group Using Propensity Score Matching

Propensity score matching required estimation of the probability customers were part of the E7 population using as many known predictors of selection as were available. The predictors included:

- Annual usage
- Annual usage interacted with climate region
- Annual usage interacted with CARE status
- Annual bill
- Annual bill interacted with climate region
- Annual bill interacted with CARE status
- Annual cooling degree hours (CDH)
- Probability of having central air conditioning
- Probability of having central air conditioning interacted with CDH
- CARE status
- Whether the customer received efficiency rebates between 2005 and 2009
- The correlation between the customer's monthly usage and monthly CDH
- Median year built of dwellings in the customer's census block group[30]
- Share of households that are homeowners in the census block group

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[30] A census block group (CBG) is a geographical unit used by the United States Census Bureau. It is smaller than a census tract and larger than a census block. A CBG is the smallest geographical unit for which the bureau publishes sample data (i.e. data collected from a fraction of all households rather than from all households). CBGs generally contain between 600 and 3,000 people, with an optimal size of 1,500 people. California has a total of 22,133 CBGs, of which approximately 7,686 are in PG&E's service territory.

- Median age of the population in the census block group
- Percent of mobile homes in the census block group.

Based on these variables, a probit regression was developed to calculate each customer's probability of choosing the E7 rate, given these known characteristics. The model may have included irrelevant variables because the potential cost of an omission error in propensity score matching (bias) is greater than cost of including too many variables (larger standard errors). A linear model was specified to identify the key drivers, which were subsequently interacted with CDH, climate zone, annual consumption and annual bill, to assess whether such interactions were statistically significant. The final model divided some of these key variables into deciles and included interactions to address potential non-linearities in the effect of these variables on a customer's probability of choosing the E7 rate. The model was then assessed for its ability to predict the distribution of E7 and E1 customers across a variety of dimensions.

After it was determined that the model accurately predicted the likelihood of choosing the E7 rate, the propensity score was used to select an optimal control group from the customers on the E1 rate. Each E7 customer was matched to a customer on the E1 rate using a nearest-neighbor caliper matching algorithm, with replacement. This created a control group of E1 customers who matched the E7 customers across several variables that determine selection onto the E7 rate.

Figure 5-1 presents the histogram of the propensity scores for E1 and E7 customers prior to matching. The difference in range of propensity scores was significant, indicating that any comparison without adequate matching would be invalid. In total, of the 117 E7 customers in the load research group, matches were identified for 93 of them. Not all E7 customers were matched because they either were missing a variable used for developing propensity scores or lacked an E1 neighbor. The match is designed to produce equivalent groups on average, not perfect individual matches. A total of 67 of the 635 customers in the E1 load research group were selected as matches. Some E1 customers in this control group were weighted up to 3 times because they were the closest match for multiple E7 customers.

Figure 5-1
Histogram of Propensity Scores Prior to Matching

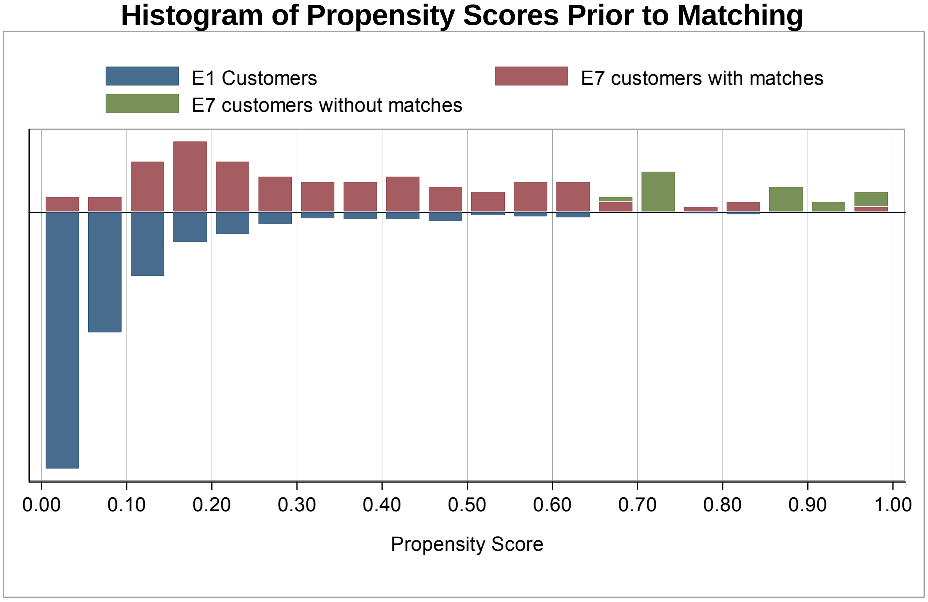

Table 5-1 compares the selected E1 match control group to the E7 customers across key customer characteristics. The differences between the control and match groups are minimal and always statistically insignificant.

Finally, the load shapes of the E7 and control group customers were compared across a variety of day types. The load shapes for the matched control group were much more similar to the E7 group than the load shapes for the E1 group, both for individual days and for average day types.

Table 5- 1:
Comparison of E7 Load Research Sample to Matched Control Group

Characteristic	E7 Population	Match Group	t Value	Probability
Annual consumption (kWh)	10,799.00	11,685.00	-1.01	0.31
Annual PG&E bill ($)	1,730.00	2,069.40	-1.4	0.16
Annual cooling degree hours (heat intensity)	37,031.00	36,796.00	0.07	0.94
CARE status (1=care customer)	0.13	0.2	-1.38	0.17
Probability of having central air conditioning	0.44	0.44	-0.11	0.91
Energy efficiency rebate in 2009 (1=received rebates)	0.05	0.04	0.34	0.73
Correlation between monthly consumption and heat intensity	0.04	0.06	-0.21	0.84
Median year home built in CBG	1,972.70	1,973.60	-0.52	0.6
CBG Owner to renter ratio	0.68	0.68	-0.04	0.97
Median CBG age	40.27	40.45	-0.16	0.88
High density (>40% of homes) of mobile homes in CBG	0.01	0.02	-0.58	0.56
Climate zone R	0.24	0.27	-0.5	0.62
Climate zone S	0.26	0.2	0.87	0.39
Climate zone T	0.15	0.16	-0.2	0.84
Climate zone X	0.35	0.37	-0.15	0.88
% of population of CBG that has a basic education	0.67	0.68	-1.1	0.27
% of population of CBG that speaks English	0.74	0.74	-0.14	0.89
Median home value in CBG ($)	550,000.00	560,000.00	-0.34	0.73
Median household income in CBG ($)	76,798.00	84,051.00	-1.05	0.3
Average family size in CBG	3.23	3.25	-0.33	0.74

5.1.2. Ex-Post Regression Model Development

Hourly whole-building energy use was analyzed using regression methods to isolate the effect of TOU pricing. Average usage in the control and TOU group was modeled using panel regression with corrections for auto correlated errors.[31] For all customers, factors used to estimate whole-building usage patterns included two basic types of variables:

[31] In this model, the dependent variable is average use across each sample at each time period. This gives the same coefficients as a panel model on individual customer use, but takes less time and computing

- Indicator variables that equal one at particular times; for example, between one and two pm on weekdays. These allow the model to account for different average customer usage at various times of day, times of the week and times of year;

- Weather variables interacted with time indicators. These allow the model to take into account different customer reactions to weather conditions at different times of day, times of the week and times of year. For example, a residential customer's energy usage might respond strongly to high temperatures on a Saturday afternoon when he/she is at home, while it might not respond at all on a Wednesday afternoon when he/she is at work;

The final regression model of whole-building usage for residential and commercial customers is quite rich in that it allows for many different types of time-based and temperature-based effects. The model for the TOU group and the control group is:

$$
\begin{aligned}
kw_t = {} & a + b * CDH_t + c * (CDH_t)^2 + d * CDH_t * \ln(nightCDH_t) + e * CDH_t * \ln(nightCDH_t)^2 \\
& + \sum_{h=1}^{24} f_h * I_h * CDH_t + \sum_{h=1}^{24} g_{h*} I_h * {CDH_t}^2 + \sum_{h=1}^{24} j_h * I_h * HDH_t + \sum_{h=1}^{24} k_{h*} I_h * {HDH_t}^2 \\
& + \sum_{m=1}^{12} m_m * I_m + \sum_{d=1}^{7} n_d * I_d + \sum_{h=1}^{24} p_h * I_h + \sum_{h=1}^{24} q_h * I_h * T_1 + \sum_{h=1}^{24} r_h * I_h * T_2 + \sum_{h=1}^{24} s_h \\
& * I_h * T_3 + \sum_{h=1}^{24} t_h * I_h * T_4 + \sum_{h=1}^{24} u_h * I_h * CDH_t * T_1 + \sum_{h=1}^{24} v_h * I_h * CDH_t * T_2 + \sum_{h=1}^{24} w_h \\
& * I_h * CDH_t * T_3 + \sum_{h=1}^{24} x_h * I_h * CDH_t * T_4 \sum_{h=1}^{24} y_h * I_h * CDH_t^2 * T_1 + \sum_{h=1}^{24} z_h * I_h \\
& * CDH_t^2 * T_2 + \sum_{h=1}^{24} \alpha_h * I_h * CDH_t^2 * T_3 + \sum_{h=1}^{24} \beta_h * I_h * CDH_t^2 * T_4 + \gamma_t
\end{aligned}
$$

The subscript *t* indicates time. Table 5-2 defines the variables and describes the effects they seek to identify.

---

power in this context where we do not need load estimates for every customer individually. The "autoregressive" component corrects for correlation in regression errors over time.

Table 5-2:
Description of Energy Use Regression Variables

Variable	Description
a-β	a-β are estimated parameters
I_m	Dummy variables for month of the year, designed to pick up seasonal effects
I_d	Dummy variables for day of the week, designed to pick up day of the week effects
I_h	Dummy variables representing the hours of the day, designed to estimate the effect of daily schedule on usage behavior
CDH	Cooling degree hours (defined as the maximum of 0 or temperature minus 65 degrees) which is correlated with cooling load.
CDH^2	The square of CDH, designed to identify nonlinearities in the relationship between temperature and usage behavior
HDH	Heating degree hours (defined as the maximum of 0 or 65 degrees minus temperature) which is correlated with heating load.
HDH^2	The square of HDH, designed to identify nonlinearities in the relationship between temperature and usage behavior
nightCDH	The sum of CDH from midnight to six am on a given day which identifies the effect of high overnight temperatures on energy usage the next day
T_1	Indicator variable for TOU rate during summer weekdays, designed to identify the effect of summer weekday pricing as compared to E1
T_2	Indicator variable for TOU rate during summer weekends, designed to identify the effect of summer weekend pricing as compared to E1
T_3	Indicator variable for TOU rate during winter weekdays, designed to identify the effect of winter weekday pricing as compared to E1
T_4	Indicator variable for TOU rate during winter weekends, designed to identify the effect of winter weekend pricing as compared to E1
γ	The error term

5.1.3. Model Accuracy and Validity Assessment

The most important feature of load impact analysis is the ability to predict accurately customer load and load reductions under the extreme conditions for which demand response is designed to provide a reliable resource. The accuracy of load impact estimates depend more on the accuracy of the regression coefficients representing the load impacts than on how well the regression predicts customer load. For TOU, it possible to not only to assess the accuracy of the models across temperature ranges, months, and prices – i.e., within customer comparisons- it was also possible to assess accuracy of the model for the control group.

Figure 5-2 shows the compares actual and regression predicted average hourly energy use of TOU participants for different summer weather conditions. It is a within group comparison for accuracy. The figure illustrates that the models perform well for both normal and high temperature conditions. The predict load under the same rate conditions mirrors the actual load across the hours of the day for both moderate and high temperatures. The figure also highlights the fact that the TOU group is weather sensitive. As temperature conditions increase, the TOU customer loads increase. This indicates they are not TOU solely customers with preferential load shapes. Many are weather sensitive and engage in load shifting over the peak period.

Figure 5-3 is similar, with one key difference – it compares how well the regression model explains the hourly load shapes of the both the TOU and matching control group for days over 90 F, when load response is more likely to be needed. The actual loads of the control group closely match the estimated reference load of the TOU customers. In addition, the regression estimates predict the loads of both the TOU and control group relatively well.

Figure 5-2
Comparisons of Regression Predicted and Actual Load
For Weekdays with Daily Maximum Temperatures above Selected Thresholds

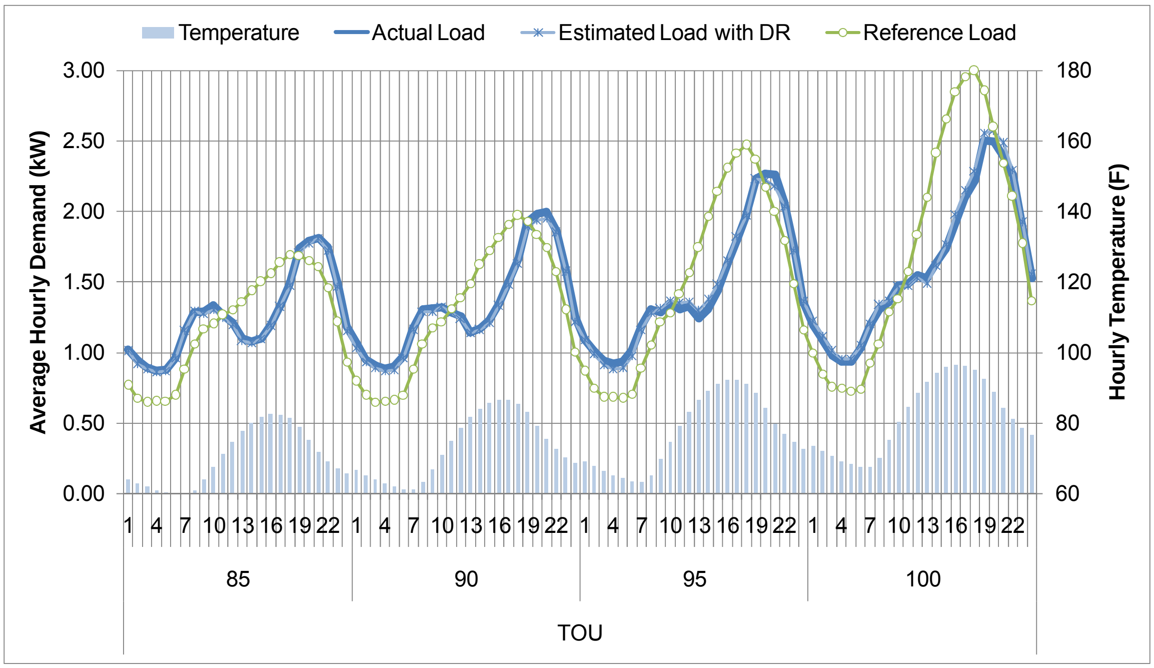

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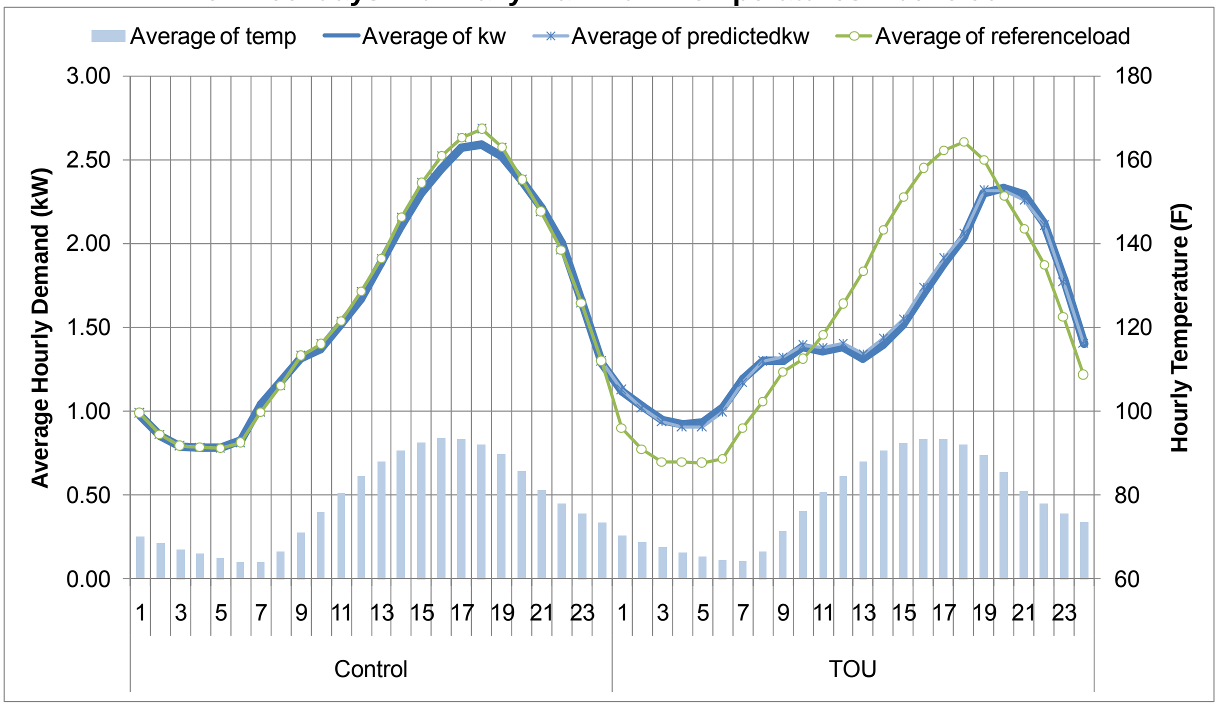
Figure 5-3
Comparisons of Regression Predicted and Actual Load
For Weekdays with Daily Maximum Temperatures Above 90°F



5.2. LOAD IMPACT RESULTS

This subsection presents the ex post load impact estimates for E7 customers who are on standard TOU meters. As noted in Section 2, the estimates presented do not apply to the 12,500 E7 customers who are net metered.

Table 5-3 shows the average change in peak-period energy use for a typical weekday for each month.[32] The peak period for the E7 tariff is from noon to 6 pm every week day and is the same in both summer and winter months. The average reduction across the year is 0.14 kW. The greatest average week day load reduction, 0.21 kW, occurs in September and the lowest average, 0.11 kW, is found in each month from November through April. The percentage reduction in peak period usage peaks in September, at 12.2%, and is lowest in December, at 6.8%. While the average kW reduction is essentially the same during all winter months, the percentage reduction varies.

[32] Keep in mind that the impacts are for October 2008 through the end of September 2009, as this is the time period covered by the available data.

Table 5-3:
Average Weekday Peak Period Load Reduction for the E7 Tariff by Month
(October 2008 through September 2009, Peak Period from noon to 6 pm)

Month	Reference Load	Estimated Load with DR	Impact	Percent Reduction	Average Temperature
	(kW)	(kW)	(kW)	(%)	(F)
Jan-09	1.40	1.29	0.11	7.6%	58.1
Feb-09	1.35	1.25	0.11	7.9%	57.3
Mar-09	1.24	1.13	0.11	8.6%	63.0
Apr-09	1.25	1.14	0.11	8.5%	66.9
May-09	1.36	1.22	0.14	10.0%	76.1
Jun-09	1.52	1.37	0.15	10.0%	77.6
Jul-09	1.91	1.70	0.20	10.7%	83.8
Aug-09	1.79	1.59	0.20	11.3%	83.4
Sep-09	1.72	1.51	0.21	12.2%	83.4
Oct-08	1.27	1.14	0.14	10.7%	75.4
Nov-08	1.26	1.15	0.11	8.5%	63.4
Dec-08	1.56	1.45	0.11	6.8%	52.4
Total	**1.47**	**1.33**	**0.14**	**9.6%**	**70.2**

Tables 5-4 and 5-5 show the load impact estimates for each hour for the average week day in each month. It should be noted that E7 customers display significantly higher loads during off peak hours relative to E1 customers, indicating that there is a good deal of load shifting occurring or that these customers own end use equipment, such as spas and swimming pools, that produce significant loads during off-peak hours.

Table 5-4
Average Weekday Hourly Impacts (kW) by Month for E7 Tariff
October 2008 to September 2009

Hour Ending	Jan 2009	Feb 2009	Mar 2009	Apr 2009	May 2009	Jun 2009	Jul 2009	Aug 2009	Sep 2009	Oct 2008	Nov 2008	Dec 2008	Average
1	-0.07	-0.07	-0.07	-0.07	-0.12	-0.12	-0.12	-0.12	-0.12	-0.12	-0.07	-0.07	-0.10
2	-0.08	-0.08	-0.08	-0.08	-0.12	-0.12	-0.12	-0.12	-0.12	-0.12	-0.08	-0.08	-0.10
3	-0.08	-0.08	-0.08	-0.08	-0.12	-0.12	-0.12	-0.12	-0.12	-0.12	-0.08	-0.08	-0.10
4	-0.08	-0.08	-0.08	-0.08	-0.11	-0.11	-0.11	-0.11	-0.11	-0.11	-0.08	-0.08	-0.09
5	-0.08	-0.08	-0.08	-0.08	-0.11	-0.11	-0.11	-0.11	-0.11	-0.11	-0.08	-0.08	-0.09
6	-0.12	-0.12	-0.12	-0.12	-0.13	-0.13	-0.13	-0.13	-0.13	-0.13	-0.12	-0.12	-0.13
7	-0.10	-0.10	-0.10	-0.10	-0.14	-0.14	-0.14	-0.14	-0.14	-0.14	-0.10	-0.10	-0.12
8	-0.04	-0.04	-0.04	-0.04	-0.11	-0.12	-0.12	-0.12	-0.11	-0.11	-0.04	-0.04	-0.08
9	0.04	0.04	0.04	0.04	-0.06	-0.06	-0.05	-0.06	-0.06	-0.06	0.04	0.04	-0.01
10	0.04	0.04	0.04	0.04	-0.06	-0.05	-0.05	-0.05	-0.05	-0.06	0.04	0.04	-0.01
11	0.08	0.08	0.08	0.08	0.01	0.01	0.01	0.01	0.02	0.01	0.08	0.08	0.04
12	0.07	0.07	0.07	0.07	0.05	0.06	0.07	0.07	0.07	0.05	0.07	0.07	0.06
13	0.13	0.13	0.13	0.13	0.13	0.14	0.17	0.17	0.17	0.12	0.13	0.13	0.14
14	0.15	0.15	0.15	0.15	0.16	0.17	0.22	0.22	0.23	0.16	0.15	0.15	0.17
15	0.13	0.13	0.13	0.13	0.17	0.18	0.24	0.24	0.25	0.17	0.13	0.13	0.17
16	0.11	0.11	0.11	0.11	0.15	0.17	0.23	0.23	0.24	0.15	0.11	0.11	0.15
17	0.09	0.09	0.09	0.09	0.13	0.15	0.20	0.20	0.21	0.13	0.09	0.09	0.13
18	0.04	0.04	0.04	0.04	0.09	0.11	0.16	0.16	0.16	0.09	0.04	0.04	0.08
19	-0.03	-0.03	-0.03	-0.03	-0.02	-0.01	0.02	0.02	0.01	-0.02	-0.03	-0.03	-0.02
20	-0.06	-0.06	-0.06	-0.06	-0.06	-0.06	-0.05	-0.05	-0.05	-0.06	-0.06	-0.06	-0.06
21	-0.07	-0.07	-0.07	-0.07	-0.10	-0.10	-0.10	-0.10	-0.10	-0.09	-0.07	-0.07	-0.09
22	-0.07	-0.07	-0.07	-0.07	-0.12	-0.12	-0.13	-0.13	-0.13	-0.12	-0.07	-0.07	-0.10
23	-0.07	-0.07	-0.07	-0.07	-0.12	-0.12	-0.13	-0.13	-0.13	-0.11	-0.07	-0.07	-0.10
24	-0.07	-0.07	-0.07	-0.07	-0.11	-0.11	-0.11	-0.11	-0.11	-0.11	-0.07	-0.07	-0.09
Total	**-0.01**	**-0.01**	**-0.01**	**-0.01**	**-0.03**	**-0.03**	**-0.01**	**-0.01**	**-0.01**	**-0.03**	**-0.01**	**-0.01**	**-0.01**

Table 5-5
Average Weekday Hourly Percent Load Reduction Month for E7 Tariff
October 2008 to September 2009

Hour Ending	Jan 2009	Feb 2009	Mar 2009	Apr 2009	May 2009	Jun 2009	Jul 2009	Aug 2009	Sep 2009	Oct 2008	Nov 2008	Dec 2008	Average
1	-8.1%	-8.3%	-9.3%	-10.2%	-17.3%	-15.2%	-12.4%	-13.5%	-15.2%	-18.4%	-8.9%	-7.3%	-11.9%
2	-9.9%	-10.2%	-11.6%	-12.9%	-19.2%	-16.8%	-14.0%	-15.5%	-17.6%	-20.3%	-11.0%	-8.9%	-13.8%
3	-9.7%	-10.0%	-11.5%	-13.0%	-20.0%	-17.5%	-14.6%	-16.1%	-18.7%	-21.1%	-11.0%	-8.6%	-14.0%
4	-9.4%	-9.7%	-11.0%	-12.4%	-17.7%	-15.6%	-13.1%	-14.3%	-16.6%	-18.4%	-10.5%	-8.5%	-12.8%
5	-9.0%	-9.2%	-10.5%	-11.9%	-17.6%	-15.6%	-13.3%	-14.7%	-16.8%	-18.2%	-10.1%	-8.1%	-12.4%
6	-12.1%	-12.5%	-14.2%	-16.0%	-20.3%	-18.2%	-15.6%	-17.2%	-19.5%	-20.7%	-13.7%	-11.1%	-15.5%
7	-7.3%	-7.5%	-8.5%	-9.4%	-15.9%	-14.7%	-13.1%	-14.2%	-15.6%	-15.7%	-8.3%	-6.8%	-10.8%
8	-2.5%	-2.6%	-2.9%	-3.2%	-10.9%	-10.4%	-9.5%	-10.1%	-10.8%	-10.6%	-2.8%	-2.3%	-5.9%
9	2.2%	2.2%	2.5%	2.7%	-4.9%	-4.5%	-4.0%	-4.4%	-4.7%	-4.9%	2.5%	2.0%	-0.7%
10	2.4%	2.4%	2.7%	2.9%	-4.8%	-4.4%	-3.8%	-4.1%	-4.4%	-4.9%	2.7%	2.2%	-0.7%
11	4.9%	5.0%	5.6%	6.0%	0.6%	0.8%	1.0%	0.9%	1.2%	0.4%	5.5%	4.5%	3.1%
12	4.6%	4.7%	5.2%	5.5%	3.9%	4.1%	4.5%	4.7%	5.3%	3.8%	5.2%	4.2%	4.6%
13	8.7%	9.0%	9.8%	10.2%	10.0%	9.9%	10.2%	10.7%	11.7%	10.3%	9.7%	7.9%	9.8%
14	10.5%	10.8%	11.7%	11.8%	12.1%	11.9%	12.4%	13.1%	14.1%	12.7%	11.5%	9.6%	11.9%
15	9.8%	10.0%	10.9%	10.7%	12.6%	12.3%	13.0%	13.7%	14.9%	13.5%	10.6%	8.8%	11.9%
16	8.4%	8.6%	9.4%	9.1%	11.1%	11.0%	11.8%	12.5%	13.5%	12.1%	9.1%	7.5%	10.6%
17	6.8%	7.1%	7.7%	7.5%	9.0%	9.2%	9.9%	10.5%	11.3%	9.9%	7.6%	6.1%	8.8%
18	2.5%	2.6%	2.9%	2.9%	5.8%	6.4%	7.6%	8.0%	8.5%	6.1%	2.9%	2.2%	5.1%
19	-1.9%	-1.9%	-2.2%	-2.2%	-1.3%	-0.4%	0.9%	0.8%	0.7%	-1.3%	-2.2%	-1.7%	-0.9%
20	-3.4%	-3.5%	-3.9%	-4.0%	-4.1%	-3.3%	-2.2%	-2.5%	-3.0%	-4.3%	-3.9%	-3.0%	-3.4%
21	-4.4%	-4.5%	-4.9%	-5.1%	-6.5%	-5.9%	-5.2%	-5.5%	-5.9%	-6.5%	-4.9%	-4.0%	-5.3%
22	-4.8%	-4.9%	-5.4%	-5.6%	-8.8%	-8.4%	-7.7%	-8.0%	-8.5%	-8.9%	-5.3%	-4.4%	-6.7%
23	-5.3%	-5.5%	-6.0%	-6.3%	-10.3%	-9.8%	-8.9%	-9.2%	-10.0%	-10.5%	-5.9%	-4.8%	-7.7%
24	-6.7%	-6.9%	-7.6%	-8.2%	-13.2%	-11.7%	-9.4%	-10.0%	-11.1%	-13.8%	-7.4%	-6.0%	-9.2%
Total	**-0.5%**	**-0.5%**	**-0.6%**	**-0.6%**	**-2.7%**	**-2.1%**	**-0.7%**	**-0.8%**	**-0.7%**	**-2.8%**	**-0.6%**	**-0.5%**	**-1.0%**

Table 5-6 shows the average load reduction on monthly system peak days for E7 customers. The percentage load reductions are comparable to those observed on the average week day and the absolute load reductions during winter months are nearly identical on the average week day and the monthly system peak day. However, the absolute peak-period load reduction during the key summer months of June through August are significantly higher than on the average week day. For example, the peak period reduction on the July system peak day is 0.36 kW, which is approximately 80% higher than the peak-period reduction on an average week day.

Table 5- 6:
E7 Monthly System Peak Day Load Reductions by Month (12-6 pm)
October 2008 to September 2009

Month	Reference Load	Estimated Load with DR	Impact	Percent Reduction	Avg. Temp
	(kW)	(kW)	(kW)	(%)	(F)
Jan-09	1.49	1.59	0.11	7.2%	45.9
Feb-09	1.40	1.50	0.11	7.6%	51.9
Mar-09	1.11	1.22	0.11	9.6%	58.8
Apr-09	1.57	1.67	0.11	6.8%	83.9
May-09	2.25	2.53	0.27	12.2%	94.1
Jun-09	2.20	2.56	0.36	16.4%	93.1
Jul-09	2.42	2.83	0.40	16.6%	95.5
Aug-09	2.21	2.55	0.34	15.4%	92.6
Sep-09	2.13	2.50	0.37	17.3%	94.0
Oct-08	1.31	1.51	0.20	15.3%	84.2
Nov-08	1.19	1.30	0.11	9.0%	73.9
Dec-08	1.68	1.79	0.11	6.3%	45.3
Total	**1.78**	**2.00**	**0.22**	**12.3%**	**76.5**

Tables 5-7 and 5-8 show the E7 load impacts and percent load reductions for each hour of each monthly system peak day. The impacts for the off-peak hours are consistently lower throughout the peak period and higher during off peak. This is true for summer and winter months. However, winter peak period load reductions are lower during winter months, as expected, due to smaller differences between peak and off-peak prices. The period from 11am-12pm and from 6-7pm also show load reduction for most months even though they are subject to off-peak. Both hours are immediately adjacent to the peak period and the impacts are likely due to a transition of customer to and from the peak period.

Table 5-7
TOU (E7) Monthly System Peak Day Hourly Impacts (kW)
October 2008 to September 2009

Hour Ending	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Average
	2009	2009	2009	2009	2009	2009	2009	2009	2009	2008	2008	2008	
1	-0.07	-0.07	-0.07	-0.07	-0.11	-0.11	-0.11	-0.11	-0.11	-0.12	-0.07	-0.07	-0.09
2	-0.08	-0.08	-0.08	-0.08	-0.13	-0.13	-0.13	-0.13	-0.12	-0.12	-0.08	-0.08	-0.11
3	-0.08	-0.08	-0.08	-0.08	-0.12	-0.12	-0.13	-0.13	-0.12	-0.12	-0.08	-0.08	-0.10
4	-0.08	-0.08	-0.08	-0.08	-0.09	-0.10	-0.10	-0.10	-0.10	-0.11	-0.08	-0.08	-0.09
5	-0.08	-0.08	-0.08	-0.08	-0.10	-0.11	-0.11	-0.11	-0.11	-0.11	-0.08	-0.08	-0.09
6	-0.12	-0.12	-0.12	-0.12	-0.12	-0.13	-0.15	-0.14	-0.13	-0.13	-0.12	-0.12	-0.13
7	-0.10	-0.10	-0.10	-0.10	-0.10	-0.13	-0.14	-0.14	-0.14	-0.14	-0.10	-0.10	-0.11
8	-0.04	-0.04	-0.04	-0.04	-0.12	-0.13	-0.13	-0.12	-0.11	-0.11	-0.04	-0.04	-0.08
9	0.04	0.04	0.04	0.04	-0.05	-0.04	-0.04	-0.04	-0.05	-0.06	0.04	0.04	0.00
10	0.04	0.04	0.04	0.04	-0.07	-0.04	-0.04	-0.04	-0.05	-0.05	0.04	0.04	-0.01
11	0.08	0.08	0.08	0.08	0.02	0.04	0.05	0.04	0.04	0.02	0.08	0.08	0.06
12	0.07	0.07	0.07	0.07	0.11	0.14	0.16	0.14	0.13	0.08	0.07	0.07	0.10
13	0.13	0.13	0.13	0.13	0.23	0.28	0.32	0.29	0.28	0.18	0.13	0.13	0.20
14	0.14	0.14	0.14	0.14	0.31	0.35	0.41	0.36	0.37	0.24	0.14	0.14	0.25
15	0.13	0.13	0.13	0.13	0.32	0.39	0.46	0.40	0.42	0.25	0.13	0.13	0.25
16	0.11	0.11	0.11	0.11	0.31	0.40	0.44	0.38	0.42	0.22	0.11	0.11	0.24
17	0.09	0.09	0.09	0.09	0.27	0.38	0.42	0.33	0.38	0.18	0.09	0.09	0.21
18	0.04	0.04	0.04	0.04	0.22	0.35	0.36	0.28	0.33	0.12	0.04	0.04	0.16
19	-0.03	-0.03	-0.03	-0.03	0.08	0.16	0.15	0.08	0.12	-0.01	-0.03	-0.03	0.04
20	-0.06	-0.06	-0.06	-0.06	-0.02	0.02	0.01	-0.02	-0.01	-0.06	-0.06	-0.06	-0.03
21	-0.07	-0.07	-0.07	-0.07	-0.08	-0.06	-0.07	-0.09	-0.09	-0.10	-0.07	-0.07	-0.08
22	-0.07	-0.07	-0.07	-0.07	-0.09	-0.09	-0.10	-0.13	-0.12	-0.14	-0.07	-0.07	-0.09
23	-0.07	-0.07	-0.07	-0.07	-0.09	-0.06	-0.09	-0.12	-0.11	-0.14	-0.07	-0.07	-0.08
24	-0.07	-0.07	-0.07	-0.07	-0.09	-0.09	-0.09	-0.10	-0.10	-0.11	-0.07	-0.07	-0.08
Total	**-0.01**	**-0.01**	**-0.01**	**-0.01**	**0.02**	**0.05**	**0.06**	**0.03**	**0.04**	**-0.01**	**-0.01**	**-0.01**	**0.01**

Table 5-8
TOU (E7) Monthly System Peak Day Hourly Percent Load Reductions
October 2008 to September 2009

Hour Ending	Jan 2009	Feb 2009	Mar 2009	Apr 2009	May 2009	Jun 2009	Jul 2009	Aug 2009	Sep 2009	Oct 2008	Nov 2008	Dec 2008	Average
1	-7.6%	-7.8%	-9.4%	-10.1%	-12.0%	-11.2%	-10.2%	-10.9%	-12.3%	-18.0%	-9.2%	-6.9%	-10.1%
2	-9.2%	-9.6%	-11.6%	-13.1%	-16.8%	-15.2%	-13.6%	-14.8%	-16.0%	-20.8%	-11.3%	-8.4%	-13.1%
3	-9.0%	-9.3%	-11.4%	-13.8%	-17.8%	-16.0%	-14.3%	-15.5%	-16.9%	-21.6%	-11.3%	-8.1%	-13.3%
4	-8.8%	-9.1%	-10.9%	-13.8%	-13.2%	-13.1%	-11.9%	-12.8%	-14.8%	-19.1%	-11.0%	-8.1%	-11.7%
5	-8.4%	-8.6%	-10.3%	-13.6%	-14.9%	-15.6%	-12.9%	-14.3%	-17.0%	-19.0%	-10.7%	-7.8%	-12.2%
6	-11.4%	-11.7%	-13.8%	-19.0%	-16.8%	-16.8%	-16.8%	-17.6%	-19.7%	-22.1%	-14.8%	-10.7%	-15.3%
7	-7.0%	-7.1%	-8.1%	-12.4%	-11.0%	-14.4%	-13.0%	-13.9%	-15.7%	-17.2%	-9.4%	-6.7%	-10.5%
8	-2.4%	-2.4%	-2.7%	-4.3%	-11.5%	-12.6%	-11.2%	-11.1%	-11.0%	-11.7%	-3.2%	-2.3%	-6.4%
9	2.0%	2.1%	2.4%	3.3%	-3.8%	-3.1%	-2.8%	-3.3%	-4.1%	-5.2%	2.7%	1.9%	-0.3%
10	2.2%	2.2%	2.6%	3.3%	-5.4%	-2.9%	-2.6%	-3.0%	-3.5%	-4.8%	2.9%	2.0%	-0.4%
11	4.5%	4.6%	5.5%	6.3%	1.2%	2.8%	3.2%	2.7%	2.5%	1.5%	5.9%	4.2%	3.7%
12	4.1%	4.3%	5.2%	5.2%	6.4%	7.6%	8.1%	7.5%	7.7%	6.5%	5.3%	3.7%	6.1%
13	7.8%	8.1%	9.8%	8.8%	11.3%	13.7%	14.2%	13.6%	14.5%	14.0%	9.7%	7.0%	11.3%
14	9.5%	9.9%	11.8%	9.3%	13.1%	15.5%	16.0%	15.3%	16.5%	16.8%	11.1%	8.6%	13.2%
15	8.7%	9.2%	11.0%	7.7%	12.4%	15.8%	16.3%	15.6%	17.0%	16.6%	9.9%	7.8%	13.0%
16	7.4%	7.8%	9.6%	6.2%	11.4%	14.7%	14.7%	13.9%	15.5%	14.2%	8.6%	6.5%	11.7%
17	5.9%	6.3%	7.9%	5.1%	9.7%	13.3%	13.3%	12.1%	13.8%	11.4%	7.3%	5.2%	10.1%
18	2.1%	2.2%	2.9%	2.1%	8.0%	11.9%	11.5%	10.0%	11.8%	7.4%	2.9%	1.8%	7.3%
19	-1.6%	-1.7%	-2.2%	-1.8%	3.0%	5.6%	5.0%	3.1%	4.5%	-0.9%	-2.3%	-1.4%	1.6%
20	-2.9%	-3.1%	-3.8%	-3.3%	-0.7%	0.9%	0.5%	-1.0%	-0.5%	-4.0%	-4.0%	-2.7%	-1.5%
21	-3.9%	-4.1%	-4.9%	-4.5%	-3.7%	-2.6%	-2.9%	-4.3%	-4.0%	-6.8%	-5.0%	-3.6%	-3.9%
22	-4.4%	-4.6%	-5.4%	-5.0%	-4.9%	-4.2%	-4.5%	-6.6%	-6.2%	-9.9%	-5.4%	-4.0%	-5.1%
23	-4.8%	-5.0%	-6.0%	-5.7%	-5.8%	-3.7%	-4.6%	-7.4%	-6.8%	-11.9%	-5.9%	-4.4%	-5.6%
24	-6.1%	-6.4%	-7.6%	-7.7%	-7.9%	-6.9%	-6.3%	-7.7%	-8.0%	-11.9%	-7.5%	-5.6%	-7.2%
Total	**0.0%**	**0.0%**	**0.0%**	**0.0%**	**0.0%**	**0.0%**	**0.0%**	**0.0%**	**0.0%**	**0.0%**	**0.0%**	**0.0%**	**0.0%**

6. SMARTAC EX POST IMPACT ANALYSIS

As discussed in Section 2, SmartAC is an emergency program that to date has been called infrequently. Few events have dispatched the full load reduction capability of the program, though research samples have dispatched far more frequently to better understand customer load reduction and the potential of the program for providing ancillary service in the California ISO market. The only event called in 2009 was a test event on September 10th. The control period on this date was from 3 pm to 7 pm. Sections 6.1 and 6.2 present estimates of the ex post load impacts for residential SmartAC customers. Section 6.3 presents estimates of the ex post load impacts for non-residential SmartAC customers.

6.1. ANALYSIS APPROACH

Under contract to PG&E, FSC selected a sample of SmartAC participants and installed end-use loggers on the air conditioning units for these households to obtain data for use in both ex post and ex ante load impact analysis for 2009. Unfortunately, a programming error by PG&E's SmartAC program contractor created a situation where the switches and PCTs that control air conditioners for the research sample did not operate when signaled. Thus, the original evaluation plan, which would have provided a more robust database for analysis, had to be abandoned.

The load impact estimates for residential customers presented here were based on analysis of whole building energy use for a sample of SmartAC participants for which SmartMeters had been installed prior to the September 10th event date. The sample was reweighted to properly represent the distribution of SmartAC customers across climate regions.

Whole-building energy use was analyzed using regression methods to isolate the effect of the September 10, 2009 SmartAC event. Our primary interest is in the air conditioning component of the whole-building use. The air conditioning component is also what we are best able to model because it varies strongly with weather, which is observable for all customers. This fact drives the model specification, which is heavily weather-dependent. The regression also includes various hourly and seasonal variable designed to quantify weather insensitive patterns tied to average occupancy schedule. These variables describe changes in energy use but do not explain the underlying end use driving the electricity consumption. This is because we cannot observe such variables. Regardless, identifying these energy use patterns, despite not being able to explain the underlying driver is critical because both air conditioner use and other household loads are directly related to occupancy patterns.

Each customer has a different usage pattern over time, and each customer's usage is likely to respond differently to changes in weather. This led us to estimate separate regressions for each customer in the sample, but using a common regression model in each case. For all customers, factors used to estimate whole-building usage patterns included two basic types of variables:

- Indicator variables that equal one at particular times; for example, between one and two pm on weekdays. These allow the model to account for different average, weather insensitive customer usage at various times of day, times of the week and times of year;

- Weather variables interacted with time indicators. These allow the model to take into account different customer reactions to weather conditions at different times of day, times of the week and times of year. For example, a residential customer's energy usage might respond strongly to high temperatures on a Saturday afternoon when he/she is at home, while it might not respond at all on a Wednesday afternoon when he/she is at work;

The final regression model of whole-building usage for residential customers is quite rich in that it allows for many different types of time-based and temperature-based effects. The specific type of regression used was the Prais-Winsten regression, which takes into account correlation in the error term over time. The model for a given individual customer is:

$$
\begin{aligned}
Usage_t &= a + b * rh_t + \sum_{m=5}^{9}\sum_{h=1}^{24} c_{mh} * I_m * I_h + \sum_{d=1}^{5}\sum_{h=1}^{24} d_{dh} * I_d * I_h + \sum_{w=1}^{2}\sum_{h=1}^{24} e_{wh} * I_w * I_h * CDH_t \\
&+ \sum_{w=1}^{2}\sum_{h=1}^{24} f_{wh} * I_w * I_h * (CDH_t)^2 + \sum_{w=1}^{2}\sum_{h=1}^{24} g_{wh} * I_w * I_h * CDH_t * CDD_t \\
&+ \sum_{w=1}^{2}\sum_{h=1}^{24} h_{wh} * I_w * I_h * (CDH_t * CDD_t)^2 + \sum_{h=1}^{24} i_h * I_h * CDD_t + \sum_{h=1}^{24} j_h I_h * (CDD_t)^2 \\
&+ \sum_{h=1}^{24} k_h * I_h * (CDD_t)^3 + \sum_{w=1}^{2}\sum_{m=6}^{9} l_{wm} * I_w * I_m * CDH_t + \sum_{w=1}^{2}\sum_{h=1}^{24} m_{wh} * I_w * I_h * CDH_t * nightCDH_t + U_t
\end{aligned}
$$

The subscript *t* indicates time. Table 6-1 defines the variables and describes the effects they seek to identify.

Table 6-1:
Description of AC Load Regression Variables

Variable	Description
a	a is an estimated constant
b-m	b-v are estimated parameters
rh	Relative humidity which is correlated with AC usage behavior
I_m	Dummy variables for month of the year, designed to pick up seasonal effects
I_d	Dummy variables for day type, designed to pick up day of the week effects
I_w	Dummy variables designed to pick up weekend versus weekday effects
I_h	Dummy variables representing the hours of the day, designed to estimate the effect of daily schedule on usage behavior
CDH	Cooling degree hours (defined as the maximum of 0 or temperature – base temperature) which is correlated with cooling load. Base temperature is chosen based on the best fitting base for each customer
CDH^2	The square of CDH, designed to identify nonlinearities in the relationship between temperature and usage behavior
CDD	Cooling degree days (defined as the daily sum of cooling degree hours) which is correlated with cooling load and which identifies the effect of prolonged heat versus short term heat. Base temperature is chosen based on the best fitting base for each customer
CDD^2	The square of CDD, designed to identify nonlinearities in the relationship between CDD and usage behavior
CDD^3	The cube of CDD, designed to identify nonlinearities in the relationship between CDD and usage behavior
nightCDH	The sum of CDH from midnight to six am on a given day which identifies the effect of high overnight temperatures on energy usage the next day
U	The error term

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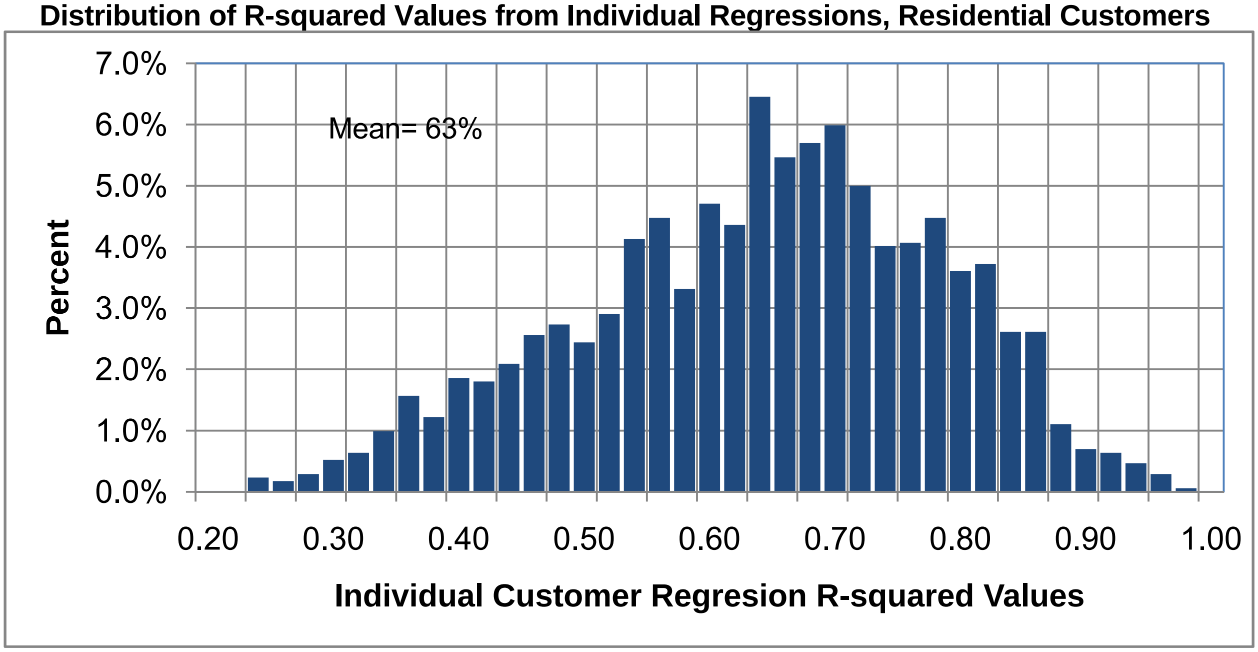
6.1.1. Goodness of Fit Measures

Although the regressions were performed at the individual customer level, from a policy standpoint, the focus is less on how the regressions perform for individual customers than on how the regressions perform for the average participant and for specific customer segments. Overall, individual customers exhibited more variation and less consistent energy use patterns than the aggregate participant population. Likewise, the regressions explained better the variation in electricity consumption and load impacts for the average customer (or average customer within a specific segment) than for individual customers. Put differently, it is more difficult to explain fully how a specific customer behaves on an hourly basis than it is to explain how the average customer behaves on an hourly basis. Because of this, we present measures of the explained variation, as described by the R-squared goodness-of-fit statistic, for the individual regressions and for specific segments as well as for the average customer.

Figure 6-1 shows the distribution of R-squared values from the individual residential customer regressions. The average R-squared among the residential customer regressions is 63%. The maximum R-squared is 96% and the minimum is 22%. Over 75% of the regressions have R-squared values above 50%. This means that even at an individual level, the model explains over half of the variation in load for the bulk of the population.

Figure 6-1
Distribution of R-squared Values from Individual Regressions, Residential Customers



While the individual customer regressions do a reasonably good job of explaining the variation in electricity use, in aggregate, nearly all of the variation in energy use across hours is explained by the model specification. When the predicted and actual values are aggregated across the individual results, the model explains 99% of the variation in energy use. Put another way, only about 1% of the variation in energy use over time is explained by variables that are not included in the model. In order to estimate the average customer R-squared values, the regression-predicted and actual electricity usage values were averaged across all customers for each date and hour. This process produced regression predicted and actual values for the average customer, which enabled the calculation of errors for the average customer and the calculation of the R-squared value. The same process was performed to estimate the amount of explained variation for the average customer in specific segments. The R-squared values for the average participant and for the average customer by segment were estimated using the following formula:

$$R^2 = 1 - \frac{\sum_t (\hat{y}_t - y_t)^2}{\sum_t (\hat{y}_t - \bar{y})^2}$$

Where:

y_t is the actual energy use at time t

$\hat{y}_t$ is the regression predicted energy use at time t

$\bar{y}$ is the actual mean energy use across all time periods.

Table 6-2 summarizes the amount of variation explained by the regression model for the average customer by device type and by local capacity area. The lowest value in the table is 87% for PCTs among customers in Sierra. The highest value is 99% for switches among residential customers in Greater Fresno.

Table 6-2
R-squared For Aggregate Load Data by Device Type and LCA

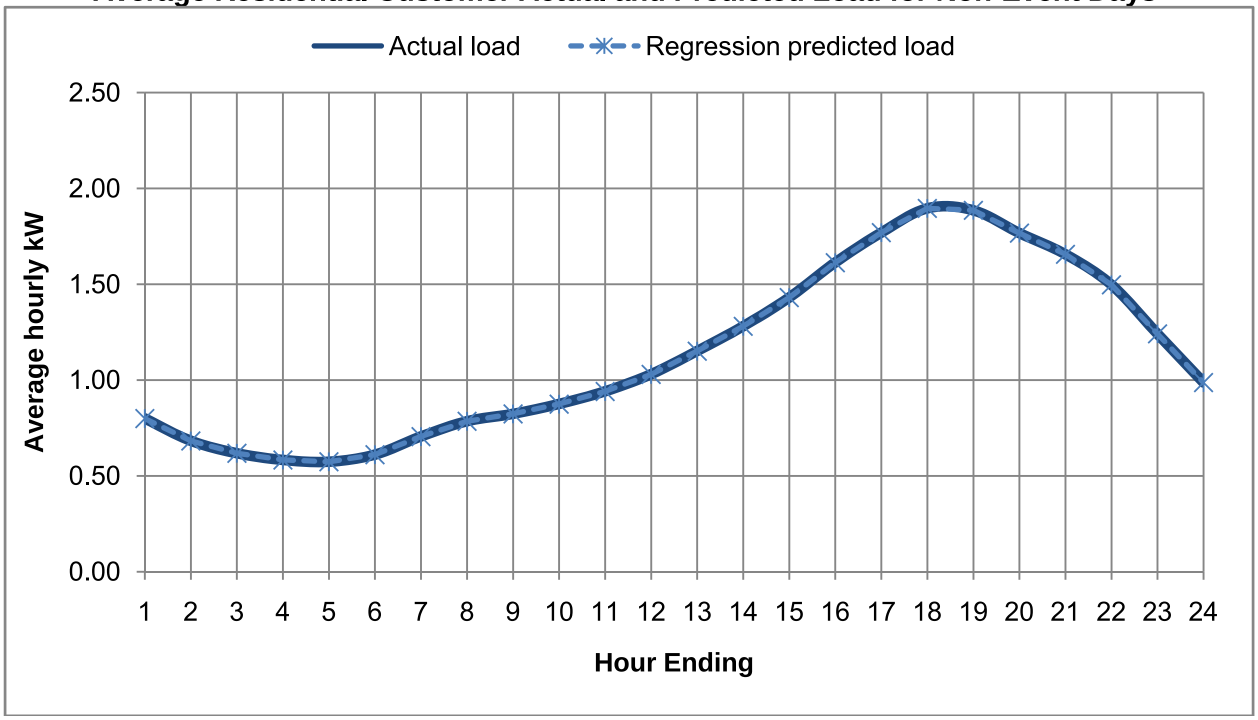
LCA	PCT	Switch	Total
Greater Bay Area	0.95	0.97	0.97
Greater Fresno	0.98	0.99	0.99
Kern	0.96	0.91	0.96
Other	0.94	0.97	0.97
Sierra	0.87	0.97	0.97
Stockton	0.95	0.97	0.97
Total	**0.99**	**0.99**	**0.99**

6.1.2. Model Accuracy and Validity Assessment

The most important feature of load impact analysis is the ability to predict accurately customer load and load reductions under the extreme conditions for which demand response is designed to provide a reliable resource. The accuracy of load impact estimates depends directly on the ability of the model to predict load during event periods. To assess the accuracy and validity of the model, we compared actual and predicted average load values across hour and temperature. These diagnostics reinforce the evidence that the impact estimates are accurate, on the average.

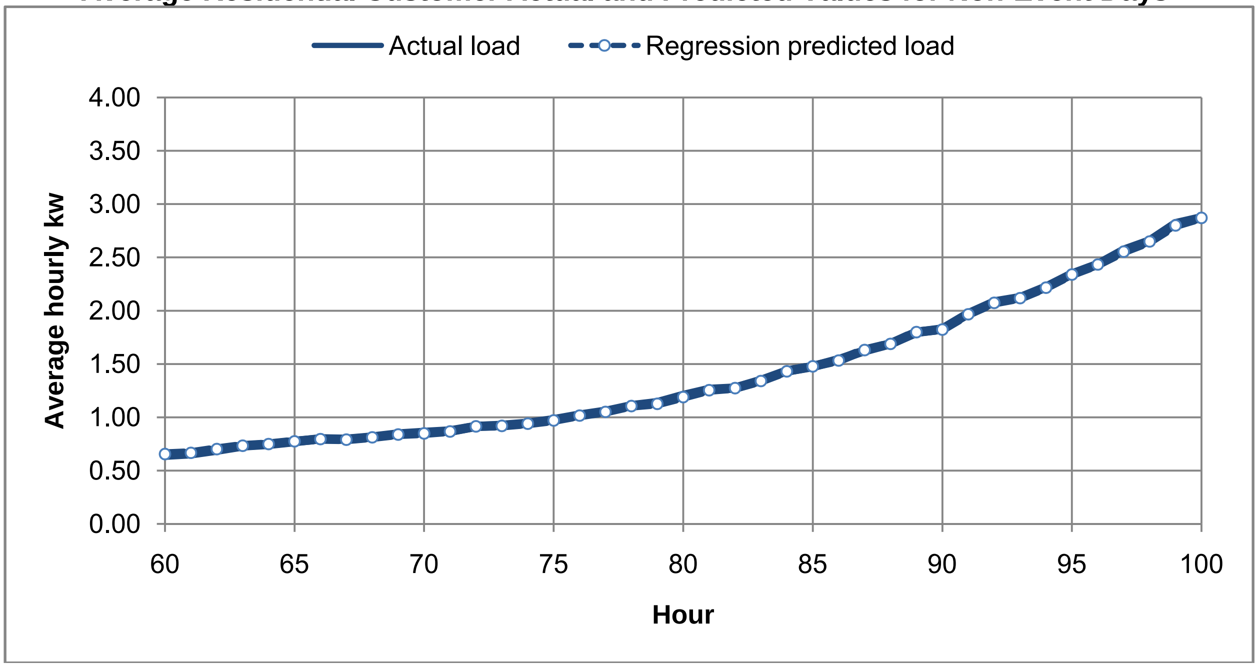
Figure 6-2 shows the actual average hourly energy use of residential customers on non-event days compared to the regression predicted average customer energy use. The close match between predicted values and actual values reflects the ability of the regressions to predict accurately overall.

Figure 6-2
Average Residential Customer Actual and Predicted Load for Non-Event Days



In addition to accuracy across hours of the day, accurately estimated impacts require predicted loads to be accurate across different temperature conditions. Figure 6-3 shows that the predicted loads match the actual loads quite well across a wide range of temperatures on non-event days. On the event day, reference loads naturally deviate from actual loads at high temperatures due to the event itself and the snap-back effect after the event.

Figure 6-3
Average Residential Customer Actual and Predicted Values for Non-Event Days



Similar comparisons of actual and predicted values were conducted by month, day of week, individual days, and various other iterations – all of which indicated that the results were not only unbiased for the average day and average customer, but also unbiased across multiple customer segments and temporal characteristics.

6.1.3. Bias Correction

Figure 6-4 compares the actual load and reference load by hour on the single event day—September 10, 2009. Despite the high overall predictive power, matching predicted reference load to observed load in the pre-event hours on one particular day may not be possible using a finite dataset. For example, in the 2008 SmartAC ex post results[33], reference loads match observed loads very well on certain event days—mainly the hottest days—but do not match well at all on others[34]. For a model to have predictive value, it must make generalizations about what load shapes will be like at particular times and particular temperatures. Inevitably, this means that the model cannot possibly fit all days perfectly.

In this case, our regression model does not fit the pre-event observed load perfectly for residential customers on September 10, 2009. There is a noticeable upward bias in the reference load of approximately 0.2 kW (when averaged over all customers). Essentially, this means that on similarly hot days during the summer of 2009, residential customers tended to use more AC load in the morning and early afternoon than they did on September 10th. Alternatively, on those days

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[33] See load impact tables from KEMA's 2008 Ex-Post SmartAC report.
[34] This is true based on both KEMA's analysis of 2008 SmartAC data and FSC's.

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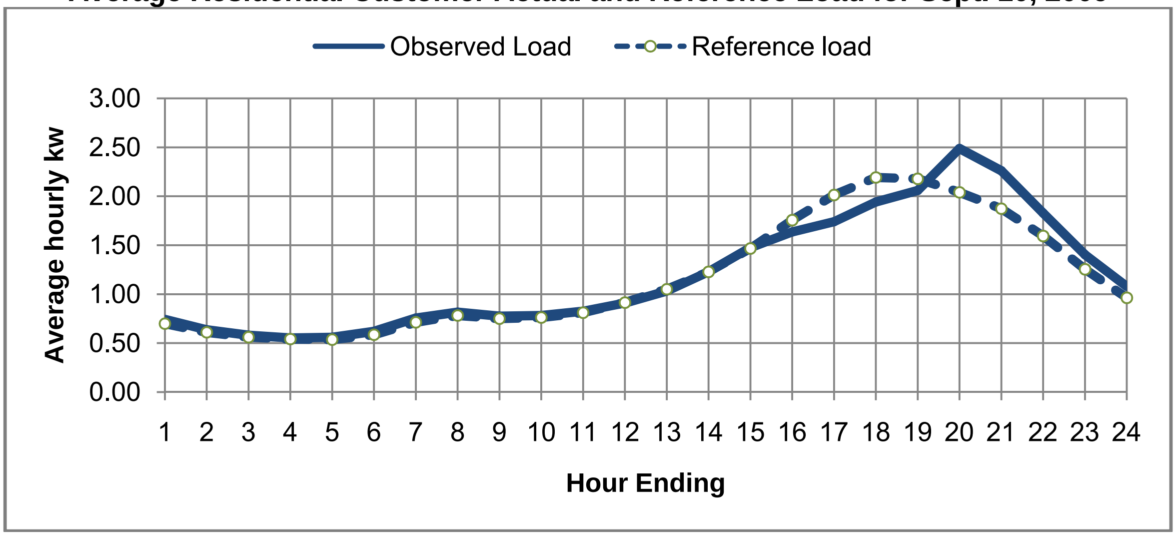
in which customers' morning and early afternoon AC load looked similar to that on September 10th, AC load never reached the level that it did on September 10th. FSC verified this result with several regression specifications, as well as several day-matching algorithms.

Figure 6-4
Average Residential Customer Actual and Reference Load for Sept. 10, 2009



In this correction, the reference load for the entire day was adjusted down by the average percent bias during the four hours immediately preceding the event (11 am-3 pm). By design, this adjustment varied according to the bias present in the relevant sample. Zone R, for example, required virtually no adjustment on average, while zone S required a small adjustment and zone X required a larger adjustment. As shown in Figure 6-3, the adjustment gives conservative, reference load shapes and impacts in light of the large air conditioner snapback immediately after the event.

The results shown in Figure 6-4, as well as those shown in the CPUC tables, reflect a bias correction that we believe reflects the actual event impact as accurately as possible given the available data. The bias was identified when hourly event day binary variables were specified for the entire day. The hours preceding the event showed an impact although the program had not been dispatched. In other words, the regressions were confounding error with event conditions since there was only one event.

A key difference between day matching methods and regression analysis is that the accuracy of the impacts are primarily the results of the regression parameters. Parameters may be unbiased despite error in the reference load for a particular day while day matching methods are highly sensitive the fit for the day and over and under predictions of the reference load can lead to substantially larger errors in the estimated load impacts.[35] With a single event day and no control

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[35] To better understand this, consider the following simplified example. If the accurate reference load and percent load reduction were 1000 MW and 15% respectively, an upward bias of 5% in the reference load estimates would result in load impact estimates of 200 MW (1050-850), an overestimate of 33% if the regression or day matching method is unable to distinguish the error from the impacts. If the impact coefficient is uncorrelated with the error, the same bias in the reference load would lead to either no error or,

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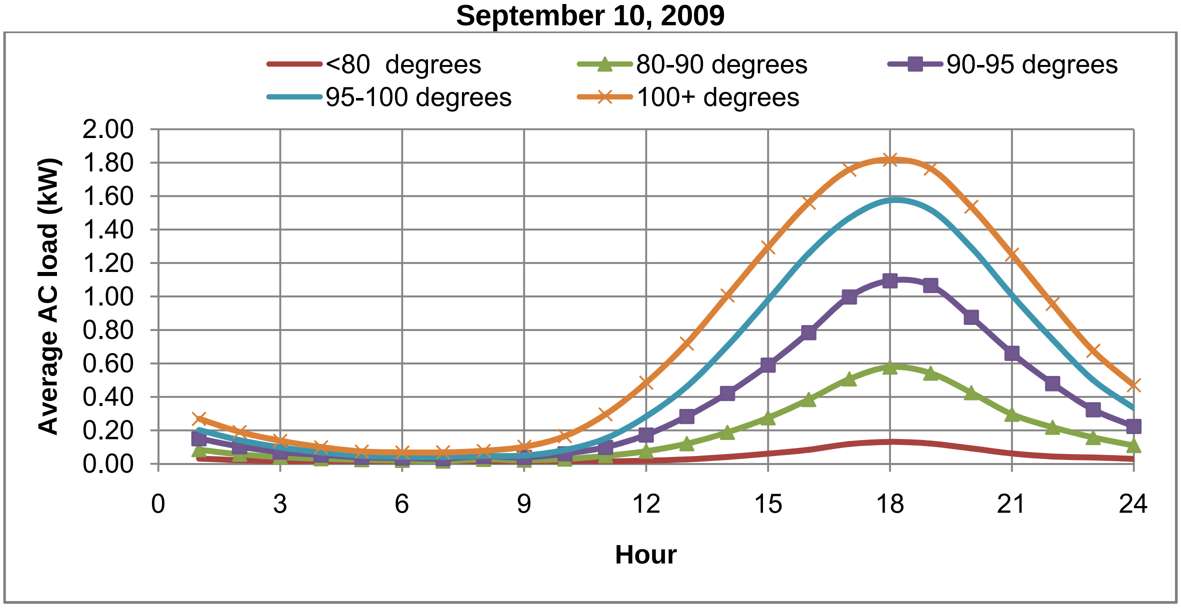
group, regression methods are essentially equivalent to day matching and become highly sensitive to any error in the reference load. With hourly impacts for a single event day, the regressions are unable to distinguish the impacts from the error in the reference loads.

6.2. RESIDENTIAL AIR CONDITIONER LOAD PATTERNS

Residential air conditioner load is highly sensitive to weather conditions. Importantly, the load reduction capability of the program is directly tied to the amount of air conditioner load. For SmartAC, participant behavior and targeting determines the load, but it is the control device that supplies the load reduction. In general, the cycling and control algorithms tend to provide larger percent load reductions at higher temperatures when air conditioner run times are higher. Air conditioner load and load reduction capability is higher for the extreme weather conditions that drive the system load peak and the need for DR.

Figure 6-5 illustrates the sensitivity of the air conditioner load to weather conditions. It reflects actual metered air conditioner load, weighted for the SmartAC participant population. The program average air conditioner hourly demand is almost twice as high in a day with a maximum temperature between 90 and 95 degrees than on a day with a maximum temperature between 80-90 degrees. On a day that exceeds 100° F, the air conditioner load is, on average, three times as high.

Figure 6-5
Hourly Average AC Load for Residential SmartAC Customers by Daily Maximum Temperature
September 10, 2009



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at most, an error of 5% because the impacts are based on the regression coefficients—that is, the load impacts reflect the difference between the predicted load with the demand response event and the load without the event.

6.3. RESIDENTIAL SMARTAC LOAD IMPACT RESULTS

Table 6-3 shows the hourly load impacts for the average residential SmartAC customer on September 10th, the only SmartAC event day held in 2009. The average estimated load reduction is 0.19 kW,[36] which constitutes about 10% of the total household load for this group of customers. As seen in Table 6-3, the load reduction across the four hour event window, from 3 pm until 7 pm, varies from a low of 0.12 kW in the first and last hour of the event, to 0.27 kW in the second hour and 0.25 kW in the third hour.

September 10th was a relatively cool day, with the average temperature across the four hour event period equal to only 93.8°F and the maximum temperature equal to only 95°F. By comparison, the maximum temperature is lower than maximum on 11 of the 15 SmartRate event days that were summarized in Table 3-2 in Section 3.

As seen in Figure 6-5 (above), average AC load per customer[37] varies at each hour of the day for and is higher with higher daily maximum temperatures. On a day with temperatures like those on September 10, average AC load peaks around 1.1 kW. In contrast, on the hottest days, average AC load peaks around 1.8 kW. The ex-post test event day was designed to test program operations, but it did not reflect the more extreme weather conditions that would lead to an actual event, nor did the estimated impacts for the day reflect the program load reduction potential. Although the test event day was relatively warm, temperatures were not as extreme as conditions that warrant an actual event. As a result, air conditioner loads were likely lower than under event conditions.

Clearly, impacts from September 10, 2009 should not be used to project SmartAC impacts at times of system peak or the program load reduction potential. Not only are average reference loads higher on hotter days, but impacts as a fraction of reference load will be higher as well because ACs will be running at higher duty cycles. In addition, the bias correction that was applied lowers impact estimates substantially, and, arguably, too much given the fact that air conditioner snapback exceeds event period load reductions by over 60 percent

Load impact estimates were developed separately for SmartAC customers with PCTs and switches. Recall from Section 2 that almost 80% of SmartAC households are controlled using switches, and the remaining 20% are controlled using PCTs. The average impact on September 10th for households with switches was 0.19 kW, or 9.5%. The average impact for households with PCTs was 0.21 kW, which is slightly higher in absolute terms than for households with switches. However, households with PCTs have higher whole-building reference loads (2.3 kW) than do households with switches (2.0 kW).

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[36] This is the average hourly ex-post load impact per customer for reporting purposes. Note that this number should not be used for capacity planning purposes.
[37] From the original 2009 SmartAC M&E Sample.

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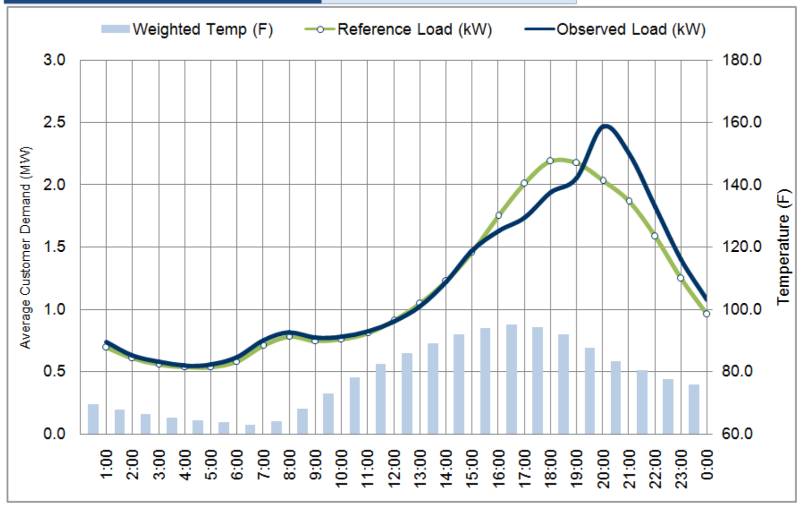
Table 6-3
Hourly Load Impacts for Residential SmartAC Customers
September 10, 2009

TABLE 1: Menu options

Type of Results	Average Customer
Customer Class	Residential
Device Type	All
Climate Region	All
Customer Type	All

TABLE 2: Event Day Information

Event Date	Tuesday, September 10, 2009
Event Start	3:00 PM
Event End	7:00 PM
TOTAL ENROLLED ACCOUNTS	106,621
Avg. Load Reduction for Event Window	0.19
% Load Reduction for Event Window	9%



Hour Ending	Reference Load (kW)	Observed Load (kW)	Load Impact (kW)	%Load Reduction	Weighted Temp (F)	Uncertainty Adjusted Impact - Percentiles				
						10th	30th	50th	70th	90th
1:00	0.69	0.74	-0.05	-6.8%	69.4	-0.07	-0.05	-0.05	-0.04	-0.03
2:00	0.61	0.63	-0.03	-4.2%	67.7	-0.04	-0.03	-0.03	-0.02	-0.01
3:00	0.56	0.58	-0.02	-3.7%	66.2	-0.04	-0.03	-0.02	-0.01	0.00
4:00	0.54	0.55	-0.01	-1.6%	65.3	-0.03	-0.02	-0.01	0.00	0.01
5:00	0.53	0.56	-0.02	-4.4%	64.4	-0.04	-0.03	-0.02	-0.02	-0.01
6:00	0.58	0.62	-0.04	-6.1%	63.8	-0.05	-0.04	-0.04	-0.03	-0.02
7:00	0.71	0.75	-0.04	-6.1%	62.9	-0.06	-0.05	-0.04	-0.04	-0.02
8:00	0.78	0.81	-0.03	-4.4%	64.0	-0.05	-0.04	-0.03	-0.03	-0.02
9:00	0.75	0.77	-0.03	-3.7%	68.2	-0.05	-0.03	-0.03	-0.02	-0.01
10:00	0.76	0.78	-0.02	-2.6%	73.0	-0.04	-0.03	-0.02	-0.01	0.00
11:00	0.81	0.82	-0.02	-2.2%	78.0	-0.04	-0.03	-0.02	-0.01	0.00
12:00	0.91	0.90	0.01	0.7%	82.5	-0.01	0.00	0.01	0.01	0.03
13:00	1.05	1.02	0.02	2.0%	86.0	0.00	0.01	0.02	0.03	0.04
14:00	1.22	1.22	0.00	0.2%	89.1	-0.02	-0.01	0.00	0.01	0.02
15:00	1.46	1.47	-0.01	-0.8%	92.0	-0.03	-0.02	-0.01	0.00	0.01
16:00	1.75	1.63	0.12	6.8%	94.0	0.10	0.11	0.12	0.13	0.14
17:00	2.01	1.73	0.27	13.7%	95.0	0.25	0.27	0.27	0.28	0.30
18:00	2.18	1.93	0.25	11.5%	94.1	0.23	0.24	0.25	0.26	0.27
19:00	2.17	2.05	0.12	5.5%	91.8	0.10	0.11	0.12	0.13	0.14
20:00	2.03	2.47	-0.44	-21.5%	87.7	-0.46	-0.45	-0.44	-0.43	-0.41
21:00	1.86	2.25	-0.39	-20.8%	83.2	-0.41	-0.40	-0.39	-0.38	-0.37
22:00	1.59	1.82	-0.24	-15.0%	80.4	-0.26	-0.25	-0.24	-0.23	-0.22
23:00	1.24	1.40	-0.15	-12.4%	77.6	-0.17	-0.16	-0.15	-0.15	-0.13
0:00	0.96	1.08	-0.12	-12.5%	75.8	-0.14	-0.13	-0.12	-0.11	-0.10

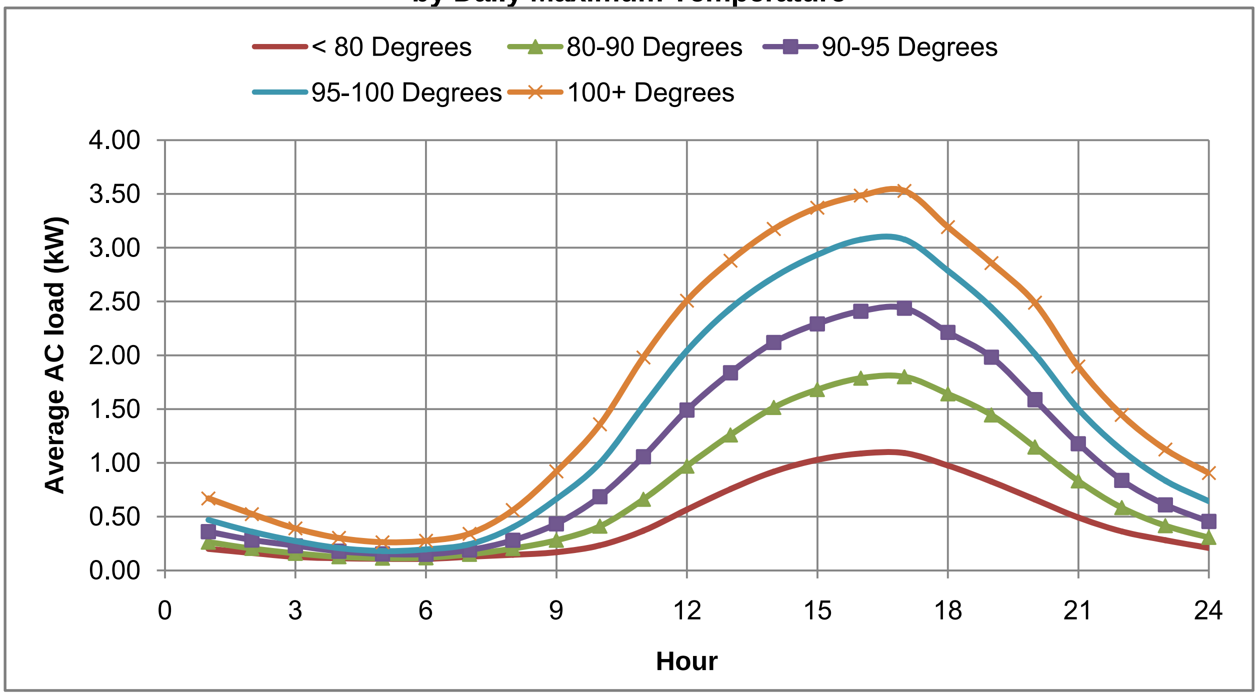
	Reference Energy Use (kW)	Observed Energy Use (kW)	Total Load Impact (kW)	% Daily Load Change	Cooling Degree Hours (Base 75)	Uncertainty Adjusted Impact - Percentiles				
						10th	30th	50th	70th	90th
Daily	27.74	28.59	-0.86	-3.1%	104.6	1.74	1.22	0.86	0.49	-0.03

Note: A positive value % Daily Load Change indicates the use of less energy for the day.
Note: Residential loads are whole-building loads

6.4. NON- RESIDENTIAL AIR CONDITIONER LOAD PATTERNS

Figure 6-6 also reflects the large load reduction potential among non-residential customers. In comparison to Figure 6-5, non-residential air conditioner loads are nearly twice as large per unit as residential air conditioners under similar weather conditions. This is partly due to different occupancy and air conditioner use patterns, and partly due to differences in the size of air conditioners. Moreover, non-residential customers are more likely to have multiple air conditioner units per site, leading to potential efficiencies in recruitment and installation.

Figure 6-6
Hourly Average AC Load for Non-Residential SmartAC Customers by Daily Maximum Temperature



6.5. NON-RESIDENTIAL SMARTAC LOAD IMPACT RESULTS

While in principle it should be possible to identify event impacts in non-residential customers using whole-building data, in this case, the sample is not large enough. The fundamental issue is signal versus noise. The residential whole-building sample contains 1,722 customers, while the non-residential whole-building sample contains 190 customers due to schedule of the smart meter roll out. The larger sample reduces the noise by smoothing out idiosyncrasies in load.[38] Also, the background whole-building load is smaller compared to AC load in the residential sample. In the residential sample, the peak event day reference load for the average customer is 2.18 kW. In the non-residential sample, it is 7.33—more than three times greater. Patterns in AC load (the signal) stand out much more among a smaller background reference load (the noise).

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[38] This is the same as saying that the standard error of the estimated reference load is smaller.

In the non-residential sample, event impacts do not stand out enough among random fluctuations in load for us to measure them accurately. This was true for the many regression specifications and several day-matching algorithms we tried.

The implication for evaluating the non-residential SmartAC program is that AC loggers should be used, or else sample sizes must be very large, to ensure accurate event impact measurements.

For reporting purposes, we have calculated ex post estimates using essentially the same method we used for ex ante estimates. We found the average per customer AC load in the original SmartAC Non-Residential M&E sample during the event period on September 10, 2009 and we applied percent impact values taken from the analysis done on the 2008 SmartAC Residential Sample.[39] The key difference was that for ex-post, actual, directly measured air conditioner load was available, while for ex-ante it had to be estimated. Impacts are applied as a percent of reference load based on temperature during the event and device type. The results for the average non-residential customer are shown in Table 6-4. Average per customer impact over the event period is 0.71 kW. Impact is higher in the first two hours of the event—around 0.8 kW—before falling off in the last two hours.

For the average non-residential customer, September 10th, 2009 was not an extremely hot event day. Weighted average temperature peaked below 96 degrees. As shown in Figure 6-6, there is substantial scope for higher AC loads (and hence higher impacts) among this group when temperatures get above 100 degrees. Weighted average reference load on September 10th peaked at 3.2 kW (which dovetails fairly well with the overall average reported in Figure 6-6). We can expect average reference loads roughly 10% higher when temperatures get above 100 degrees (and higher still if we isolate days above 105, for example).

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[39] See Non-Residential SmartAC Load Impact Analysis in FSC's Ex Ante Report for more detail on this method.

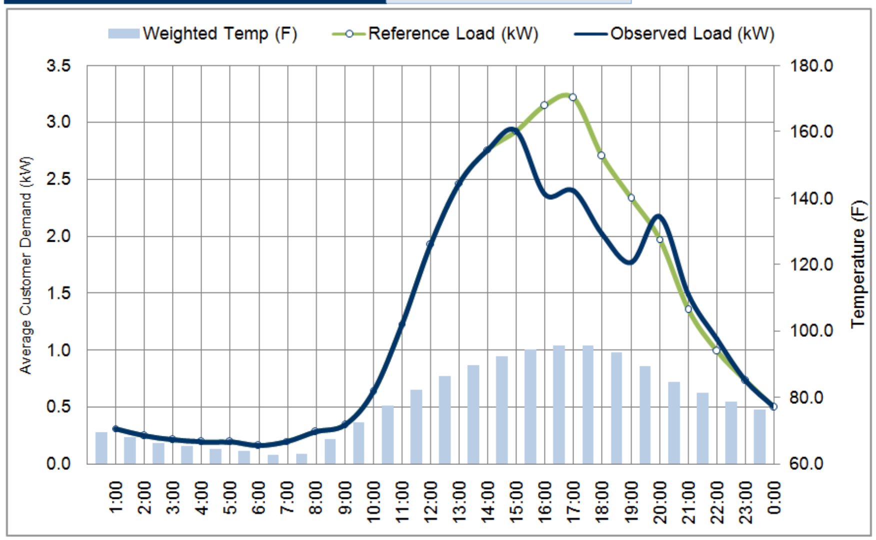
Table 6-4
Hourly Load Impacts for Non-residential SmartAC Customers
September 10, 2009

TABLE 1: Menu options

Type of Results	Average Customer
Customer Class	C&I
Device Type	All
Climate Region	All
Customer Type	All

TABLE 2: Event Day Information

Event Date	Tuesday, September 10, 2009
Event Start	3:00 PM
Event End	7:00 PM
TOTAL ENROLLED ACCOUNTS	1,001
Avg. Load Reduction for Event Window	0.71
% Load Reduction for Event Window	25%



Hour Ending	Reference Load (kW)	Observed Load (kW)	Load Impact (kW)	%Load Reduction	Weighted Temp (F)	Uncertainty Adjusted Impact - Percentiles				
						10th	30th	50th	70th	90th
1:00	0.31	0.31	0.00	0.0%	69.5	0.00	0.00	0.00	0.00	0.00
2:00	0.25	0.25	0.00	0.0%	68.1	0.00	0.00	0.00	0.00	0.00
3:00	0.21	0.21	0.00	0.0%	66.3	0.00	0.00	0.00	0.00	0.00
4:00	0.19	0.19	0.00	0.0%	65.3	0.00	0.00	0.00	0.00	0.00
5:00	0.19	0.19	0.00	0.0%	64.5	0.00	0.00	0.00	0.00	0.00
6:00	0.16	0.16	0.00	0.0%	63.9	0.00	0.00	0.00	0.00	0.00
7:00	0.20	0.20	0.00	0.0%	62.7	0.00	0.00	0.00	0.00	0.00
8:00	0.28	0.28	0.00	0.0%	62.9	0.00	0.00	0.00	0.00	0.00
9:00	0.34	0.34	0.00	0.0%	67.5	0.00	0.00	0.00	0.00	0.00
10:00	0.63	0.63	0.00	0.0%	72.4	0.00	0.00	0.00	0.00	0.00
11:00	1.23	1.23	0.00	0.0%	77.6	0.00	0.00	0.00	0.00	0.00
12:00	1.93	1.93	0.00	0.0%	82.4	0.00	0.00	0.00	0.00	0.00
13:00	2.47	2.47	0.00	0.0%	86.4	0.00	0.00	0.00	0.00	0.00
14:00	2.76	2.76	0.00	0.0%	89.6	0.00	0.00	0.00	0.00	0.00
15:00	2.93	2.93	0.00	0.0%	92.4	0.00	0.00	0.00	0.00	0.00
16:00	3.15	2.37	0.78	24.7%	94.3	0.39	0.62	0.78	0.94	1.17
17:00	3.21	2.40	0.81	25.3%	95.7	0.42	0.65	0.81	0.98	1.21
18:00	2.70	2.03	0.68	25.0%	95.7	0.28	0.51	0.68	0.84	1.07
19:00	2.33	1.77	0.56	24.1%	93.7	0.18	0.40	0.56	0.72	0.95
20:00	1.97	2.17	-0.20	-10.0%	89.5	-0.54	-0.34	-0.20	-0.06	0.15
21:00	1.35	1.49	-0.14	-10.0%	84.7	-0.41	-0.25	-0.14	-0.02	0.14
22:00	0.99	1.09	-0.10	-10.0%	81.5	-0.34	-0.20	-0.10	0.00	0.14
23:00	0.73	0.73	0.00	0.0%	78.7	0.00	0.00	0.00	0.00	0.00
0:00	0.50	0.50	0.00	0.0%	76.2	0.00	0.00	0.00	0.00	0.00
	Reference Energy Use	Observed Energy Use	Change in Energy Use	% Daily Load	Cooling Degree	Uncertainty Adjusted Impact - Percentiles				
						10th	30th	50th	70th	90th
Daily	31.03	28.63	2.40	7.7%	0.0	-0.03	1.40	2.40	3.39	4.83

Note: Non-residential loads are AC loads

Note: A positive value % Daily Load Change indicates the use of less energy for the day.