What Have We Learned from Evaluations of Residential Peak Time Rebate Programs in the U.S. over the Past Decade?

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ABSTRACT

A number of utilities in the U.S. have conducted and evaluated demand response experiments involving peak time rebate (PTR) programs, as well as dynamic pricing plans such as critical peak pricing (CPP) over the decade 2005 through 2014. Interest in these programs has grown along with expansion of smart metering installations, which provide the hourly interval usage data that is needed to bill customers accordingly. Activity was also boosted by federal "smart grid" funding following the financial crisis of 2007-08. This paper summarizes a meta-evaluation of the findings of at least eight of the major PTR impact evaluations available publicly. A fundamental finding from the study is that average event-period demand reductions average approximately 6.5 percent. However, there is considerable variability in estimated impacts, both across programs and across events within programs in cases where event-specific results are reported.

INTRODUCTION

Peak time rebate programs are often characterized as offering the *carrot* of a bill credit for a load reduction on a limited number of "event" days, in contrast to the *stick* of a high peak price for customers enrolled in a dynamic pricing plan such as critical peak pricing (CPP). Under PTR, when an event is called, the utility calculates a *customer baseline load* (CBL) for the event window (*e.g.*, 2:00 p.m. to 6:00 p.m.) for each enrolled customer, and compares their observed usage during that period to their baseline load. For any load reductions below the baseline level, customers receive a credit on their next bill, based on the program's incentive payment (*e.g.*, \$0.30 to \$1.75 per kWh).[1] The customer baseline load is typically defined as an average of the customer's usage over a certain number of days prior to the event during the event window (*e.g.*, the average of the previous 3 to 5 non-holiday, non-event weekdays, or the average of the highest three of the previous 5 to 10 weekdays).

PTR programs may differ according to factors such as the following:

- Number of hours in the *event window* (*e.g.*, four hours);
- The *starting hour* of events;
- The amount of *advance notice* that customers receive about when an event will occur (typically day-ahead or day-of notice);
- The *maximum number* of events that may be called (*e.g.*, 5 to 10 events, or more, per summer season);
- The type of *notification* provided by the utility to enrolled customers (*e.g.*, email, text, automated phone call, website announcement);

[1] For example, for a *baseline load* of 5 kWh over the event window, and *observed usage* of 3 kWh over the same period, the load reduction for which a bill credit would be paid would be 2 kWh. Some concerns have been expressed about the degree of accuracy of baseline load methods in representing what customers' loads would have been on event days had events not been called. Inaccurate baselines can lead some customers to receive credits for "phantom" load reductions that result from *over-stated* baseline loads, while others who made attempts to reduce load receive no credit because their baseline was *under-stated*.

- Whether *enabling technologies* such as programmable communicating thermostats (PCTs) are provided, and if so, whether the devices are controlled by the customer or the utility;
- The method used to calculate enrolled customers' baseline loads.

PTR programs may in principle also differ according to how customers are enrolled, such as whether they are *defaulted* into the program, or recruited to enroll (*i.e.*, opt in) so as to be eligible to receive incentive payments. Relatively few full-scale PTR programs (as compared to pilots or experiments) have been adopted, and most, if not all, are opt-in programs.

Previous and existing PTR programs, experiments and pilots

Impact evaluation studies have been conducted and reported for a number of PTR programs, including pilots, experiments, and full-scale programs. PTR programs conducted over the past decade, for which some description of analysis methods and findings are available, include those in the following list. Key features are summarized in the listing, and additional quantitative information is provided in Table 1.

- *Baltimore Gas and Electric* (Experimental program in 2008 and 2009, including CPP and PTR treatments; tested two PTR incentive levels; estimated customer demand model and associated elasticities of substitution; simulated load impacts; event-specific load reductions not reported)[2]
- *FirstEnergy – Ohio* (Three-year experiment, 2012-14 tested several PTR treatments, including PTR with PCTs controllable by either the customer or the utility; experimental design using a control group; customer-level fixed-effects analysis to estimate event-specific load impacts)[3]
- *Green Mountain Power* (Two-year experiment with a control group, 2012 -2013; customer-level fixed-effects analysis to estimate event-specific load impacts)
- *San Diego Gas & Electric* (Pilot in 2011, full-scale default in 2012 and 2013, opt-in in 2014; fixed-effects aggregate difference-in-differences analysis for variety of subgroups using matched control groups; we focus on results for the Inland region, which likely has AC penetration rates more similar to most utilities)
- *Southern California Edison* (Full-scale default in 2012 and 2013, opt-in in 2014; fixed-effects difference-in-differences analysis for variety of subgroups using matched control groups; we focus on the results for customers who do not have automated AC load control)
- *PEPCO-DC* (Two-year experiment in 2008-09; CPP, PTR, and hourly pricing treatments; customer-level fixed-effects analysis)[4]

[2] BG&E currently offers a full-scale PTR program; however, findings for that program have not yet been reported.
[3] Customer-level fixed-effects regression analysis is often used in an experimental setting that includes samples of both treatment and control groups. The analysis produces *difference-in-differences* estimates of program impacts. Hourly data for the program period, for both treatment and control customers, are pooled in the same regression, with separate "fixed-effects" variables included for each customer to control for customer-specific effects. The coefficient on an interactive variable that indicates that a particular day is an event day, and a particular customer is in the treatment group represents a difference-in-differences estimate of the *average load impact* for the treatment group; a separate *treatment* variable on non-event days controls for any differences in load between the control group and treatment group on non-event days.
[4] Pepco currently offers a permanent PTR program marketed jointly with an AC cycling program.

- *Connecticut Light and Power* (Experiment in 2009; TOU, CPP and PTR treatments; tested two PTR incentive levels; estimated customer demand model and associated elasticities of substitution; simulated load impacts; event-specific load reductions not reported)
- *City of Anaheim Public Utility* (California; 2005; PTR pilot)
- *Entergy New Orleans* (2011-12; Smart metering pilot; focus on low-income customers; included PCTs)[5]
- *Sacramento Municipal Utility District (SMUD)* (Experimental design; 2014-2015; includes utility-controlled PCT)[6]

Key features of the first eight of these programs, which are examined in detail below, are summarized in Table 1.

Table 1: Key Features of Most Relevant PTR Programs

Utility	Year	Treatment	Incentive ($/kWh-reduced)	# of Treated Customers	Design**	Event Window	Ref. Load (Avg. Peak kW)	% Load Impact
Baltimore G&E	2008	PTR-L	$1.16	126	RS+Opt-in	2 to 7pm	2.75	18%
	2008	PTR-H	$1.75	127				21%
	2009	PTR	$1.50	268				23%
FirstEnergy	2012	PTR + cust. cntrl PCT	$0.40	241	RS+Opt-in	2 to 6pm	2.85	8%
	2013		$0.40	233			2.66	4%
	2014		$0.40	243			2.46	0%
Green Mountain Power	2012	PTR	$0.60	350	RS+Opt-in	1 to 6pm	0.90	5%
	2013		$0.60	300			0.89	2%
San Diego G&E	2014	PTR (Inland climate)	$0.75	27,000	Opt-in	11am to 6pm	1.47	6%
So. Cal. Edison	2014	PTR (no AC control)	$0.75	300,000	Opt-in	2 to 6pm	1.68	4%
Pepco DC	2008 & 2009 Summer	PTR (incl. some PCTs)*	$0.76	300	RS+Opt-in	2 to 6pm	na	13%
	2008/'09 Winter	PTR (incl. some PCTs)	$0.36	300		6 to 8am & 6 to 8pm	na	5%
Connecticut L&P	2009	PTR-L	$0.78	108	RS+Opt-in	2 to 6pm	2.17	7%
	2009	PTR-H	$1.74	100				11%
Anaheim	2005	PTR	$0.35	71	RS&A	12 to 6pm	na	12%

* % load impact for no PCTs is 11%.

** RS+Opt-in -- Random selection to treatment cell from eligible target population; opt-in via recruitment
RS&A -- Random selection and assignment to treatment/control

Some notable features of the programs shown in the table include the following:

- All of the treatments (third column) involve basic PTR designs that for the most part do not include enabling technologies. The relevant treatment for FirstEnergy

[5] Study not included due to lack of information, presence of PCTs, and focus on low-income customers.
[6] Results of this program, which focuses on utility-controlled PCTs, are not currently available, pending acceptance of a report on the 2014 program.

included PCTs that were controllable by the customer.[7] The Pepco-DC experiment included some customers with PCTs; some findings for those without PCTs are reported separately. The results shown for SCE exclude PTR customers who are also enrolled in an AC direct load control program. The results for SDG&E are confined to customers residing in an Inland (as distinct from Coastal) climate zone, and who are not enrolled in AC load control.

- The incentive payments (fourth column) generally range from $0.35 to $0.75 per kWh-reduced; the two experiments that tested two alternative incentive levels had considerably higher incentives reaching $1.75.
- Most of the experiments had treatment sample sizes ranging from about 100 to 300 customers. As indicated in the sixth column, several were randomized control trials in which treatment customers were recruited (opt-in) from a pool of eligible customers who were randomly assigned to a particular PTR treatment cell, and control groups of comparable or larger sample sizes were also randomly selected. As described in a previous footnote, the SCE and SDG&E programs in 2014 were full-scale opt-in programs in which customers were required to enroll to receive electronic notification (email, text, or both) of events in order to be eligible to receive credits for load reductions.
- Event windows, shown in the next column, indicate that the most common window was the four hours ending at 6 p.m. A few programs had event windows that were an hour or two longer, with the longest window being SDG&E's seven hours.
- The next to last column indicates average customer size (where available), showing average hourly usage (kW) during the event window on non-event days. Note that the customers in a number of the programs were relatively small, with peak loads averaging approximately 2 kW or less.
- The final column shows overall average percentage load reductions. These are discussed in greater detail below.

OVERVIEW OF PTR PER-CUSTOMER LOAD REDUCTIONS

Given the range of customer sizes across utilities, it is helpful to employ a normalized measure of load reductions, such as *percentage* load reductions (relative to a reference load that represents the counterfactual load that would have occurred had events not been called), to compare results across utilities. This is the case in part because percentage load reductions are one of the findings most commonly used in reports to summarize program results, but also because it is generally a more consistent factor than, for example, reported *levels* of load reductions. These can vary considerably across utilities and regions due to differences in typical weather and customer load levels.

Figure 1 illustrates high-level findings from evaluations of the PTR programs listed above. The heights of the bars show estimated average *percentage peak load reductions* for a particular program or sub-program offered by the utilities listed along the horizontal axis. The vertical lines in the graph set off several pairs of estimates that reflect either alternative incentive payment amounts, or different program years. For example, the pairs of bars for BG&E and

[7] Other treatments not included in this review involved PCTs that were controllable by the utility, with different options such as the number of degrees that the thermostat would be adjusted.

CL&P indicate load reductions for the two incentive levels that were part of their respective experimental designs. In both cases, the reported load impacts are larger for the higher incentive levels.[8] The pairs of bars for FirstEnergy and GMP show separate results for the first two years of those experiments, with smaller percentage load impacts estimated for the second year in both cases.[9] The two bars for SDG&E show results for the last year (2012) of the default program (where the average load impact shown applies to those customers who requested event notification), and for the most recent year (2014) of the opt-in program.

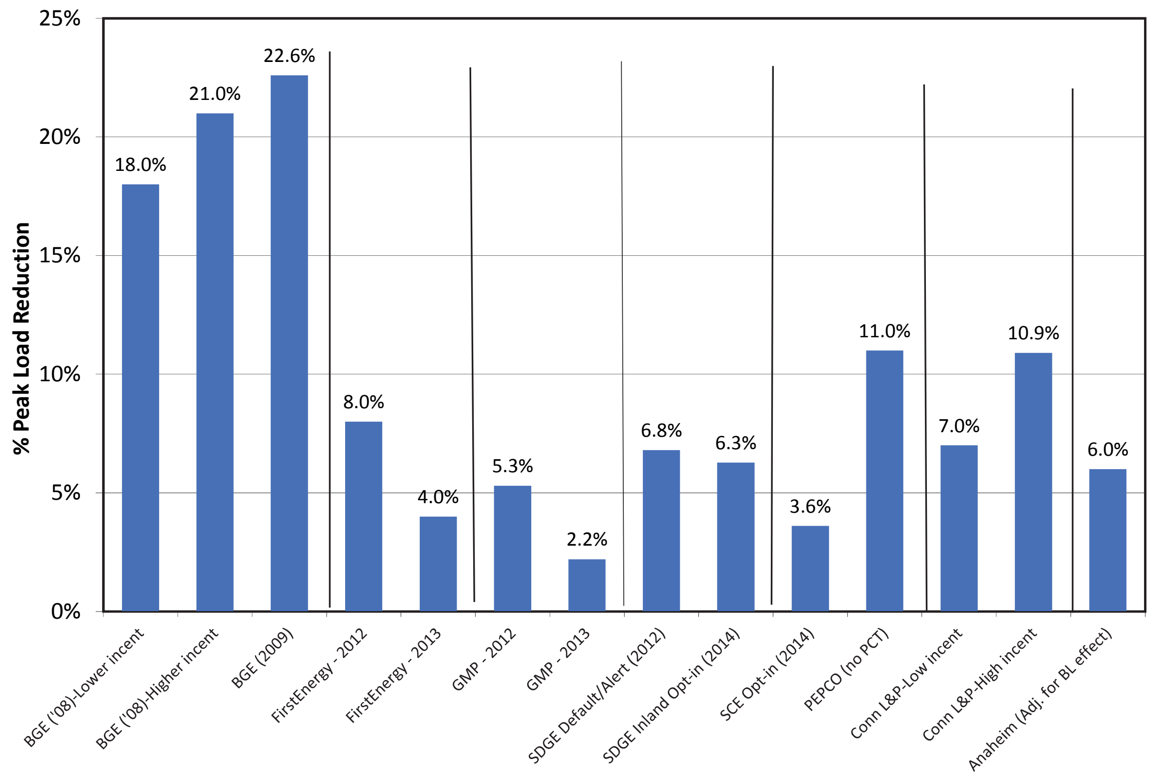

Figure 1: Estimated Percentage Peak Load Reductions in Recent PTR Studies

Aside from the first three bars for BG&E, estimated percentage peak load reductions across the other experiments/programs range from about 2 to 11 percent of the reference load that would have occurred in the absence of the programs, averaging about 6.5 percent.[10] Not shown are the results for programs or sub-programs that included enabling technologies such as PCTs, for which substantially larger peak load reductions are typically found.

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[8] Unlike the case for most evaluations, the load reductions reported in the BG&E and CP&L studies do not reflect direct estimates of load impacts for each event. Instead, they are based on simulations from a consumer demand model characterized by *elasticity of substitution* parameters that were estimated using the program data. The elasticities reflect consumers' load shifting between peak and off-peak periods at different incentive levels and weather conditions. The results shown in the figure represent average values simulated for the two incentive levels.

[9] In the case of FirstEnergy, analysis of a third year of the experiment found no statistically significant load reductions. It is not clear what factors may have led to the drop-off in estimated load reductions over the three years.

[10] The results shown for the City of Anaheim are adjusted based on evidence cited by the author of the study that the design of the program's baseline load calculation provided an incentive for participants to increase usage on a few days to artificially increase their baseline load, and thus their calculated load reductions.

Some other reasonably consistent high-level findings from studies of the PTR programs listed above, and shown in the figure include the following:

- The two programs that tested different incentive levels found that larger incentives produce larger load reductions (see Baltimore Gas and Electric and Connecticut Light & Power);[11]
- Load reductions can vary due to differences in weather conditions, however there is not always a clear relationship between *percentage* load reductions and hotter summer temperatures (see below);
- For some programs, there can be considerable variation in estimated load impacts *across events* (see below), which creates some uncertainty regarding expected load impacts for any given event;
- There is considerable variation in peak load reductions *across customers*, with a number of customers appearing to not reduce load in any significant amount, and some percentage of customers reducing by much greater than average amounts;[12]
- Customers with relatively larger loads tend to produce greater load reductions than customers with smaller loads, presumably due to the presence of more major appliances like central air conditioning, whose operation may be controlled relatively easily;
- Programs that include enabling technologies such as in-home displays and PCTs tend to produce percentage load reductions that are as much as twice the magnitude of programs that do not include these technologies; and programs in which the technologies are controlled by the utility, which make them similar to AC direct load control programs, produce the greatest load reductions.

Variability of load impacts across events

Some evaluations of PTR programs report estimated load impacts *for each event* during the analysis period, typically a summer season. Some also report the statistical significance of those estimates. This information is useful for assessing the uncertainty associated with projections of load impacts for future events. It can also be useful in examining the effect of weather on estimated load impacts. The following figures show estimated load reductions for each event and the average event, at the four utilities for which such information is available.

Figure 2 shows average event-period per-customer load impacts for each 2014 event and the average event for the Inland climate zone for SDG&E, along with the associated average temperature during the event. Percentage load reductions are reasonably consistent across events, ranging from nearly 6 percent (last four events) to 9 percent (first two events), with a weighted average of 6.3 percent.[13] Also, the magnitudes of the percentage load reductions are

[11] Our interpretation of these results (the methodology is the same on both studies) is that they may be an artifact of the methodology, since load impacts at different incentive levels were not directly estimated. Instead, an elasticity of substitution between peak and off-peak usage is estimated, which can be used to simulate changes in peak load reductions at different incentive levels. However, it is reasonable to suppose that there is some relationship between the level of demand response and the amount of the incentive.

[12] This finding is not often reported in studies of PTR load reductions, but the phenomenon has been examined in several evaluations, particularly those conducted for the major California utilities.

[13] The average load reduction across events is constructed by applying weights to the event-specific results, where the weights reflect the number of enrolled customers as of each event. Enrollment increased substantially from May (about 16,000) through September (about 27,000), so some of the differences in estimated load impacts between the May and September events may be due to changes in the composition of the enrolled customers.

approximately directly related to average event-period temperature (*i.e.*, larger percentage load impacts at higher temperatures).[14]

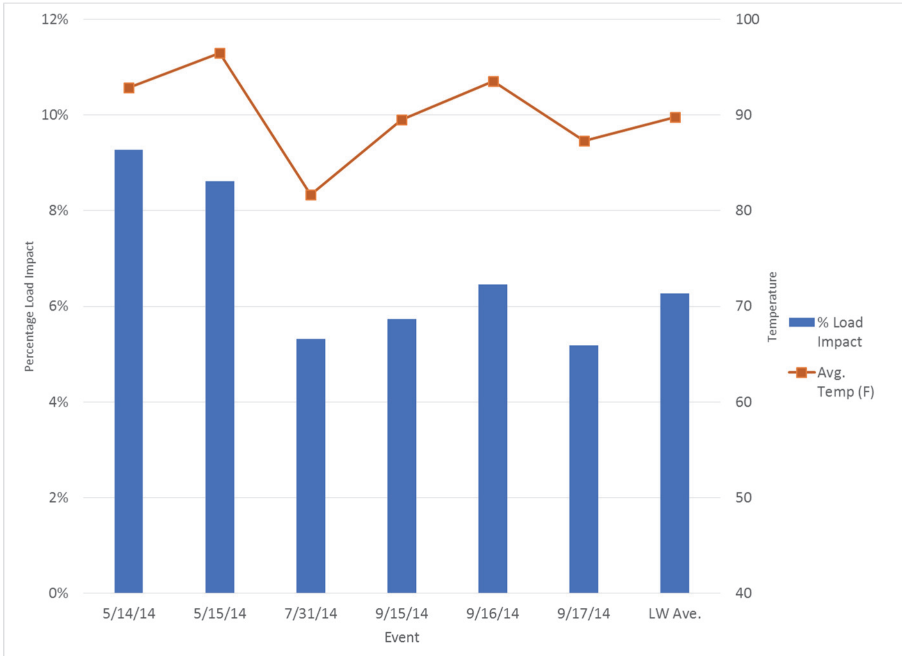

Figure 2: Percentage Peak Load Reductions and Temperature, by Event – *SDG&E (2014)*

Figure 3 provides similar information for SCE. Percentage load impacts range from 2 percent to 5 percent, averaging 3.6 percent. In this case, load reductions and temperature level appear somewhat inversely related. The evaluation report for SCE's PTR program included a more detailed analysis of the relationship between load reductions and weather conditions, using data for individual weather stations, and concluded that the load reductions were largely insensitive to temperature conditions.

Figure 4 shows percentage load impacts and temperature conditions by event for the two-year GMP program. Also shown are indications of the statistical significance of the event-specific estimates, as reported by the study's authors. As seen in the figure, only four of the fourteen events had estimates of load reductions that were statistically significantly different from zero (using a 90% confidence level). The variability of estimates across events is presumably due to factors other than temperature conditions. Of particular interest in the GMP results is five consecutive events called during July 2013 at very similar temperature conditions. No significant load reductions occurred on the first two events. Then the third event had the largest and most highly statistically significant load reduction of both program years, followed by smaller but still statistically significant reductions on the last two days of the week. It should be noted that the level of customer loads in the GMP study was the lowest among all of the

[14] It appears that the SDG&E analysis did not directly estimate load impacts for each event. Instead, it estimated load impacts as a function of weather conditions, and simulated load impacts for each event at the temperatures on the event day. This approach may contribute to the apparent relationship between temperature and size of load impacts.

programs studied. The apparently small number of end uses available for customers to adjust may contribute to the variability in the load reduction estimates and their statistical significance.

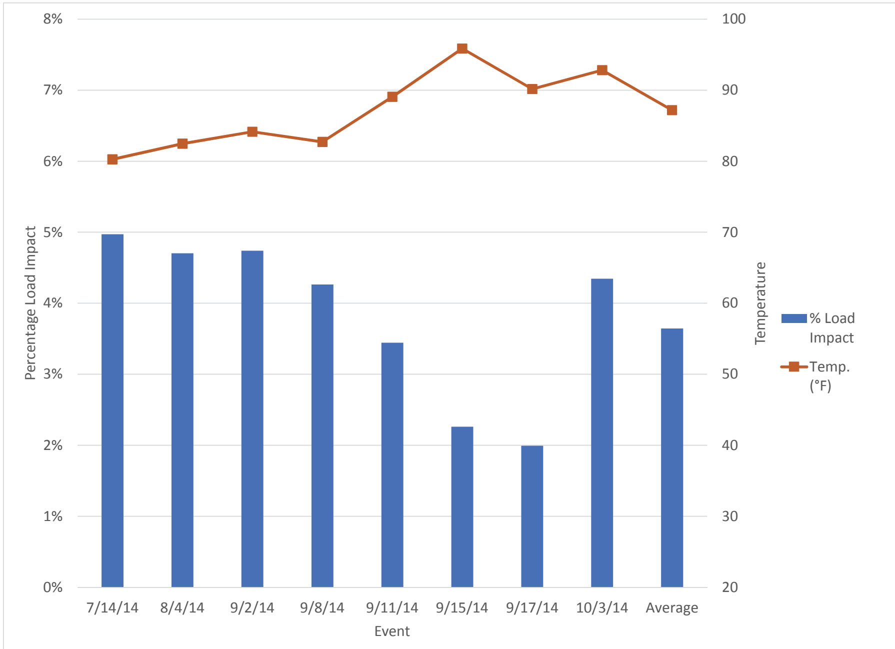

Figure 3: Percentage Peak Load Reductions and Temperature, by Event – *SCE (2014)*

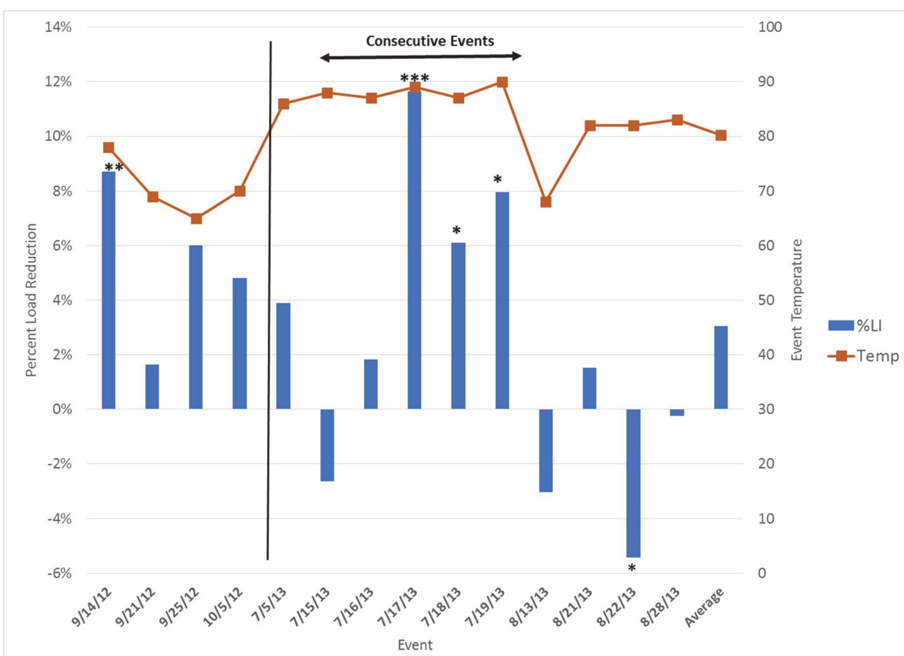

Figure 4: Percentage Peak Load Reductions and Temperature, by Event – *GMP*

Figure 5 shows percentage load reductions and temperature conditions for each event and the average event at FirstEnergy in 2012 and 2013, along with indications of the statistical significance of estimated load impacts for indicated numbers of event hours (shown in the figure's legend). Statistically significant load reductions were found in less than half of the events across the two years, and load impacts in 2013 were noticeably lower and more variable than in 2012. No definite relationship between temperature and size of load reductions is evident.

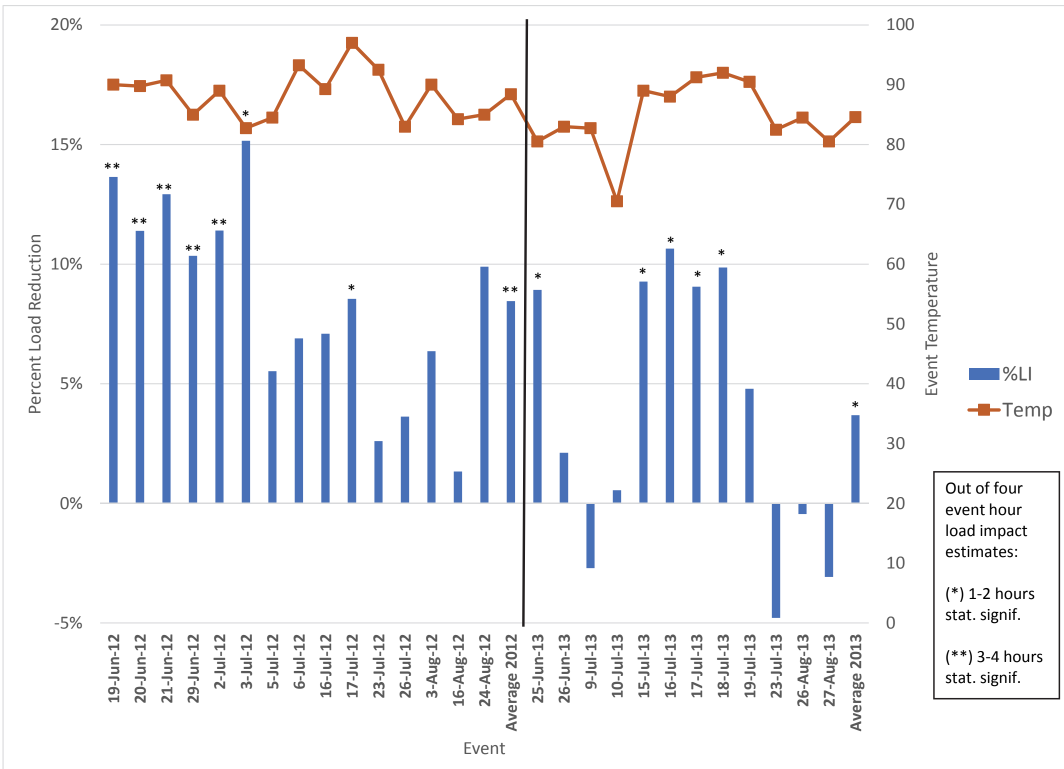

Figure 5: Percentage Peak Load Reductions and Temperature, by Event – *FirstEnergy*

Conclusions

With the exception of one of the programs reviewed in this paper (BG&E), reported percentage load reductions average approximately 6.5 percent, ranging from about 2 percent to 11 percent. The few programs that offered different incentive levels found somewhat greater load reductions at higher levels. The results for BG&E, which reported load reductions of around 20 percent, are outliers. It is possible that these findings are related to the method used, which was simulation using an elasticity-based demand model, rather than direct estimation of load reductions for specific events, as in most of the other studies.

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