Peak-Coincident Demand Savings from Residential Behavior-Based Programs: Evidence from PPL Electric's Behavior and Education Program

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ABSTRACT

This study reports on the effects of PPL Electric's behavior-based program on residential electricity use during the utility's system peak hours. Between June 2010 and May 2013, PPL Electric sent home energy reports to approximately 100,000 residential customers as part of a large field experiment. The reports encouraged customers to adopt energy-saving measures, many of which would also help to reduce the utility's system peak.

We collected hourly energy-use data between June and September 2012 for 20,000 residential customers. Panel regression analysis of 44 million hourly energy use records indicated that the average peak demand savings were about 0.07 average kW per home. The program reduced PPL Electric's system peak by about 6.5 MW.[1] The cost of demand savings was about $185/average kW. This compares to a national utility average cost of savings of $164/average kW from residential load management programs (EIA, 2012). The program also resulted in energy savings of 36 million kWh per year at an average cost of $0.07/ kWh.

The study findings show that residential behavior programs can help utilities manage their system peak loads. While PPL Electric's behavior-based program was slightly more expensive than traditional demand-response programs, more targeted messaging about reducing peak energy use may help such programs achieve cost parity.

Introduction

Increasingly, utilities in the United States are employing load-management strategies to reduce residential electricity use during system peak hours when the marginal cost of supplying electricity is high. Examples of these strategies include direct load-control and dynamic-pricing programs. Direct-load-control programs enable the utility to reduce customer loads through remote communication and control technologies installed on customer air conditioners and water heaters. Dynamic-pricing programs charge customers higher prices for electricity during system peak hours. Both types of programs are effective at reducing system peak loads (Allcott 2011; Wolak 2006; Faruqui & Sergici 2009; Newsham & Bowker 2010).

This paper discusses the effectiveness of another type of intervention to help electric utilities to manage system-peak loads: residential behavior-based programs. Applying insights from the behavioral social sciences, behavior-based programs encourage customers to reduce electricity consumption across a variety of end-uses.[2] Behavior-based programs have the potential to help utilities to manage peaks loads because they target electricity end-uses that significantly contribute to peak loads such as air conditioning.

1 The total peak load reduction from all of PPL Electric's demand-response and energy-efficiency programs was approximately 350 MW.

2 Many programs provide customers with feedback about their energy use, educate them about energy-efficiency opportunities, compare their energy use to that of their peers, provide them with rewards for conserving energy, or encourage them to participate in tournaments, competitions, and games. For an overview of behavior-based strategies, see Ignelzi, Lutzenhiser, & Peters 2013. For more information on how programs impact energy use, see Allcott 2011; and Agnew, Gaffney, & Rosenberg 2013.

In addition, they can reach thousands of customers, so that even a small reduction in average peak energy use at the individual home can translate into a large overall reduction in demand at the utility. Finally, behavior-based programs may help utilities reduce peak energy consumption of residential customers who may not be interested in participating in dynamic-pricing or direct-load-control programs.

PPL Electric's Behavior-Based Program

PPL Electric serves residential and nonresidential customers in several large metropolitan areas as well as in surrounding exurban and rural areas in Pennsylvania. The utility experiences peak loads in the summer, typically during warm afternoons and evenings when air conditioning loads are high. All of the utility's residential customers have smart meters installed that record energy use at hour intervals.

This utility's behavior-based program began in April 2010 when the program implementer, Opower, sent the first home energy reports to 50,000 of the utility's residential customers. All eligible customers had: (1) detached, single-family dwellings; (2) above-average energy use (at least 16,000 kWh/year), which indicated the home likely had electric heat and air conditioning; (3) a complete monthly billing history at the same address in the previous 12 months; and (4) a sufficient number of neighbors with similar characteristics.

In May 2011, PPL Electric expanded the program and sent home energy reports to an additional 55,000 residential customers. Customers in this group either had above-average energy use or had previously participated in one of PPL Electric's energy-efficiency programs. We refer to the original group of homes that received reports as the legacy group (LG) and the second group of homes to receive reports as the expansion group (EG).

PPL Electric customized each home energy report, which included three modules. The first module provided an analysis of the home's energy use during the previous 24 months and indicated how energy use in the current year compared to the previous year. The second module compared the home's energy use to approximately 100 similar neighbors. The third module provided action steps and custom tips for reducing energy use at each home. The action steps promoted PPL Electric programs, which included rebates on energy-efficient appliances such as clothes washers, refrigerators, and air conditioners. The tips targeted end-uses contributing to PPL Electric's system peak load.

PPL Electric implemented its behavior-based program as a randomized control trial, which greatly facilitated evaluation of the savings impacts. Opower identified homes eligible for the program and randomly assigned them to a treatment or control group. Homes in the treatment group received energy reports. Homes in the control group did not receive reports and were not informed about the study. The LG control group comprised 50,000 homes, and the EG control group comprised about 25,000 homes. Because homes were selected to receive home energy reports at random, receiving the treatment was uncorrelated with energy use, and any difference between treatment and control group homes in post-treatment energy use should have equaled the program's savings. We verified that the annual consumption in homes in the treatment and control groups during the 12 months before the program started was statistically indistinguishable, consistent with the random assignment of homes to the treatment.

While the study focused on estimating demand savings during system peak hours between June and September 2012, we also estimated the energy savings during the first and second years of the program. Between June 2011 and May 2012, the second program year, LG homes saved an average of 306 kWh/year or 0.035 kWh/hour. EG homes saved 317 kWh/year or 0.036 kWh/hour. The savings estimates were based on panel regression analysis of energy use in the 12 months before and either 12 or 24 months after Opower sent the first reports.[3]

3 The savings estimates were based on a panel regression analysis of monthly average daily consumption on homes' fixed effects, month-by-year fixed effects, and interactions between the month-by-year fixed effects, and an indicator for

Energy-Use Data

Data for this study came from PPL Electric's customer information and billing system as well as from Opower. PPL Electric provided energy-use data from AMI meters installed at residential customers' premises. PPL Electric also identified the 100 hours of highest system electric demand during the summer of 2012 (June – September) and supplied some customer demographics, socio-economics, and housing characteristics. Opower provided data about which homes received home energy reports and report frequency.

We randomly sampled 5,000 treatment group homes and 5,000 control group homes from each of the LG and EG populations for the demand savings analysis. The energy-use data covered 2,232 summer hours between June 15, 2012 and September 15, 2012.[4] Altogether, the data include over 44 million hourly energy-use records for 20,000 homes.

Random sampling of homes from the LG and EG populations had the potential to introduce sampling error in the savings estimates.[5] To minimize the potential for error, we used monthly electricity-use data to verify that the electricity use of sampled and non-sampled homes (as well as of sampled homes in the treatment and control groups) in the year before the program was balanced. Table 1 shows the tests of balance results for sampled homes.

Table 1. Tests of Balance Between Sampled Treatment and Control Homes

	Control Group	Treatment Group	N	p value
Legacy Group				
Pre-treatment annual adc (kWh)	51.7	51.9	9,994	0.610
Pre-treatment summer adc (kWh)	50.3	50.4	9,996	0.761
Expansion Group				
Pre-treatment annual adc (kWh)	61.9	62.0	9,993	0.869
Pre-treatment summer adc (kWh)	74.5	74.6	10,000	0.917

Note: adc is average daily consumption in kWh. p value is based on t-test of equality of mean consumption between treatment and control groups.

None of the differences between the homes in the treatment and control groups in the LG and EG samples were statistically significant. Balance between the groups is important because hourly energy-use data were not available for summer hours before the program started and the estimated program treatment effects were therefore based on simple differences rather than difference-in-differences of energy use. Any significant time-invariant differences in average energy use between homes in the treatment and control groups could have biased the demand savings estimates.

membership in the treatment group. Confidence intervals were estimated using Huber-White standard errors clustered on homes. (See PPL Electric 2012).

4 We are not aware of other papers that have estimated behavior program peak demand savings using hourly energy-use data. One study used daily energy-use data to estimate energy savings and savings persistence and durability from Opower's home energy reports program (Allcott & Rodgers 2012). Another study finds that homes reduce their energy use during afternoon and early evening peak energy-use hours in the week after receiving their utility bill (Gilbert & Graff Zivin, 2013).

5 Instead of analyzing energy use of all program homes before and after the start of the program, we sampled from the program population and collected data for summer months during the program. This minimized the burden on the utility, since it would not have to provide a large quantity of energy-use data.

Residential Energy Use During System Peak Hours

Pennsylvania's Act 129 defines peak hours as the top 100 hours of a utility's system demand during the summer (June – September) of 2012. In 2012, PPL Electric's top 100 hours occurred on 16 summer weekdays (three in June, nine in July, and four in August) when outdoor temperatures and air-conditioning loads were very high. Figure 1 shows the distribution of the utility's system peak hours across hours of the day and the average temperature for each hour.

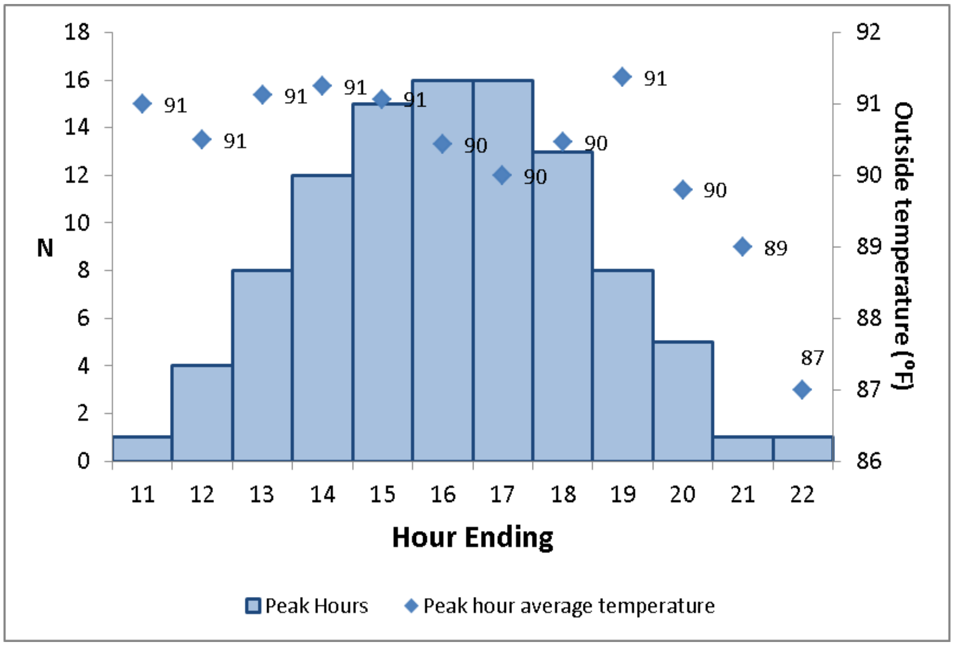


Figure 1. Distribution of Top 100 System Peak Hours

About 90% of peak hours occurred between 12:00 p.m. and 7:00 p.m. The average temperature during peak hours was about 90 degrees.

Figure 2 and Figure 3 show average electricity use for homes in the control group for both the LG and EG populations during summer weekday and weekend hours. For both LG and EG homes, energy use increased over the day, reaching a peak between 4:00 p.m. and 6:00 p.m., which coincides with a large number of PPL Electric's system peak hours. This increase in residential energy use over the day likely reflected the effect of higher afternoon temperatures and demand for air-conditioning. Energy use during the late afternoon and evening was higher on weekdays than weekends. Energy use between 8:00 a.m. and 4:00 p.m. was greater on weekends than weekdays, reflecting occupancy and weekday work schedule for most homes. Energy use between 6:00 a.m. and 8:00 a.m. was greater on weekdays than weekends, which again reflects normal workday patterns.

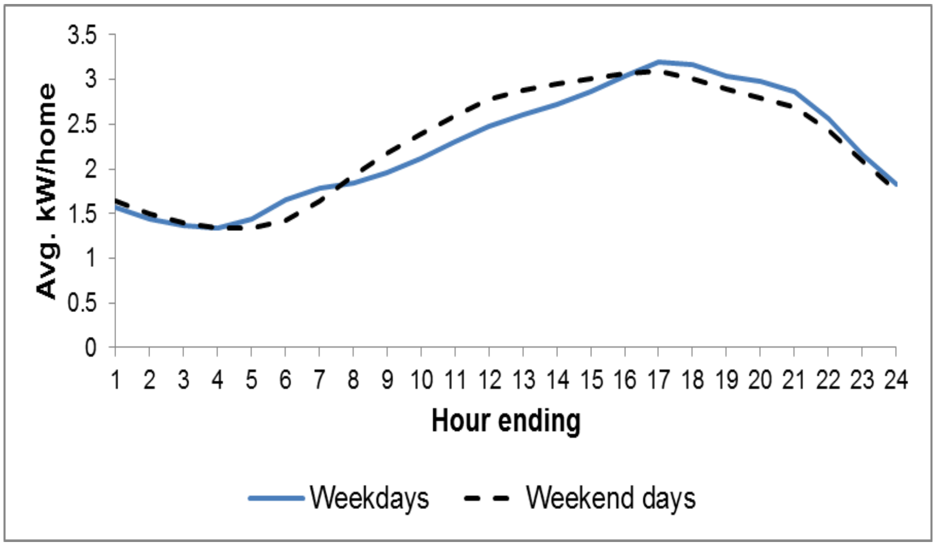


Figure 2. Legacy Group: Weekday Hourly Energy Use of Homes in Control Group

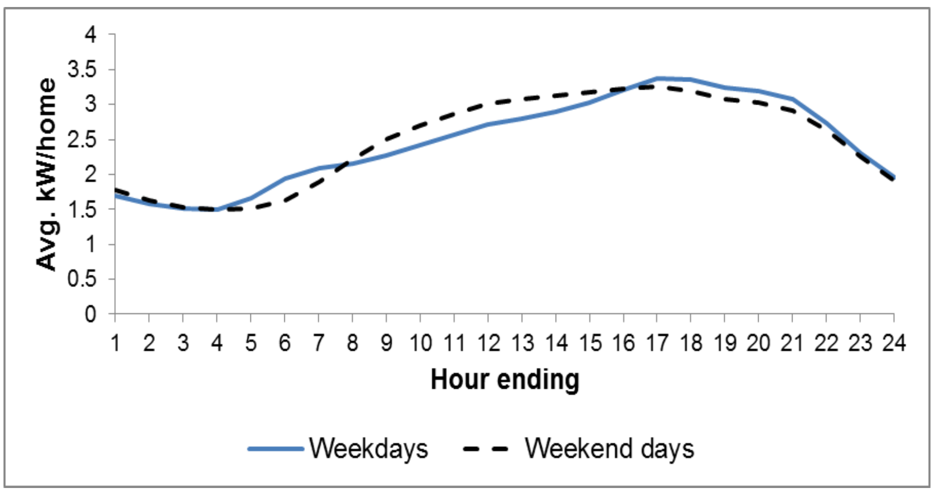


Figure 3. Expansion Group: Weekday Hourly Energy Use of Homes in Control Group

Peak-Coincident Demand Savings Estimates

We estimated the average treatment effect of the behavior program during the top 100 hours of PPL Electric system demand in 2012. Residential loads, particularly for air conditioning, were a significant contributor to the utility's peak load. As such, it is reasonable to assume that the behavior-based program, which encouraged more efficient use of air conditioning, may have resulted in significant demand savings.

We used the following panel regression of hourly energy use to estimate the average savings per treated home in the LG and EG populations during the top 100 hours of PPL Electric's system demand:

$$kWh_{it} = \beta_1 Top100(1)_{it}*Treat(1)_{it} + \beta_2(1\text{-}Top100(1)_{it})*Treat(1)_{it} + \tau_t + \varepsilon_{it}$$

Where each variable is:

kWh_{it} = energy use in kWh of home i during hour t
$Top100(1)_{it}$ = one if hour *t* was a peak hour in summer 2012 and equals zero, otherwise.
$Treat(1)_{it}$ = one if the home was in the behavior program treatment group and equals zero, otherwise.
τ_t = average energy use of homes in hour *t*. The regression includes hour fixed effects to control for differences between hours in average energy use.
ε_{it} = model error term.
β_1 = the average treatment effect of the behavior program on demand during system peak hours.
β_2 = the average treatment effect in all other hours.

The model includes hour fixed effects to control for positive correlation between electricity use and system peak hours caused by residential demand for air conditioning. Air conditioning of homes caused average electricity use to be high and contributed to system peaks. If this positive correlation were ignored, the savings estimates would be biased downward.[6] By including hour fixed effects or $Top100_t$, we were able to measure savings net of any difference in average energy use between peak and non-peak hours. This approach will control for all variables, not just those related to weather, that might be correlated with both residential energy use and system peak hours.

Also, because of the behavior-based program's experimental design, the treatment effects are net of other activities that may have reduced peak demand, such as participation in the utility's demand-response programs. In addition, the estimated treatment effect is an "intent to treat" because some homes were "non-compliers." They opted out of the program, or the householders who manage the use of electricity and pay the energy bills disregarded or failed to notice the reports. Therefore, the estimated treatment effects reflect the average effect of complying and non-complying homes on peak energy use. (However, phone surveys in 2012 of treated homes did indicate most householders recalled receiving the reports. Over 96% of survey respondents said they remembered receiving and at least glancing at one or more reports (95% confidence with ±3% precision).

We estimated separate models for homes in the LG and EG populations. The models were estimated by ordinary least squares (OLS), with Huber-White standard errors clustered on homes to account for correlation in each home's energy use across hours.

Table 2 shows the regression results. In both of the models, the interaction variables between the indicator for receiving the treatment and the indicators for peak and non-peak hours were negative and statistically significant—indicating savings occurred during these hours. The estimates of demand savings per home in both the legacy and expansion groups were statistically significant at the 1% and 10% levels, respectively. The R^2 show that these simple models can account for, respectively, 15 and 21% of the variation in hourly energy use.

6 Another way to control for this correlation is to include weather variables such as cooling degree hours as explanatory variables on the right side of the equation . A cooling degree hour (CDH) is the maximum of 0 and the difference between outside temperature and a base temperature, say, 65 degrees Fahrenheit. It is supposed to capture the effect of outside temperature on electricity demand for space cooling. A drawback of this approach, however, is the necessity to make functional form assumptions about the relationship between weather and energy use. Another drawback is that the approach would not control for correlation between ε_{it} and $Top100_t$ caused by other non-weather-related unobservable variables.

Table 2. Panel Regression Analysis of Hourly Energy Use

Hourly Energy Use per Hour	**Legacy**	**Expansion**
Top100(1)*Treat(1)	-0.0798** (0.0289)	-0.0609* (0.0366)
(1-Top100(1))*Treat(1)	-0.0512** (0.0169)	-0.0397* (0.0226)
Hour fixed effects	Yes	Yes
R^2	0.208	0.145
Number of homes	9,994	9,996
Number of observations	22,255,467	22,239,390

*Indicates statistical significance at the 10% level.
**Indicates statistical significance at the 1% level.
Notes: Dependent variable was hourly energy use. Models estimated by OLS. Standard errors are Huber-White clustered on homes.

Table 3 shows the average demand savings per home and the average demand savings for the program during system peak hours with 95% confidence intervals. We estimated the program peak savings by multiplying the per-home demand savings by the average number of homes in the population that received the treatment and had active billing accounts during system peak hours.[7]

Table 3. Estimated Peak-Coincident Behavior Program Demand Savings

Group	**Peak Demand Savings per Home (average kW)**	**90% Confidence Interval Lower Bound**	**90% Confidence Interval Upper Bound**	**Program Peak Demand Savings (average MW)**	**90% Confidence Interval Lower Bound**	**90% Confidence Interval Upper Bound**
Legacy	0.080	0.032	0.127	3.45	1.39	5.50
Expansion	0.061	0.001	0.121	3.02	0.04	6.00
Total	0.070	0.025	0.114	6.46	3.87	9.06

Notes: Demand savings were the average kW/home in top 100 hours of utility system demand in 2012. Cadmus based the savings estimates on panel regression of hourly energy use with standard errors clustered on homes (see Table 2).

For the legacy group, the behavior-based program average treatment effect reduced energy use by approximately 0.08 kWh/hour during system peak hours. For the expansion group, it reduced energy use by about 0.06 kWh/hour. These effects are equivalent to turning off one 60-watt or 80-watt light bulb or reducing the running time of a typical residential central air conditioner by six to eight minutes per hour. The peak demand savings were about 2.2% and 1.7%, respectively, of LG and EG control home peak hour energy use.[8]

7 A small number of residential customers (less than 2%) opted out of the program after receiving one or more home energy reports. Because they received at least one report, Cadmus considered them treated and included them in the energy-use analysis.

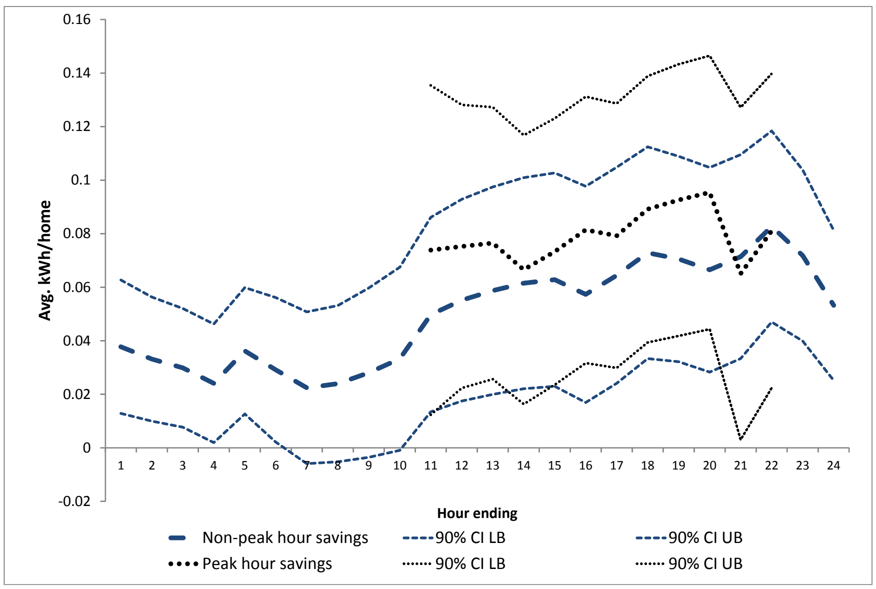
8 For homes in the control group, average demand during the top 100 hours was 3.60 kW for the legacy group and 3.65 kW

For treated homes, the total demand savings over the top 100 hours was about 3.5 MW for the legacy group and 3.0 MW for the expansion group.[9] The peak demand savings for the entire program was 6.5 MW, which was enough electricity to meet the peak demand of approximately 1,800 homes in the control group.

Comparison of Demand Savings in Peak and Non-Peak Hours

The average demand savings during system peak hours was between 0.06 and 0.08 kWh/hour per home. But what about savings in other summer hours? According to Table 2, the average demand savings during non-peak hours was about 0.05 kWh/hour per LG home and about 0.04 kWh/hour per EG home. Thus, demand savings were higher on average during system peak hours.

Figure 4 and Figure 5 provide additional data about demand savings during system peak hours, showing the average demand savings per home in the LG and EG populations during system peak and non-peak weekday hours.



Notes: Savings estimates for system peak hours based on panel regression of hourly energy use on indicators for hours between 10:00 a.m. and 10:00 p.m. and hour indicators and Treat(1). Savings estimates for non-peak hours based on panel regression of hourly energy use on 24 indicators for hours between 1:00 a.m. and 12:00 p.m., 24 interaction variables between the hour of the day variables and an indicator for the weekend, and 48 interaction variables between Treat(1), and the previous two sets of variable. Standard errors were clustered on homes.

Figure 4. Legacy Group: Average Demand Savings During Weekday Hours

In the LG (Figure 4), average demand savings during system peak and non-peak hours increased over the day, reaching a maximum in the late afternoon and early evening. In addition, average demand savings were greater during system peak than non-peak hours except for the hours between 8:00 p.m. and 10:00 p.m., when savings were approximately equal. These patterns suggest two findings: First, behavior program savings in LG homes were positively correlated with utility system

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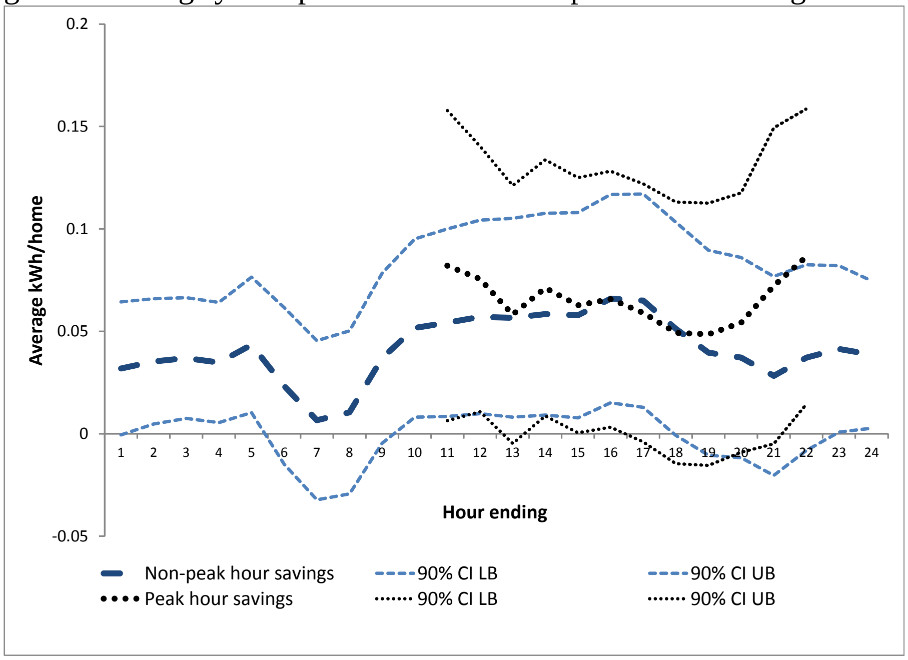
for the expansion group.

9 The number of treated homes with an active billing account during the top 100 hours was 43,208 for the legacy group and 49,510 for the expansion group.

demand. Second, electricity savings derived from air-conditioning efficiency measures. Electricity used for air conditioning would have increased during the afternoon and early evening and been greatest during system peak hours when temperatures were high.



Notes: See Figure 4 for description of estimation.

Figure 5. Expansion Group: Average Demand Savings During Weekday Hours

In contrast, in the EG (Figure 5), average demand savings did not increase over the day, remaining approximately constant (non-peak hours) or slightly decreasing (system peak hours) between 12:00 p.m. and 7:00 p.m. In addition, savings during system peak and non-peak hours were approximately equal. These patterns suggest that, in contrast to LG homes, there was little correlation between behavior program savings in EG homes and PPL Electric system peaks and that savings in EG homes were not correlated with temperature or hour of the day. The participation of many EG homes in PPL Electric efficiency programs before the start behavior program could explain this pattern. If EG homes previously installed measures that increased air-conditioning efficiency, their electricity use and savings would show less sensitivity to outside temperature.

Figure 4 and Figure 5 reveal some other interesting demand savings patterns. For homes in the legacy group, demand savings during weekday non-peak hours largely followed a pattern similar to that of energy use—increasing over the day and decreasing after 10:00 p.m. Homes in the expansion group displayed a different pattern. This group showed relatively flat savings during the middle of the day and significantly smaller savings between 6:00 a.m. and 9:00 a.m. and after 5:00 p.m. Homes in the LG also show a reduction in demand savings between 6:00 a.m. and 9:00 a.m. We will explore the causes of these energy savings patterns in another paper.

Cost of Demand Savings from Behavior-Based Programs

How much did peak demand savings from the behavior-based program cost PPL Electric? Table 4 shows the average cost per kW of peak-coincident savings for homes in the LG and EG. For these calculations, Cadmus assumed the utility's cost of the behavior-based program between June 2010 and

May 2012 was $13.50 per treated home per year.[10] The main objective of the behavior-based program was to yield energy savings, which benefit PPL Electric customers and count toward the utility's electricity savings goals mandated by Pennsylvania's Act 129. Demand savings were a secondary objective. As such, a high cost per kW does not imply that the program was not cost-effective, nor does it imply it is more costly than other types of demand-reduction programs (such as direct load-control programs). In fact, the behavior-based program proved to be highly cost-effective from the perspective of total resource cost in each evaluation year (PPL Electric, 51).

Table 4. PPL Electric's Behavior-Based Program Demand Savings Cost

	Cost per kW of savings	**90% Confidence Interval Lower Bound**	**90% Confidence Interval Upper Bound**
Legacy	$169	$106	$419
Expansion	$221	$111	$18,443
Average	$185	$125	$429

Notes: Cost per kW based on regression estimate of average demand reduction during peak hours.

In 2012, the cost of the demand savings from the behavior-based program was about $169/kW in the LG ((1/0.061)*$13.50) and $221/kW in the EG ((1/0.080)*$13.50). Overall, the weighted average cost of peak demand savings was about $185/kW. However, the 90% confidence intervals are wide and reflect uncertainty about the true demand savings (see Table 3). The higher cost of savings for homes in the expansion group reflects the fact that they had smaller peak-coincident savings in 2012.

Comparison to Utility Demand Response Programs

How do the savings from the behavior-based program compare to those of other residential demand-response programs?[11] Most residential demand response programs fall into one of two categories: dynamic pricing or direct load control. Dynamic-pricing programs charge customers time-varying prices, typically a higher price for electricity during peak times and a lower one during non-peak times. The programs include real-time pricing, critical peak pricing (CPP), and time-of-use pricing. Many studies have shown that these programs substantially reduce residential demand during system peak hours (Allcott 2011; Faruqui & Sergici 2009; Wolak 2007). Studies also show that savings increase when participants have access to control technologies such as programmable thermostats or in-home displays (Faruqui & Sergici 2009). Average savings from CPP often range between 30 and 40% of peak loads (Faruqui & Sergici 2009; Bowker & Newsham 2010).

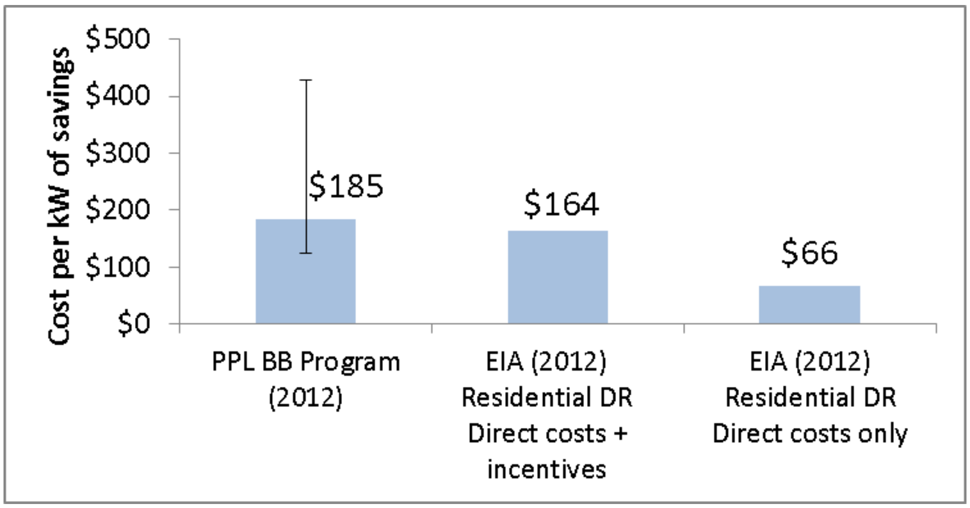
Direct load-control programs enable a utility to control customer air-conditioning and water-heating loads during peak hours. Demand savings from residential air conditioning direct load-control (AC-DLC) programs range from 0.5 kW to 1.2 kW per home depending on: (1) the cycling or thermostat control strategy, (2) the time of day when events are called, (3) outside temperature, and (4) underlying air-conditioning use (Newsham and Bowker 2010). Demand savings from water heating direct load-control (WH-DLC) programs typically range from 0.3 kW per home to 0.7 kW per home and depend on a similar set of factors.

10 This calculation assumes the program implementer sent reports to 50,000 homes in the LG for two years and 55,000 homes in the EG for one year. (PPL Electric, 51)

11 Another important difference is the ability of the utility to call on many demand-response resources as needed. In contrast, most behavior-based programs cannot be called upon to produce peak demand savings on an as-needed basis.

Peak demand savings from PPL Electric's behavior-based program was about 2% or 0.06 kWh/hour to 0.08 kWh/hour per home. This is approximately 5% to 6.5% of the expected demand savings per home for a typical CPP program, 5% to 10% of savings per home for a typical AC-DLC program, and 10% to 25% of savings per home for a typical WH-DLC program. In other words, the utility would need to deliver home energy reports to 15 to 20 homes for every home on a CPP rate, 10 to 20 homes for every home in an AC-DLC program, and four to 10 homes for every home in a typical WH-DLC program. In 2012, the savings from sending energy reports to 9 PPL Electric homes were approximately equal to the average savings per home achieved by the utility's residential air-conditioning direct load control program (0.62 kW/home).

How does PPL Electric's average cost of demand savings of $185/kW from the behavior-based program compare to the average cost of savings for utility residential demand response programs in the United States? Figure 6 compares the behavior program's savings cost with the average cost of savings for residential demand response programs. It should be kept in mind that this comparison ignores energy savings, which are the primary benefit of the behavior-based program.



Source: Author's calculation and utility-reported data from EIA Form 861 (2012).

Figure 6. kW Savings Cost Comparison

According to U.S. Department of Energy's Energy Information Administration, in 2012, utilities in the United States paid an average of $164 in direct costs and customer incentives per kW of peak savings from residential demand response programs.[12] Thus, the cost of acquiring peak demand savings through PPL Electric's behavior-based program was about 112% of U.S. utilities' average cost. To achieve cost parity with the average demand-response program, PPL Electric's behavior-based program would have needed to generate peak-coincident demand savings of approximately 0.08 kW per home. If customer incentives, transfers from utilities to participants, are excluded, PPL Electric paid 280% of the utility average cost of demand savings from residential load management programs. Thus, from a societal resource perspective, kW savings from the behavior-based program were significantly more expensive than those from load management programs.

12 We obtained 2012 cost and kW savings from EIA Demand Side Management Program data available at http://www.eia.gov/electricity/data/eia861/. We collected data on load management program actual peak reductions (MW) and load management annual direct costs and incentives in the residential sector for U.S. utilities in 2012.

Conclusions

PPL Electric's behavior-based program resulted in system peak-coincident demand savings of approximately 0.07 average kW per home, or about 6.5 average MW overall. The average cost of savings was approximately $185/kW. Although PPL Electric's behavior-based program cost slightly more than other types of utility residential demand-response programs, the difference in cost per kW of savings was not particularly large and the program produces energy savings that other types of demand-response programs do not. If messaging is focused on achieving demand savings, behavior-based programs may be able to reach cost parity with some direct load-control and dynamic-pricing programs. Another key consideration when assessing the cost-effectiveness of PPL Electric's behavior-based program is that it may have motivated customers to reduce energy consumption who may not have participated in the utility's demand-response programs.

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